



Using artificial intelligence to combat hydro-meteorological hazards in Africa

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Dissertation accepted in fulfilment of the requirements for the degree *Master of Science in Environmental Sciences with Disaster Risk Sciences* at the North-West University

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Graduation: July 2025

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DEDICATION

To my late grandfather, Johan Redelinghuys, for being one of the most driven people I have ever known.

PREFACE

In recent years climate change has exemplified the effects of hydrometeorological hazards in Africa. With extreme vulnerability to hazards, most of Africa has difficulty in growth and development. With the constant rise in various 4.0 technologies, it has shown to be an efficient means for facilitating disaster risk reduction (DRR). The use of artificial intelligence (AI) for combatting hydrometeorological hazards in Africa presents innovative solutions to the region's most pressing DRR challenges. With Africa's lack in access to digital environments, much of its AI efforts and developments are left without record.

Therefore, this study aims to document AI projects involved in hydrometeorological hazard reduction and explore the complexity associated with various digital interventions in Africa. The purpose is to identify the formation of an African 'AI ecosystem' reducing hydrometeorological hazards. Through using the lens of complex adaptive systems (CAS) theory, hydrometeorological hazard specific projects are identified and documented. These projects are selected with particular focus on their uses in various African countries and the involvement of autonomous agents in their execution. The data is graphed to resemble a co-occurring network of interconnected agents.

This network resembles an ecosystem of complex connections, which are fuelled by various AI projects. Documenting these projects aids in adding to the body of scientific knowledge, accountability of agents, observational research, and understanding CAS in African DRR. It is therefore integral to build a body of knowledge on subjects such as AI in Africa and how it is being used to facilitate development. Through looking at the fundamentals of CAS theory, the study formulates a framework whereby the research is conducted.

CAS characteristics are extensively discussed to establish a theoretical lens through which the research is conducted. Secondly, the research concepts of AI, DRR, and hydrometeorological hazards are conceptualized. This is to familiarize the reader with the theoretical framework of the study and the complexity associated with its investigation. Third, the study looks at the use of AI in general hydrometeorological hazard reduction. Which is done to establish trends and popular uses for AI in DRR. Fourth, AI is explored for its general uses in Africa. It considers the potential uses of AI in various governmental sectors namely agriculture, economics, finances, healthcare, transportation, and education.

Furthermore, it considers the vast international involvement in AI implementation and identifies autonomous agents. Fifth, various AI projects reducing hydrometeorological hazards in Africa are

systemically explored. These projects are discussed according to function, agent involvement, and African country of use. This creates a small database wherefrom qualitative pattern analysis can be applied and coded. Lastly, the project data is coded into a network graph for illustrating the complexity associated with AI for reducing hydrometeorological hazards in Africa. It shows the non-linear nature of relationships between autonomous agents and African countries, connected by various AI projects.

The research concludes that AI for reducing hydrometeorological hazards in Africa is a dynamic and complex phenomenon. Consisting of a multitude of autonomous agents and African countries set on creating sustainable growth and environments. Due to the extreme complexity of AI for reducing hydrometeorological hazards in Africa, more research is needed to properly document the development of disruptive technology and to ensure extensive accountability is set in place.

ACKNOWLEDGEMENTS

First, I would like to thank my Godly father for giving me opportunities, strength and the drive to carry on. I would like to sincerely show my immense gratitude to my mother, Monia Naude, for always supporting me in my dreams (no matter how long they may take) and for being an inspiration for hard work and dedication. To my grandmother, Isabella Redelinghuys, for emotionally supporting me whenever I felt hopeless. To my father, Johann Grobler, for being a positive light and spiritual guide. To my supervisor, Prof. Dewald van Niekerk, for having patience with me and allowing me to determine my own academic journey and growth. And to the love of my life, Jacobus Johannes Lubbe, thank you for being a pillar of support and motivation.

ABSTRACT

The rise of hydrometeorological hazards in Africa has caused developmental devastation to the region. This devastation has led to a desperate call for intervention which has involved the likes of artificial intelligence (AI) and other 4.0 technologies. Although AI is a sought-after solution to these hazards, its implementation brings with it many complexities. The likes of which lack research and documentation. Existing research has explored the general use of AI in Africa; however, it neglects stressing hazard specific applications and their ecosystemic complexity. This research aims to explore and present the complexities of AI for reducing hydrometeorological hazards in Africa. It evaluates qualitative data through using a systemic literature review and formulates a network graph using ATLAS.ti²⁴. The results indicate an inherent mismatch between systemic interactions and the potential output of the phenomenon. For instance, the prominent disparities between the abundance of AI projects and the actual disaster risk reduction results in Africa. Furthermore, the results indicate an increased difficulty in complete comprehension of the system with a persistent gap in fully grasping the impact of AI projects on African hydrometeorological hazards. Consequently, AI for reducing hydrometeorological hazards in Africa is considered a complex adaptive system in need of further research and investigation.

Key terms

Complex Adaptive Systems (CAS) theory; Artificial Intelligence (AI); Machine Learning (ML); 'smart' technology; Disaster Risk Reduction (DRR); Africa; hydrometeorological hazards; water management; Land Use and Land Cover (LULC); floods; drought; landslides; wildfires; cyclones; climate change adaptation (CCA).

LIST OF ABBREVIATIONS

ACA	Ant-Colony Algorithm
ACET	African Centre for Economic Transformation
ACP	African Caribbean Pacific
AdaBoost	Adaptive Boosting
AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
AI4D	Artificial Intelligence 4 Development
AI4PEP	Artificial Intelligence for Pandemic, Epidemic, Preparedness and Response
AIFA	Artificial Intelligence for Africa
ANFIS	Adaptive Neuro-Fuzzy Interface System
ANN	Artificial Neural Networks
ANP	Artificial Neural Process
ANPR	National Agency for Scientific Research Promotion
APET	African Union High Level Panel on Emerging Technologies
API	Application Programming Interface
AR	Auto-Regression
ARC	African Risk Capacity
ARIMA	Autoregressive Integrated Moving Average
AU	African Union
AUC	Area Under Curve

AUDA	African Union Development Agency
AV	Automated Vehicle
BLR	Binomial Logistic Regression
BNB	Bayesian Negative Binomial
BRT	Boosted Regression Trees
CA	Cellular Automata
CAIR	Centre for Artificial Intelligence Research
CA-Markov	Cellular Automata - Markov
CART	Classification and Regression Trees
CAS	Complex Adaptive Systems
CAWESDEA	Building Capacity in Water Engineering for Addressing Sustainable Development Goals in East Africa
CCA	Climate Change Adaptation
CGA	Centre for Geographical Analysis
CGIAR	Consultative Group for International Agricultural Research
CHAI	Clinton Health Access Initiative
CITADEL	Interdisciplinary Centre of Excellence in AI for Development
CNN	Convolutional Neural Networks
CSI	Committee on Spatial Information
CSIR	Counsel for Scientific and Industrial Research
CSTD	Commission on Science and Technology for Development
DA4TI	Digital Agenda for Tanzania Initiative
DAIRU	Defence Artificial Intelligence Research Unit

DEA	Development of Environmental Affairs
DES	Dynamic Ensemble Selection
DHASA	Digital Humanities Association of Southern Africa
DL	Deep Learning
DMCsim	Disaster Management Coordination Simulation
DNN	Deep Neural Networks
DR	Disaster Risk
DRIP	Detecting Real-Time Increased Precipitation
DRL	Deep Reinforcement Learning
DRR	Disaster Risk Reduction
DRM	Disaster Risk Management
DTR	Decision Tree Regression
DTSI	Directorate of Science, Technology, and Innovation
EEMD	Ensemble Empirical Mode Decomposition
EIA	The Ethical Impact Assessment
EKRT	Electro-Kinetic Remediation Technology
ELM	Extreme Learning Machine
EOD	Earth Observational Data
ETC	Extra Trees Classification
ETS	Educational Testing Services
EU	European Union
FICUDC	Flemish Interuniversity Council for University Development Cooperation

Fuzzy-AHP	Fuzzy Analytical Hierarchy Process
FAO	Food and Agriculture Organization
FARA	The Forum for Agricultural Research in Africa
FCNN	Fully Convolutional Neural Network
FEMA	Federal Emergency Management Agency
FFNN	Feed Forward Neural Networks
FL	Fuzzy Logic
FR	Frequency Ratio
GA	Genetic Algorithm
GAIR	Global Artificial Intelligence Readiness Index
GARID	The Greater Accra Resilient and Integrated Development
GBC	Gradient Boosting Classifier
GED	Gaussian Error Distribution
GEE	Google Earth Engine
GENOFIS	Geno Fuzzy Interface System
GEP	Gene Expression Programming
GFDRR	Global Facility for Disaster Reduction and Recovery
GIP	Geneva International Platform
GIS	Geographic Information System
GIZ	German Agency for International Cooperation
GMDH	Group Method of Data Handling
GNSS-R	Global Navigation Satellite System Reflectometry

GRACE	Gravity Recovery and Climate Experiment
GRU	Gated Recurrent Units
GSMA	Global System for Mobile Communications Association
GTB	Gradient Tree Boost
HC	Hierarchal Clustering
HM	Hydrological Model
HOTOSM	Humanitarian Open Street Maps
IBM	International Business Machines
IBTrACS	International Best Track Archive for Climate Stewardship
IC	Image Classification
ICJRI	Interregional Crime and Justice Research Institute
ICT	Information and Communication Technology
ICUN	International Union for Conservation of Nature
IDRC	International Development Research Centre
IFRC	International Federation of Red Cross
IIPGH	Institute of ICT Professionals Ghana
ILO	International Labour Organization
IM	Inundation Model
INFORM	Index for Risk Management
INNOVUS	University Industry Interaction and Innovation Company
IoT	Internet of Things
ISG	Intelligent Systems Group

ITIKI	The Information Technology and Indigenous Knowledge with Intelligence
ITU	The International Telecommunications Union
IWMI	International Water Management Institute
KNN	K-Nearest Neighbour
KNOW DRR	Know Disaster Risk Reduction
LEGEMP	Linear Support Vector Regressive Gradient Descent Jaccardized Deep Multilayer Perceptive Classifier
LightGBM	Light Gradient Boosting Machine
LMT	Logistic Model Tree
LR	Logistic Regression
LST	Land Surface Temperature
LSTM	Long Short-Term Memory
LULC	Land Use and Land Cover
MADIS	Multimedia-Aided Disaster Information Integration System
MCDM	Multi-Criteria Decision-Making
MDA	Multivariate Discriminant Analysis
MDT	Multiple Decision Trees
ME	Maximum Entropy
MENA	Middle East and North Africa
MIIAfrica	Machine Intelligence Institute of Africa
MINICT	Ministry of Information and Communication Technology and Innovation
ML	Machine Learning

MLC	Maximum Likelihood Classification
MLP	Multi-Layer Perceptron
MLPNN	Multi-Layer Perceptron Neural Network
MLR	Multi Linear Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
MR-CNN	Mask region-convolutional neural network
MVRE	Mobilisation et Valorisation des Ressources en Eau (Mobilisation and Enhancement of Water Resources)
NASA	National Aeronautics and Space Administration
NB	Naïve Bayes
NBT	Naïve Bayes Trees
NCC	Nigerian Communications Commission
NCSTDG	National Council for Scientific and Technological Development Grant
NDMC	National Drought Mitigation Centre
NDRR	National Disaster Risk Reduction
NDVI	Normalised Difference Vegetation Index
NEPAD	New Partnership for Africa's Development
NFIP	National Flood Insurance Program
NGBoost	Natural Gradient Boosting
NGOs	Non-Governmental Organisations
NITA	National Information Technology Agency
NLP	Natural Language Processing
NMAIST	Nelson Mandela African Institution of Science and Technology

NN	Neural Networks
NOAA	National Oceanic and Atmospheric Administration
NORHED	Norwegian programme for Capacity Building in Higher Education and Research for Development
NRW	Non-Revenue Water
NSTSP	National Science and Technology Support Projects
OBIA	Object Based Image Analysis
OFA	One For All
OFE	Optical Flow Estimator
PCA	Principal Component Analysis
PRAISys	Probabilistic Resilience Assessment of Interdependent Systems
PQk-means	Product Quantized k-means
RAI	Responsible Artificial Intelligence
RAM	The Readiness Assessment Methodology
R&D	Research and Development
RF	Random Forest
RL	Reinforcement Learning
RN	Residual Networks
RNN	Recurrent Neural Network
RS	Remote Sensing
RSM	Response Surface Methodology
RTs	Regression Trees

RT	Random Tree
SA	Sentiment Analysis
SANBI	South African National Biodiversity Institute
SAS	Statistical Analysis System
SDGs	Sustainable Developmental Goals
SFDRR	Sendai Framework for Disaster Risk Reduction
SHIPS	Statistical Hurricane Intensity Prediction Scheme
SIDA	The Swedish International Development Cooperation Agency
SLIP	Sudden Landslide Identification Product
SOI	Southern Oscillation Index
SPI	Standardised Precipitation Index
ST	Stacking
STEDPEA	Strengthening Disaster Prevention approaches in Eastern Africa
SVM	Support Vector Machine
SVR	Support Vector Regression
SWAT	Soil and Water Assessment Tool
TCP-NGBoost	Tropical Cyclone Probabilistic Natural Gradient Boosting
TEIMUN	The European International Model United Nations
TRT	Turkish Radio and Television Corporation
UHI	Urban Heat Island
UN	United Nations
UNCEF	United Nations Children's Fund

UNCTAD	United Nations Committee of Trade and Development
UNDP	United Nations Development Programme
UNDRR	United Nations Office for Disaster Risk Reduction
UNEP	United Nations Environment Programme
UNESCO	United Nations Educational, Scientific and Cultural Organization
UNICEF	United Nations International Children's Emergency Fund
UNISDR	United Nations International Strategy for Disaster Reduction
UNITAR	United Nations Institute for Training and Research
UNOSAT	United Nations Satellite Centre
UN-SPIDER	United Nations Space-based Information for Disaster Management and Emergency Response
UNU	United Nations University
URIDA	The Unit for Research on Informatics for Droughts in Africa
USA	United States of America
USAID	United States Agency for International Development
VAR	Vector Auto Regressive
WA	Wavelet Analysis
WADiRE-Africa	Water Disaster Platform to Enhance Climate Resilience in Africa
WASCAL	West-African Science Service Centre for Climate Change and Adapted Land Use
WBG	World Bank Group
WFP	World Food Programme

WIMEA-ICT	Weather Information Management in East Africa- Information and Communication Technology
WUN	Water Utility Network
XBD	External Benchmarking Device
XGBoost	Extreme Gradient Boosting

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CHAPTER 1 INTRODUCTION

The fourth industrial revolution is upon us. Schwab (2023) describes it as intelligent machines managing and enabling human life in online and offline reality. A front runner in this revolution is a branch of computer science known as artificial intelligence (AI). With its focus on the deployment and development of intelligent systems (Ojokoh, *et al.*, 2020); AI has infiltrated almost every domain of human life. Its algorithms are making tremendous strides in a multitude of various domains. AlphaZero, for instance, mastered chess in a few hours of self-play training (University of Toronto Machine Intelligence Team, 2020).

MinD-Vis can visually recreate images seen in the human brain (Chen *et al.*, 2023); and the humanoid robot named Mika is the first AI Chief Executive Officer working for a drinks company in Poland (Bailey, 2023). Although there are countless uses for AI, it is best applied to reducing humanity's most pressing challenges (Anderson & Rainie, 2018). AI use in governmental sectors can contribute extensive value to developing societies. For example, in healthcare it is used for diagnosis and treatment recommendations (Wu, *et al.*, 2022); as well as disease tracking and prediction models (Prakash, *et al.*, 2020).

Additionally, it is used in education to tailor content for individual student needs (Zhang, Basham & Yang, 2020); and the transportation sector in autonomous driving cars for safer roads (Liu, Yang & Xu, 2019). Industry 4.0 technologies such as robotics, big data, and the Internet of Things (IoT) are used in conjunction with AI to better develop and aid vulnerable environments (Bushwick, 2022). With the climb in global disasters, research innovations are exploring ways to optimize AI applications and generate data that is more stable, reliable, and conclusive for disaster risk reduction (DRR) purposes (Kuglitsch, *et al.*, 2022).

According to INFORM (Index for Risk Management), Africa is deemed one of the most at-risk regions in the world (INFORM report, 2023). The United Nations Office for Disaster Risk Reduction (UNDRR) describes African disaster risk as a multifaceted and fast-changing environment. African disaster risk primarily stems from hydrometeorological and/or climatic hazards, which are exemplified by environmental exposure, vulnerability, and a lack in capacity (GFDRR & WBG, 2016). Environmental degradation, insufficient services and infrastructure, unplanned rapid growth, and fragmented governmental structures rapidly increase disaster risk in densely populated African cities (UNDRR, 2020).

As stated by the African Centre for Economic Transformation (ACET), the fourth industrial revolution is the next frontier in African progress (Floyd & Adhikary, 2021). For example, the

Sendai framework for disaster risk reduction (SFDRR) establishes the goal of assisting African resilience by prioritizing the development of technical and scientific capacity (UNISDR, 2015). The SFDRR stresses advancements in DRR efforts through better understanding hazards, strengthening government efforts in combat measures, encouraging investment for growing resilience, enhancing adaptation, and rebuilding better infrastructure (African Union, 2020).

AI reducing hydrometeorological hazards in Africa is a novel and complex phenomenon. Due to the lack of research and documentation, it becomes crucial to contextualize its complexity and examine its applications. This research aims to extract information by applying the theoretical framework of complex adaptive systems (CAS) theory. CAS is most applicable to this study as it assists in exploring the complexity associated with topics such as the advancement of technology and the opportunities and challenges associated with its development (Turner & Baker, 2019).

The study should have significance for those looking to explore the applications of AI models used in DRR. It may also interest African governments looking to expand on AI for reducing hydrometeorological hazards and in replication or development of AI based DRR measures. Stakeholders and investors looking to contribute to responsible AI development can benefit from the study through examining various advancements associated with African countries. This provides an opportunity to identify and fill gaps in African hydrometeorological hazard reduction efforts.

Startup companies and developers keen on 'AI for good' projects may also find this study useful by discovering popular applications and methods for reducing hydrometeorological hazards in Africa. The research aims and objectives are important for understanding the study. They contribute toward the purpose of the study and its method of execution.

1.1 Research Aim and Objectives

Establishing a CAS framework should provide a substantial structure for an effective literature analysis. It will aid in identifying possible variables involved in AI reducing these hazards in Africa. As the influence of AI stretches into a multitude of domains it becomes crucial to first understand the level of its integration into DRR and Africa. This integration presents different opportunities and challenges influencing the effectiveness of AI implementation. By collecting literature on the applications of AI in African DRR, the study aims to explore the general uses for AI in Africa and specifically for DRR. This is done to establish common functions and understanding in AI used for DRR efforts in Africa.

Consequently, searching for underlying dynamics driving projects in AI reducing African hydrometeorological hazards establishes contextual relevance and highlights various relationships. The study attempts to retrieve and examine relevant literature concerning these projects by investigating autonomous agent involvement and their interconnections with various African countries. Therefore, exploration pertains to uncover various AI projects set on reducing hydrometeorological hazards in Africa through considering African countries using said projects and the various autonomous agents influencing them.

The research questions which this research aims to answer are:

- a. How can the complexities associated with AI used for combatting hydrometeorological hazards in Africa be conceptualised?
- b. How is AI being utilised for reducing hydrometeorological hazards in different countries?
- c. What is the state of AI technology in Africa and what advantages and challenges does it present for the region?
- d. Who are responsible for these AI project implementations in Africa?
- e. Where are these projects located and when were they developed?
- f. What kind of networks emerge from these projects and how can they be illustrated to increase their understanding?

The research objectives are:

- a. Establish a framework for CAS theory to conceptualize the complexities involved in AI reducing hydrometeorological hazards in Africa.
- b. Explore the use of AI in DRR, and the research done on the applications of it in various countries.
- c. Investigate the state of AI in Africa and the advantages and challenges faced by its implementation.
- d. Investigate different AI projects specifically involved in reducing African hydrometeorological hazards and identify autonomous agent involvement.
- e. Formulate a network of nodes connected by AI projects and identify the most prominent nodes in the network.
- f. Discover dominant connections between nodes and establish key contributions to the formation of an African AI ecosystem.

These objectives can only be reached by collecting vast amounts of literature. Therefore, the methodological approach of a semi-systemic literature review is most appropriate. This dedicated research methodology is discussed below with reference to data collection, data analysis and research structure.

1.2 Methodology

AI being used for combatting hydrometeorological hazards in Africa is an extensively under researched field. Due to its complexities, investigating its dynamics is challenging yet integral to understanding the phenomenon. Data available on this phenomenon mainly consists of qualitative documentations and requires a literature review approach to properly record existing ventures. Therefore, the research design consists of a qualitative methodological approach. In this section, the literature review methodology was discussed with reference to data collection, data analysis and research structure.

1.2.1 Literature review

The literature review can be understood as a systematic collection of previous research and relevant literature (Tranfield, Denyer & Smart, 2003). This is done to advance knowledge and theory development on AI reducing hydrometeorological hazards in Africa (Webster & Watson, 2002). Because of the interdisciplinary nature of the study, a literature review aids in combining many different fields under one umbrella (Snyder, 2019).

The literature review methodological approach consists of multiple advantages, such as incorporating various ideas, adding to the body of academic knowledge, and amalgamating various research topics conducted in different disciplines (Lawani & Ilegbedion, 2024). The literature review approach used for this study was a semi-systematic one. The semi-systemic literature review or narrative review was perfect for this research as it is designed to combine literature from an array of disciplines and explore topics that are conceptualized in different ways (Wong, *et al.*, 2013). As this study combines the various fields of research namely AI and DRR, it is important to use a fitting research design and properly explore its dynamics.

The semi-systemic literature review allowed for a less limiting approach to literature collection retrieved from various domains. It aimed to explore the prominence of AI projects through their implementation and development in Africa (Ali & Khan, 2024). In this case, the development of AI used for reducing hydrometeorological hazards in Africa was explored and documented through various meta-narratives.

This research aimed to explore the prominence of AI projects through their implementation and development in Africa. This was explored and documented through various meta-narratives. The semi-systematic literature review was utilized to map a field of research, amalgamate the state of knowledge on a subject, and motivate possible further research on a topic (Snyder, 2019).

1.2.1.1 Data collection

Data was collected based on credibility and the inclusion of necessary information, such as, specifying the AI model, location, assisting technology, function, and agent involvement. The literature selection was done through different search engines including Google Scholar, Research Gate, Elsevier and Science Direct. It remains important to note that not all literature is reliable and may be an obstacle when literature selection takes place (Pare & Kitsiou, 2017). Moreover, instances where further relevant projects are undocumented remain a possibility. Nevertheless, the purpose of the research is not to holistically document every AI project in Africa but rather to indicate the extensive complexity associated with its development.

Therefore, projects were selected according to data availability, as they are considered part of an open system. Selecting and collecting literature requires a level of responsibility and ethical conduct. The research is conducted using the following ethical considerations.

1.2.1.2 Ethical considerations

Conducting a literature review includes basic ethical considerations. These consist of correct citation/referencing, transparency in search techniques, awareness of bias and diversity in authors (Thorley, 2019). It is important to correctly cite the literature used in the research to avoid confusion surrounding intellectual property (Kotze, 2011). The search engines used for literature collection must be credible and trustworthy sources of information (Gusenbauer & Haddaway, 2020). The researcher must be aware of any bias that may occur when collecting the literature (Smith & Noble, 2025).

Lastly, the data included must be from diverse authors and not limited to a specific group (Lerback & Wooden, 2020). Additionally, the researcher ensured ethical conduct by attaining an ethical approval letter of study from the university (NWU-01706-20-A9) with a risk category of minimal. By taking all these considerations into account, it aids the researcher in conducting the study ethically. It is important to not only collect data ethically but also use credible ways of analysing it.

1.2.2 Data analysis

The most common approach for analyzing a semi-systematic literature review is by using qualitative methods (Kiger & Varpio, 2020). The use of a thematic or content-specific analysis can be defined as identifying patterns, analyzing content, and finding methods (Braun & Clarke, 2006). Qualitative theme and pattern identification was central to assessing the literature and aimed at providing a more comprehensive understanding of AI project uses. The relevant literature was explored on hydrometeorological reduction efforts and themes were assigned to various codes.

The data was coded by ATLAS.ti.24 software. ATLAS is an ideal tool used for coding qualitative data and assists in representing the data in a quantitative manner. The different AI projects were coded to create a co-occurring network graph consisting of various connected nodes. This was done to identify overlooked themes in the research through focusing on dominant node interactions and connections. Co-occurrence analysis is a tool used for presenting codes identified from the literature in the form of a table, these codes are repeated on both the x and y axis. This indicates the weight of each code and helps identify recurring qualitative themes and patterns in the literature.

By using co-occurrence analysis and the force directed graph tool, AI combatting hydrometeorological hazards in Africa was presented in various complex interconnected network graphs. This was done to represent a simplified version of the complexity of reducing hydrometeorological hazards in Africa using AI. Simultaneous coding was used for coding the relevant data. This method assigned one excerpt to multiple codes to create individual networks. Systems within systems. Furthermore, dominant node connections were explored to identify common and prominent projects shared by various nodes.

This created an opportunity to further assess the key role-players involved in dominant projects and their relationship with other nodes. This method boasts in understanding any complex system and the interaction between its various components. The research included various sections by which it was structured to address the research objectives.

1.2.3 Research structure

The research objectives were achieved by firstly establishing a CAS framework wherein the research commenced. This framework briefly explained crucial aspects of CAS theory for better understanding ways in which the research was structured and what the dynamics of the study entailed. CAS was defined with reference to components of self-organization, interdependence, networks, adaptation, and limitations. Furthermore, the governing components of the research

were conceptualized according to CAS for establishing the inherent complexity associated with each one. These components included Artificial Intelligence (AI), Disaster Risk Reduction (DRR) and hydrometeorological hazards.

Second, AI use in DRR was discussed with reference to existing research in different countries. This section was structured according to various DRR processes. These included efforts in prospective, corrective and residual disaster risk management (DRM). This Chapter aimed to portray the various AI projects implemented for DRR and the different areas of its application. It orientated the reader and established a clear reference of the numerous project functions mentioned in Chapter 5. Additionally, it indicated the project development activities present in other countries and the way AI is utilized for DRR.

Third, the state of AI in Africa was discussed to address the various areas of influence and the implications associated with its application. Various aspects of this implementation were addressed, for example, the role of government in its growth and development, its influence on key economic sectors, and the opportunities for collaboration and investment initiatives. This was done to create a sense of the larger impact associated with the infiltration of AI, not only for DRR means but also for larger sustainable growth in Africa.

Fourth, AI for African hydrometeorological hazard reduction project examples were listed and explored. These projects were described according to two main sections namely climate change adaptation (CCA) and hydrometeorological hazard reduction (HHR). CCA was included in this Chapter to mimic prospective risk reduction measures for future HHR. CCA consisted of AI water management and land use and land cover (LULC) ventures. On the other hand, HHR consisted of projects that address existing hazards such as floods, drought, landslide, wildfire and tropical cyclones. These examples indicated existing projects in Africa developed between the year 2020 to 2024.

Each section in Chapter 5 was summarized using a detailed Table indicating the key categories of each project example. These categories consisted of the project reference, the African country of application, the AI model of use, assisting technologies included, the project function, and autonomous agent involvement. Lastly, these examples were analyzed using ATLAS.ti 24 to establish dominant nodes and connections in various network graphs. Dominant nodes identified from the data in Chapter 5 were summarized using a Table. This was used to give an overview of key role-players in the different categories of reducing African hydrometeorological hazards.

Furthermore, each category associated with HHR was coded into a network graph indicating the most weighted connection between nodes. Each graph was assessed and discussed according

to its most prominent connections. These connections were analyzed by considering the interactions between African countries, AI models, assisting technologies, project functions, and autonomous agents. Network connections indicated prominent structures present in a CAS and aided in considering the nodes responsible for creating a dynamic AI ecosystem for DRR purposes. All the project examples were combined in a geographical map of Africa (Figure 6.4), showing the holistic efforts of reducing hydrometeorological hazards in Africa.

1.3 Conclusion

In this chapter, the research was introduced with relation to its context, aims, objectives and methodology. AI technological uses for hydrometeorological hazard reduction efforts are increasing in Africa and require investigation. With the various developments in AI, considering its complex interactions become crucial to understanding the dynamics associated with its implementation. The research focus stems from systematically analyzing various AI projects in African hydrometeorological hazard reduction and establishing the complexity associated with these ventures.

The research aims and objectives used a funneling technique to build an argument that resides from a general understanding of the phenomenon towards a more specific exploration of individual projects. Initially, the lens of the research and its components were established, followed by a general depiction of AI technological use in DRR. Furthermore, it aimed to explore the general implementations of AI in Africa and the requirements associated with its use. The funneling technique become more specific and explored individual examples of this phenomenon, analyzing the complexities associated with its network structures.

The methodological approach to this research involved a semi-structured literature review, set on transforming qualitative- into quantitative-data for analysis. This not only aided in documenting and analyzing multiple AI projects used for African hydrometeorological hazard reduction, but also for better understanding the networks that exist from the phenomenological interactions between agents. With the objectives and methodological approach of the research well established, it is important to explore the theoretical lens in which it will commence.

Complexity theory plays a somewhat unique role within the framework of contemporary science and can be explained as the emergence of a post-Newtonian paradigm (Nicolis & Rouvas-Nicolis, 2007). Countless researchers throughout history have used linear systems theory (Newtonian paradigm) to build up a sophisticated and vast body of scientific knowledge (Sieniutycz, 2020). However, investigating real-world phenomena has caused a shift from reductionistic approaches toward more holistic ones (Calenbuhr, 2020).

CHAPTER 2 COMPLEX ADAPTIVE SYSTEMS THEORY

2.1 Introduction

Complex Adaptive Systems (CAS) theory can be loosely defined as a shift from linear systems theory to non-linear systems theory. It has become a method for understanding the complexities such as systemic emergence, synchronisation and evolution. Much of the phenomenon researchers are most interested in is inherently non-linear (Ladyman & Wiesner, 2020). This may be due to the unpredictability of non-linear phenomena and its overwhelming presence in systemic functions. The primary aspect of complex systems is the need for a holistic approach toward parallel organizational descriptions.

CAS can be understood as a framework for explaining, understanding and studying systems of combined agents forming global emergent properties (Carmichael & Hadzikadic, 2019). According to Giddens (1984), agency refers to the achievements of entities and not their intention to achieve. Carmichael and Hadzikadic (2019) indicates that agency is inherently related to the role of power in reproducing structures. CAS are basically networks of agents interacting and reacting to each other and the environment.

Existing information on complex system structures and their individual elemental interactions have shown to be in short supply (Kwapień & Drożdż, 2012). Therefore, there exists no agreed upon definition of a complex system. Similar information related to AI technology and its use in hydrometeorological hazard reduction in Africa are also limited. It is integral to start investigating and understanding the complexity of this phenomenon. By establishing the theoretical framework of CAS, the phenomenon of AI for hydrometeorological hazard reduction (HHR) in Africa can be conceptualized.

Complex systems are categorized as a special class of general system (Giudice, 2016). It can be defined as the composition of parts or elements and the connections or relations between them (Kast & Rosenzweig, 1972). The discipline of complex systems theory aims to make sense of and predict social and natural issues using scientific approaches (Mcsweeney, 2020). While most scientific disciplines tend to focus on the differences between components within a system, complexity theory focuses on the relation/connection between these components (Siegenfeld & Bar-Yam, 2020).

This chapter aims to change the inherently linear understanding of AI in African DRR and highlight the persistent gaps caused by traditional reductionistic approaches. The chapter attempts to

conceptualize and contextualize the research by creating a means of exploring it. In other words, to identify the systems involved in AI for reducing hydrometeorological hazards in Africa, one must first understand the dynamics of a complex system. The goal is to present a theoretical introduction to the research which then structure its execution accordingly.

Furthermore, the chapter is used as a starting point for exploring the phenomenon of HHR in Africa and aims to systematically unpack the components of CAS theory. The definition of CAS is discussed first, wherefrom a working framework for analysis is derived. This research identifies various characteristics of CAS and their methods of analysis. First, the characteristics of CAS are explored in terms of self-organization and emergence (Carmicheal & Hadzikadic, 2019); interdependence and non-linear systems theory (Pype *et al.*, 2018); connectivity and network theory (Sayama *et al.*, 2013); and adaptation and evolution (Tzafestas, 2018). Each of which are interdependent and facilitate the formation of a CAS.

Challenges in complex systems are discussed in this chapter through referring to the lack in complete understanding of a complex system and the possibility of systemic mismatches to complexity. Secondly, the chapter explores the components involved in AI reducing hydrometeorological hazards in Africa. The research identifies these as consisting of AI, DRR, and hydrometeorological hazards. CAS is used as a lens to understand the fundamentals of the components essential to the study.

AI is conceptualized using algorithmic examples such as machine learning (ML) and neural networks (NN). Furthermore, AI is discussed as a CAS by considering reinforcement learning (RL) and evolutionary algorithms mimicking CAS theory properties. Disaster risk reduction (DRR) is conceptualized through exploring its development and growth from disaster risk management (DRM). It considers the SFDRR and the interdisciplinary nature of DRR. Consequently, DRR is explored as a CAS by considering resilience and climate change adaptation (CCA).

Lastly, hydrometeorological hazards are conceptualized by considering hazards such as floods, droughts, landslides and climate change. Also, the degree to which these interactions influence the frequency and intensity of hazard formation is also considered. To effectively conduct research, the phenomenon must be clearly defined. Considering the theoretical lens of the study can assist in structuring and guiding the research. Therefore, complex adaptive systems (CAS) theory is extensively explored in the following section.

2.2 Defining Complex Adaptive Systems (CAS)

Complexity theory investigates the non-linear interactions between elements whilst considering their changes in patterns and adaptability (Kwapień & Drożdż, 2012). It is a collection of theoretical frameworks used to model and analyse complex systems in various application areas (Turner & Baker, 2019). Although complexity theory has a large variety of applications there is no agreed-upon structure or definition to this framework (Ladyman, Lambert & Wiesner, 2013). Complexity as a discipline is extensively difficult to define as the concept claims to include everything a system is compiled of, causing debates around what exactly is meant by 'everything' (Ladyman & Wiesner, 2020).

Complexity theory is identified by many different areas of study (Wolf-Branigin, 2013; Sayama, 2020) where researchers are forced to develop novel sets of methods and models to improve its accuracy in analysis (Anderson, 1999). From these different methods and models, commonalities are recognized as generic to studying CAS (Ladyman, Lambert & Wiesner, 2013). These commonalities are known as self-organization theory (Goodwin, 2001), non-linear systems theory (Spencer-Wood, 2013), network theory (Oh & Monge, 2016), and adaptive systems theory (Carmichael & Hadzikadi, 2019).

These theories are explained under related terms associated with CAS for instance, emergence (Raman & Jeppu, 2019), inter-dependence (Singh & Sinha, 2017), connectivity (Comin *et al.*, 2020), and adaptation (Allen, 2011). Even though these concepts are described independently, it is important to note that they are all integrated and fluid within the context of CAS theory. For example, non-linear networks are caused by the emergent behaviour of self-organization. Interdependence between components creates non-linear connections and the ability to self-organize adaptive measures when faced with change.

Interdependence, non-linear connections, and feedback loops explain the emergence of autonomous agents in a CAS network, which aids in visualising a system. The isolation of each component is purely to familiarise and conceptualize the workings of a CAS and formulate a working research structure used for analysis. The first characteristic explored in CAS is self-organisation.

2.2.1 Self-Organisation

Self-organisation occurs without centralised control of the system. In other words, self-organisation is the spontaneous occurrence responsible for the formation of a complex system. Self-organisation is integral to the development of a complex adaptive system. This research

identifies self-organisation by the lack of central control, emergence and entropy. The autonomous nature of CAS agents facilitates the development of dynamic environments, where spontaneous pattern and structure formation occurs without a central governing agent.

2.2.1.1 Lack of central control

Complex system components consist of distributed elements that are without centralized control (Sayama, 2020). Control is not central to the system but rather local, which may resemble various cognitive and physical dimensions (Turner & Baker, 2019). Examples include the functioning of the human brain (Basset & Gazzaniga, 2011), flocks of birds in migration (Thorstensson, 2018), and the formation of social networks (Benham-Hutchins & Clancy, 2010). The local interactions of elements and the lack of central control create the emergence of complex systems through the process of self-organization (Willshaw, 2006).

Self-organization is the spontaneous emergence of internal systemic patterns (Green, Sadedin, & Leishman, 2008). It is difficult to define as it is used in different contexts for various reasons (Gershenson, 2012). The terms 'self' and 'organization' alone are problematic concepts as their meanings are debatable across disciplines (Gershenson & Heylighen, 2003). Nevertheless, self-organization gives rise to new levels of organizational structures that start interacting with other systems in its environment (O'Sullivan, 2009).

AI combatting hydrometeorological hazards in Africa consist of various levels of organisational structures, namely: local, national and international agent interactions. These systemic agents have no central control and act autonomously whilst interacting with each other. Agent interactions have therefore produced the self-organisation of a CAS dedicated to using AI for reducing hydrometeorological hazards in Africa. Committed agents interacting creates CAS that interact with other CAS.

These interactions create a new pattern of organizational development which produces the emergence of additional levels of organization (Amagoh, 2016). The collection of ordered patterns emerges from self-organization and is known as emergent properties. These properties define a systemic level by its interaction with lower levels (Larson, 2016). Therefore, emergence is the behavioural result of systems that are difficult to predict, for instance, the human immune system (Arias & Herrero, 2018), short and long-term climate change (Ecology Center, 2022), and market price fluctuations (Nissen & Saft, 2010).

2.2.1.2 Emergence

The term emergence is common in referring to how new levels of organizations are formed, additionally, the theory of self-organisation presents concrete models for how this takes place (De Wolf & Holvoet, 2005). Emergence is the process by which larger patterns, structures, or behaviours arise from the interactions of smaller or simpler elements of the system. However, these global patterns, structures, or behaviours cannot be directly traced back to the properties of individual components of the system (Zheng, 2020).

For example, various dialects and phrases in a language develop as humans interact on a decentralised and geographically distributed basis (Macwhinney, 1998); a frozen raindrop containing a dust particle interacts with atmospheric humidity and temperature to form a snowflake (NOAA, 2022); and the development of primary care systems in Nairobi slums through the interaction between people giving and receiving medical help (Sturmberg, 2017). Emergence indicates that the ability of the individual components does not equal the ability of the components interacting (Carmichael & Hadzikadic, 2019). Therefore, it is the product of various agents' collective efforts that result in greater impact than that of the agent's individual ability.

AI combatting hydrometeorological hazards in Africa is a phenomenon consisting of various CAS interactions. These systemic interactions result in the emergence of uncertain outcomes. Ideally, the outcomes are mostly beneficial for Africa, and result in the reduction of hydrometeorological hazards. A general property of emergence is known as entropy, whereas emergence is also sometimes considered a property of entropy (Jodoin, 2015). The interconnection between the two characteristics further portrays the complexity of understanding CAS.

2.2.1.3 Entropy

Entropy can be defined as the degree of disorder or randomness in a system (Helmenstine, 2021). Entropy explores ideas and physics surrounding pattern formation, synchronization, and chemistry dissipative systems (Pismen, 2006). In other words, entropy is a term used to quantify uncertainty in a signal or message in a system (Cole, 2020). For example, entropy is high in a messy room and low in a clean room (Helmenstine, 2021); the entropy of water in a kettle is higher when it is boiling (Ox Science, 2021); and rapid urbanisation increase entropy in city development endeavours (Wiesner & Quax, 2019).

Elements governed by simple rules cause synchronized behaviour which results in the process of self-organization, also known as organizational emergent patterns (Cogdell, 2018). For example, a simple rule governs a four-way stop in the case of a broken traffic light, however non-

adherence to this rule can cause chaos. Entropy is consequently determined through scale, therefore categorising the complexity of a system, scale must be considered on multiple levels (Siegenfeld & Bar-Yam, 2020). The scale of behaviour is equal to the number of components or subsystems engaging in it (Siegenfeld & Bar-Yam, 2020).

CAS can therefore be seen as a complex system made up of many complex systems. To determine the scale of complexity in AI used for reducing African hydrometeorological hazards, each complex system involved in this phenomenon must be explored. This includes the complex systems of AI, DRR, and hydrometeorological hazards. It is important to keep in mind that these systems create uncertain emergent behaviours or levels of entropy through interdependent and non-linear connections.

Therefore, embracing a level of uncertainty in this study is a prerequisite for understanding the complexities associated with AI combatting hydrometeorological hazards in Africa. Interdependent interactions between complex systems are integral for exploring African AI used for reducing hydrometeorological hazards, as the components of the system become secondary to their systemic behaviours.

2.2.2 Interdependence

Interdependence refers to the mutual reliance of components or agents within a system or between various systems (D'Agostino & Scala, 2016). It is a dynamic set of relationships where participants are self-reliant, while simultaneously being mutually responsible to each other (Clavin, 2024). Interdependence in CAS results in various connections, functions and behaviours. The actions related to one agent can significantly impact others and create a network of dependencies that shape the overall systemic behaviour (Khan *et al.*, 2018).

Interdependence in CAS is considered by exploring non-linear connections and feedback loops (Orange, 2019). In CAS, interdependence between agents and systems often lead to non-linear population dynamics (Riaz, Morgan & Kimberley, 2024). Where small changes to the system can cause large and unpredictable emergent behaviour (Riaz, Morgan & Kimberley, 2024). Interdependence relates to the connections between agents/systems whereas non-linearity relates to the structure/pattern of these connections.

2.2.2.1 Non-linear connections

As the components of complex systems are highly interdependent (Willy, Neugebauer & Gerngroß, 2003), non-linearity is a major theme in most areas (Ratter, 2012). Non-linearity refers to the idea that cause and effect are not directly proportional or predictable (Hayes, 2023). Most

non-linear systems theory has its roots in dense and obscure physics and mathematics (Guastello & Liebovitch, 2011). Complex systems are made up of various components that function differently in isolation than they do when interacting (Sayama, 2020).

For example, individuals have their own social behaviours, however, when interacting with a network, phenomena such as viral trends occur (Cheok, Edwards & Muniru, 2017); neurons transmit electrical signals in isolation, but their interaction creates consciousness (Guy-Evans, 2024); and animals in isolation purely survive, but when interacting create a complex ecosystem (Levin, 1998). Non-linearity comes from the notion that two or more elements combined may not equal the sum of those parts in isolation (Grosser, 2017).

In other words, interdependence in non-linear component/agent connections influence the type and level of emergence. The combined labour of humans or insects, for instance, may produce synergetic results, meaning that the amalgamated efforts of individuals result in far greater accomplishments than that of individuals in isolation (Corning, 1998). Therefore, AI combatting hydrometeorological hazards in Africa can be considered a CAS made up of interdependent and non-linear connections between various autonomous agents and other complex systems. The exploration of non-linear systems is governed by the dynamics of feedback loops and non-equilibrium equations (Astrom & Murry, 2008).

2.2.2.2 Feedback loops

Feedback loops are understood as a circular process where systemic output is fed back into it as input (Merali & Allen, 2011). This may cause variants in systemic output/emergent behaviours and facilitate a highly interdependent system. Therefore, trying to model complex systems with traditional linear methods has shown to be unsuccessful (Rosenthal & Jones, 2022). The problem with interdependency in CAS is that small inputs tend to change the system states in drastic ways and show emergent behaviour in the long term (Balsa-Barreiro, *et al.*, 2020).

This is called 'sensitivity to initial conditions' and is central to chaos theory (Brock, 2001). Due to feedback loops, non-linear systems may expand or decrease at exponential rates (Astrom & Murry, 2008). These phase transitions cause an increase or decrease in connections between components and the scale of the existing structural network. For example, feedback loops are used by a thermostat to regulate room temperature (Ogata, 2010); by insulin and glucagon to regulate blood sugar levels (Alberts *et al.*, 2014); and by investment and consumption to determine economic growth (Minsky, 1975). The phenomenon of AI for reducing hydrometeorological hazards in Africa can be influenced by an array of non-linear interdependent systems interacting through synchronized or non-synchronized behaviours and feedback loops.

The phenomenon can be understood as unpredictable with far-reaching effects and requires further exploration of autonomous agent involvement. Increased interdependency between subsystems strengthens connections and forms intricate networks. The emerging networks and connections between agents involved in AI for reducing hydrometeorological hazards in Africa are important to consider. Feedback loops are not just important to consider in interdependent relationships but also play an important role in enhancing the robustness of a network during its evolution (Kwon & Cho, 2007).

2.2.3 Networks

CAS is less defined by its components and more by the flow of connections between them (Polishchuk, 2018). Networks are systems made up of nodes and connections. Networks can represent various types of relationships and structures across various phenomenon (Boccaletti, *et al.*, 2006). Networks exist due to the interconnected and non-linear structure of CAS. This study aims to portray literature concerning AI models used for reducing African hydrometeorological hazards in the form of network graphs. CAS is fundamentally a complex system of dynamic networks and contribute to efforts in visualisation and understanding network connections.

Many complex systems can be modelled as adaptive networks, for example, social network formation and dissolution due to changing social dynamics (Barabasi, 2016); financial network expansion and decrease due to market fluctuations (Battiston, *et al.*, 2012); and the internet network dynamically adjusting to network-failures and -traffic (Newman, 2010). The occurrence of co-evolution in adaptive networks make modelling them extensively challenging (Sayama *et al.*, 2013). It is crucial to consider that these networks are ever changing and that modelling them only portrays the network momentarily, and not with rigidity.

Therefore, network theory is discussed by considering the presence of connections between agents/systems and the visualisation of data. Network connectivity refers to the process whereby connections are established within various parts of a network (Rouse, 2017).

2.2.3.1 Connection

High levels of connectivity between components not only occur between individual parts but also within their functioning environment (Sayama, 2020). As connectivity increases, it becomes the structure and function of the connections that determine the system and not the properties of its components/nodes (Turnbull *et al.*, 2018). When connections are too strong between components, they tend to have limited small-scale variation and cause herd-like behaviours (Pan,

Altshuler & Pentland, 2012). For example, investors in financial markets behave based on the same information and create crashes to the system (Siegenfeld & Bar-Yam, 2020).

Overly weak connections on the other hand result in mostly independent behaviour and limited systemic coordination (Siegenfeld & Bar-Yam, 2020). For example, a work environment where communication and collaboration tools are inadequate. Therefore, it is integral to evaluate complex systems according to the relationships they form between their parts and the influence of their behaviour on the environment (Bar-Yam, 2002). The use of AI for reducing hydrometeorological hazards in Africa must be evaluated by considering the relationships between components and their connections. Network theory is integral to understanding CAS theory as most complex systems can be understood and modelled in terms of networks (Morcol & Wachhaus, 2009).

The need for network modelling is increased by the rise in computational processes and the essential role played by networks in visual information technology (Moro-Visconti, 2019). Network visualisation refers to the process whereby networks are visually represented by various nodes and links. Nodes are data points, and links are the relationships between these points (Cambridge Intelligence, 2024). Collecting basic information on agent involvement and their connection to one another aids in transforming data into visual representations of tangible networks.

2.2.3.2 Visualisation

Network science is less driven by equations and models, and more driven by understanding dense real-time datasets (Garcia-Robledo, Diaz-Perez & Morales-Luna, 2016). Real-time datasets are used to provide a visualisation of structures and interactions that exist in CAS (Mryglod *et al.*, 2017). Most often, both pattern discovery and mechanistic modelling methods are used to understand complex systems (Sayama, 2020). Networks aim to reshape the 3-dimensional understanding of space towards a more topographic one (Eickhoff, Constable & Yeo, 2018).

For example, networks can visually represent financial transactions in the financial market (Hansen, 2021); socio-political relationships in a country (Hadjikhani, Lee & Ghauri, 2008); real-time movement and migration patterns of wild animals in a national park (Latora *et al.*, 2003); and the spread of contagion during a pandemic (Higgins & Sabarwal, 2022). With the availability of new sources of data and the amalgamation of network theory, visual representations of CAS can be achieved (Scholtes, 2015). It is crucial to consider the position of the nodes in a network, which reveal their level of connectivity and importance to the system (Ladyman & Wiesner, 2020).

Prominent nodes are determined by their variety and number of connections. Connectivity is fundamental to complexity as the relationship count between components can increase or decrease their importance to a system (Da Mata, 2020). Through the competition and cooperation between components in CAS, adaption and evolution can occur.

2.2.4 Adaptation

Adaptation in CAS is the process by which agents in a system adapt and learn through interaction with one another (Carmichael & Hadzikadic, 2019). CAS can adapt and evolve to meet internal and external changes to the functioning environment. Adaptation can be determined by the presence of autonomy and evolution in a system. Autonomous adaptation refers to the ability of a node or system to spontaneously adapt to systemic or environmental changes (Rahman *et al.*, 2021).

2.2.4.1 Autonomy

As complex systems have no centralized mechanism of control, elements have a degree of autonomy (Anderson, 1972; Haken, 2006). Therefore, parts can cooperate to produce patterns of organization or synchronization of local states (Rivkin & Siggelkow, 2007). States are described as sets of variables that best characterize the system and adapt to its changes (Sayama, 2020). Autonomy of adaption causes the capacity for a variety of unpredictable responses to any given systemic input (Turner & Baker, 2019). CAS not only aims to become stable in its environment but independently responds to it on multiple structural levels (Sayama, 2020).

For instance, the brains' neural connections autonomously adapt to new information by reorganizing neural pathways to protect the brain (Custer & Dini-Andreote, 2022); key species removal from an ecosystem requires all other species to autonomously adapt to ensure ecosystemic stability (Landi *et al.*, 2018); and the human immune system autonomously adapts to foreign pathogen prevention whilst keeping the body stable (Custer & Didi-Andreote, 2022). There exists a trade-off between adaptability and efficiency (Panyam *et al.*, 2019).

Adaptability is higher within small-scale complex systems as many different components are working individually towards a greater goal. Efficiency on the other hand is higher in systems with low complexity, for example, conveyor belt assembly lines in the first industrial revolution (Zrnic, Dordevic & Gasic, 2022). Therefore, in larger-scale systems, the components work together to produce a large output with limited variation (Siegenfeld & Bar-Yam, 2020). AI combatting hydrometeorological hazards in Africa can be considered a CAS formed by autonomous agent interactions working towards a common goal.

In other words, this phenomenon consists of various autonomous agents interacting and adapting to environmental pressures in Africa. However, to deem a complex system efficient, it needs to either exceed or match the behaviour of its functioning environment (Allen, 2011). For example, in an ecosystem, a predator's ability to match or surpass the complexity associated with catching its prey is crucial to its survival. If the predator's tactics are too simple the only alternative for survival is adaption. Adaption of agents in a complex system drives the development of emergent behaviour on a macro-scale and results in the process of evolution (Anderson *et al.*, 2004). Evolution assists a CAS in autonomous adaptation to changing environmental requirements.

2.2.4.2 Evolution

Evolution is understood as the adaptation of a whole population occurring over a series of lifecycles (Heesch *et al.*, 2021). There is a variation of models that aid in understanding evolution such as replicator equations, evolutionary game theory, genetic algorithms, and fitness landscapes (Cressman & Tao, 2014). Components within CAS are subject to the evolutionary force of natural selection as those that are best suited for an environment are selected and replicated while others are not (Than, Taylor & Garner, 2021).

For example, in market environments products are subject to selection from buyers (Bergman & Tennenholtz, 2002); democratic governments are subject to selection by voters (Te Hira, 2018); and creatures in ecosystems are subject to selection by competition and cooperation (Chistiansen & Loeschcke, 1990). Successful evolution occurs when there is both cooperation and competition (Bar-Yam, 2006). Game theory becomes relevant here and is used for modelling interactions between all kinds of adaptive agents and the dynamics contained in competition and cooperation (Burguillo, 2017).

The autonomous competition and cooperation between adaptive agents create an opportunity for adaptation to environmental changes. Therefore, competition and cooperation in adaptive agents driving AI for reducing hydrometeorological hazards in Africa should be identified. This can show the dynamic nature of the interactions between various role-players and the environment of reducing hydrometeorological hazards in Africa using AI. CAS has challenges and limitations that need consideration before this framework can be applied to the research topic.

2.2.5 Challenges in CAS

Systems considered CAS are inherently complex to understand. The very nature of knowledge is built upon a linear/ Newtonian understanding of the world (Sieniutycz, 2020). Even non-linear systems are measured by their relation to linearity. For example, chaos theory (which aims to

understand non-linear systems) still relies on linear equations to simplify and describe analysis (Grosse-Erdmann & Manguillot, 2011). A phenomenon frequently seen is the emergence of mismatched complexity in systems and a lack in complete comprehension thereof.

2.2.5.1 Mismatches in complexity

Superfluous or lacking complexity in a system is not an obstacle, however, the mismatch between what the system can manage and what it needs to reconcile, is (Davidson & Bar-Yam, 2006). For instance, the human brain is bored when under-stimulated and overwhelmed when over-stimulated (Davidson & Bar-Yam, 2006). Mismatches in complexity arise from complex systems not being able to function per the required output of the environment (Siegenfeld & Bar-Yam, 2020). For example, a stock market crash often occurs when the system fails to adapt to new information (Sornette, 2017); traffic jams and congestion occurs from the system being unable to adapt to changing environmental demands (Jilani *et al.*, 2023); and urban overpopulation occurs due to the failure of the city to meet increasing requirements (Bish, 2024).

It may become tempting to ascribe CAS mismatches to a chain of events, however, if the initial mismatch in complexity is not addressed, entropy levels in the system increase (Sanbonmatsu, Cooley & Butner, 2020). Even when a system matches its environment to its appropriate scale, there can still be a mismatch due to subdivisions (He, 2011). For example, interdisciplinary schools of thought in academia indicate that presenting challenges cannot be addressed without a divide between certain academic areas (Jacobs & Frickel, 2009).

The divisions inherent to academia, once more, indicates the mismatches in systemic understanding and the linear approaches followed when defining CAS. Studying CAS in isolation creates further distorted views of its understanding. With the integration of non-linear approaches to studying CAS, an increased level of its comprehension has emerged (Carmichael & Hadzikadic, 2019). For example, the complex evolution of language acquisition is considered in relation to human transfers of informative data and environmental interactions (Hiver, Al-Hoorie & Evans, 2021).

Although, using non-linear approaches to studying CAS has shown increased comprehension of these systems, CAS still possess an inherent level of entropy (see section 2.1.1.3).

2.2.5.2 Complete comprehension

CAS has a multidimensionality to its functioning, almost as that of a Rubik's cube, when one dimension makes sense, the others shift (Carmody-Bubb, 2023). Therefore, the study of CAS is riddled with uncertain assumptions, which each describing characteristic recurrently proves to be

true. This section has shown that CAS is a difficult concept to define, however, self-organisation, interdependence, network connections, and adaptation seem to be characteristics most attempts have in common.

Self-organisation is defined by the lack of central systemic control, the spontaneous emergence of behaviour, and the inherent level of entropy. With the lack of central control in the system, any emergent behaviour is deemed spontaneous and therefore possess entropy. Interdependence is discussed in terms of the non-linear structures and the presence of feedback loops. Non-linear structures enhance uncertain outcomes/ entropy which accompany feedback loops (Lei & Lin, 2007). Networks consist of connections and the ability to visualise data.

Most important to networks are their connections, which can be used to graph data into complex systems. Adaptation is possible in CAS through autonomy and evolution. For network nodes to change behaviour shows a degree of autonomy in the system and creates the opportunity for evolution when sustained. There remain challenges in the concept of CAS theory such as mismatches in complexity and complete comprehension. There exist mismatches in complexity when a system cannot reach its environmental demands. Gaps are also present in complete comprehension of any CAS and therefore a degree of uncertainty is always present (Lei & Lin, 2007).

Applying the CAS framework to AI for combatting hydrometeorological hazards in Africa will entail determining the components that the phenomenon is made up of. In the following section, each CAS is defined and explored according to CAS theory. This is done to conceptualize and contextualize the concepts involved in the research and create an introductory foundation from which it can commence. It is worth noting that each CAS is explained in isolation to its external environment. This restricts the depth of analysis and aids in focusing on introductory-level information. As each CAS is extensively complex it becomes tempting to dive too deep into smaller scales of analysis. Therefore, the research conceptualization of each component is meant to remain very brief and provide an overview of the system dynamics.

2.3 Research Conceptualization

AI for reducing hydrometeorological hazards in Africa is an extensively complex phenomenon consisting of various complex adaptive systems. These systems can be narrowed down to AI, DRR, and various hydrometeorological hazards. Each component involved in the study represents a CAS on its own. These systems need to be conceptualized to explain the research and the important aspects that enable AI for reducing hydrometeorological hazards in Africa. The following section uses the framework of CAS to define and explore involved systems.

Exploring CAS requires identification of basic systemic components, consideration for non-linear emergent behaviors, the presence of connections, network formation, and adaptation. Firstly, AI is conceptualized using basic algorithmic examples such as machine learning (ML) and neural networks (NN). It is then applied to CAS theory by considering reinforcement learning (RL) and evolutionary algorithms. All AI models explained in this section relate to the very basics and create a foundation for understanding more complex ones mentioned later in the study.

Secondly, DRR is conceptualised by tracing its development from DRM beginnings, the interdisciplinary nature of the CAS, and how climate change adaptation (CCA) aids the system in evolutionary progress. This is useful for better understanding the jargon of the study and the basic aspects involved DRR. Lastly, the concept of hydrometeorological hazard is defined by considering its most basic components of water and wind. The interaction of these elements with vulnerable occupied environments determines their exposure to flooding, drought, landslides, wildfires, tropical cyclones and many more. Climate change is discussed as making adaption and evolution possible for hydrometeorological hazards proving that it can be considered a CAS.

AI model identification in African hydrometeorological hazard reduction is the primary purpose of this study. Therefore, exploring what exactly AI is becomes crucial to understanding the complexities of the study and the components of its results. AI remains an extraordinary feat; humans recreating their own intelligence without fully understanding it themselves. AI is a complex adaptive system with certain levels of uncertainty. In other words, just as humans do not fully understand their own intelligence, so do they also not fully understand AI.

2.3.1 Artificial Intelligence (AI)

With its foundations in biology, cybernetics, and neurology, Artificial Intelligence (AI) reports efficiency in a multitude of different fields (Gopinath, 2023). Although the use of AI excites both scepticism and enthusiasm, existing ideas are obscure when aiming to fully understand its systemic complexities (Butson & Spronken-Smith, 2024). AI in its most basic form is defined as a part of data science (Choi *et al.*, 2020). It is modelled to resemble the human cognitive process and mimic its ability to learn and solve problems (McCarthy *et al.*, 1962).

Like human cognition, AI can comprehend, sense, and act on input data (Siemens *et al.*, 2022). Its techniques consist of autonomous intelligent behaviours such as knowledge engineering, reasoning, planning, communication, and perception (Molina, 2022). It involves developing independent models written by relevant data, algorithms, specialized platforms (hardware & software), and programming languages. The emergent behaviours of these components in isolation are not nearly as dynamic as they are in connection to data or to one another.

The human brain learns and makes decisions based on information fed through its neural networks (Moghadam, Khodadad & Khazaeinezhad, 2019). Through the process of self-organization, neural networks enable the dynamic emergence of maps and patterns (Ranganathan & Kira, 2003). This is identical for AI models that work according to a set of rules applied to decision-making endeavours. Machine learning (ML) algorithms are considered a sub-system nestled inside AI systems specializing in learning from symbolic data.

2.3.1.1 Machine learning

ML's primary function is learning from symbols (Farsad *et al.*, 2002) and generating new data without explicit programming from humans (Brown, 2021). ML is seen as a probability reasoner that aids in likelihood predictions and focuses on formulating data-based algorithms (Choi *et al.*, 2020). ML processes data and learns from it through recognition, which excludes external or central control. Consequently, ML applies to methods used for the categorization and classification of remotely sensed data acquired from satellite, drone, aerial and street-level imagery (GFDRR, 2018).

For example, earth observational data and NN are used by space agencies to monitor the sustainable development goals (Helbert, 2018); ML and drones are used by farmers for precision agriculture (Trihinas *et al.*, 2021); and street level photos and ML are used by researchers to assess urban environments for planning (Zhang *et al.*, 2023). ML explored on a smaller scale reveals non-linear connections derived from sub-systems such as neural networks (NN) and deep learning (DL). For instance, ML sub-sections are known as supervised (data with annotations), unsupervised (data without annotations), semi-supervised (combination of supervised and unsupervised) and reinforcement learning (RL) (optimal reward directed data).

Supervised learning makes use of annotated training data (Nasteski, 2017) and aims to solve regression and classification problems (Mukhamediev *et al.*, 2022). Regression involves predicting numeric data through understanding the relationship between dependent and independent variables; whereas classification precedes in predicting what category data should be placed in to determine its label and definition (James *et al.*, 2013). Supervised learning is understood as being task driven and unsupervised learning as being data driven, whereas RL occurs from trial and error (Bhatt, 2018).

In RL, basic elements are considered in finding the most effective solution to problems such as the environment, state, reward, policy, and value of predictions (Bhatt, 2018). RL uses supervised and unsupervised models to learn from, whilst interacting with the external environment (Naeem, Rizvi & Coronato, 2020). RL is different from supervised and unsupervised learning as it can

adapt to changes through exploration and attain optimal strategies from experience (Naeem, Rizvi & Coronato, 2020). For example, RL is used for: planning optimal rescue paths in complex and uncertain flood scenarios (Li *et al.*, 2023); confidence-aware technology in self-driving cars (Cao *et al.*, 2022); and manipulating and training autonomous robots (Irpan & Pastor, 2018).

Another component derived from ML is known as deep learning (DL). DL uses large sets of data to identify relevant patterns and structures through multiple levels of examination (Rusk, 2016). DL uses artificial neural networks (ANN), an algorithm modelled to resemble the neural networks of the brain (James *et al.*, 2013). Simply, it is viewed as a series of logistic regression classifiers layered on top of one another (Jurafsky & Martin, 2023).

Each layer in the neural network applies a logistic regression (LR) function to its input which then passes the output to the next layer (Jurafsky & Martin, 2024). For example, LR can assist in automatically sorting emails according to filtered preferences (Sendin, 2024); predicting evacuation traffic demands during a possible hazardous event (Sun, Huang & Zhao, 2024); and determining the probability of a heart attack based on variables such as weight and exercise habits (Bobbitt, 2020).

2.3.1.2 Neural networks

Neural networks (NN) consist of artificial neurons/interconnected nodes organized in layers and processing information through propagation signals (Zhou, 2021). NN are used to accomplish multi-level examinations and discover trends that predict outcomes of various phenomena (Rusk, 2016). NN consisting of more than two layers of investigation is referred to as a deep neural network (DNN). DNN uses DL to assess large sets of data and identify relevant patterns and structures through multiple levels of examination (Rusk, 2016).

AI components are extremely dependent on one another and are difficult to define in isolation. DNN used in DL are standard feed forward neural networks (FFNN), recurrent neural networks (RNN), convolutional neural networks (CNN) and hybrid architectures (HA) (Mukhamediev *et al.*, 2022). The standard FFNN are networks that only process data in one direction and cannot be reversed (Sharma, 2024). Information starts by travelling from the input nodes (containing one or more inputs), through the hidden nodes (containing an activation function) and then through the output nodes (containing one or more outputs) with different node connections (containing kernels/weights and biases) (Dobilas, 2021).

FFNN are mainly used for prediction purposes (Dobilas, 2021) such as the early detection of floods using the IoT (Subeesh, Kumar & Chauhan, 2018); consumer behaviour using historical

retail data (Hillier, 2023); and model output statistics for short term cyclone intensity prediction using historical weather-related data (Cloud, 2019). Recurrent neural networks (RNN) are used to deal with sequential data and trained to retain historical knowledge for forecasting time-series values (Saeed, 2023). For example, weather forecasting is done by training RNN models with historical data acquired from monitoring outputs (Brownlee, 2022); and utility companies make use of RNN and historical data to forecast future consumption of energy and optimise their operational outputs (Aseeri, 2023).

Unlike FFNN, recurrent neural networks (RNN) have a feedback loop and include architectures such as bidirectional RNN, gated recurrent units, and long-short term memory (LSTM) (Saeed, 2023). Additional applications of RNN include machine translation (Wu *et al.*, 2016), speech recognition (Jurafsky & Martin, 2023), DNA analysis (Liu *et al.*, 2019a), sentiment analysis (Zhang, Wang & Lui, 2018), sound generation (Kalingeri & Grandhe, 2016) and voice to text generation (Lu *et al.*, 2018).

To better understand the complexity of AI components, it is important to explore them using CAS theory. AI is categorised as a CAS through applying the above-mentioned framework of self-organisation, interdependence, network theory, and adaptation. Exploring AI as a CAS is vital to grasping the level of uncertainty linked to its research and in extension its use.

2.3.1.3 AI as complex adaptive system (CAS)

AI functions and algorithms can be considered behaving as a CAS. AI is considered using self-organization in NN, for example, neurons autonomously adapt their weights during training programs (Grossberg, 2020). This leads to complex functionality and patterns such as language translation, gameplay, and image recognition (Hinton *et al.*, 2012). Interdependence is seen in reinforcement learning (RL) where agents learn through interaction with the environment. Non-linearity is demonstrated in AI by the sensitivity of NN data input. It shows that the slightest change to the input data results in major changes to output (Sutton & Barto, 2018).

The entire AI system depends on the connections and networks between its components (Lecun & Bengio, 1995). Resulting in an ecosystem of self-organizing and adapting agents set on responding to the environment through evolution. Evolutionary algorithms (as part of ML), for example, are modelled to mimic biological evolutionary processes that allow adaptation over time (Eiben & Smith, 2015). These models include swarm intelligence and multi-agent systems (Kaur, 2022). Categorising AI as a CAS causes a persistent uncovering of new levels of complexity rendering it nearly impossible to completely map all AI's dynamic components.

The more AI is explored, the more challenging it becomes understanding its functioning and emergent behaviours. The struggle to properly define each component in isolation portrays the high levels of interdependence present in the phenomenon. AI emergent behaviour is somewhat clear through its output, however grey areas persist in explaining its results. AI is a highly complex adaptive system using (among others) ML, NN, and DL to produce entropy and adaptation. These algorithms consist of multilevel problem-solving and feedback loops that enable systemic synchronization.

Interdependence and non-linear structures enable vast connections and form intricate networks between autonomous agents. These can adapt and evolve based on algorithms inspired by CAS reactions to the environment. Similarly, DRR is seen as an extensively complex system. Its functioning aims to match the complexity of ongoing and evolving risk development and reduce its effects. DRR conceptualisation is important for understanding the extensive complexity involved in amalgamating it with AI.

2.3.2 Disaster Risk Reduction (DRR)

Disaster risk reduction (DRR) evolved from the discipline of disaster management. Disaster management started as a multi-sectoral and multidisciplinary process composed of planning and implementing various measures associated with emergency events (Department of Cooperative Governance and Traditional Affairs, 2003). When disasters became less attributed to bad luck, risk studies assisted in assessing and altering disaster impacts through means of management (Van Niekerk, 2006). The concept of 'risk' has gradually become part of disaster studies from around the time of World War II (Van Niekerk, 2006).

'Risk' is seen as the interactions between environmental hazards, exposure, and vulnerability. These conceptual interactions are interdependent which produce complex systemic behaviours (UNDRR, 2019). Disaster risk management (DRM) traditionally consists of mitigation, preparedness, response, and recovery (Wagle, 2018). Mitigation and preparedness relate to pre-disaster, and response and recovery relate post-disaster. DRM is best understood as a combination of systems that function simultaneously.

2.3.2.1 Disaster risk management (DRM)

All DRM measures work towards a common goal of recovering from a disaster. It is interesting to note that the traditional DRM model is centred around an impending disaster. This indicates a strong response-orientated approach to hazards. Boshier, Chmutina, and van Niekerk (2021), indicate that traditional cyclical understandings of disaster risk management processes, overly

simplify its representation and conceptualisation. They propose that the structure associated with understanding DRR should resemble a helix (an upward turning spiral) and present a discussion on how to move away from a reoccurring cycle (Bosher, Chmutina, & van Niekerk, 2021).

Efforts in working towards impending disaster mainly focus on mitigating measures and preparing for its response and recovery. Working away from disaster includes preventing possible disaster risk (DR), reducing current DR, and preparing for residual DR (Peters, 2019). DRR attempts to move away from disaster-focused approaches and embrace more preventative ones (UNDRR, 2019).

According to the SFDRR, DRR consists of actions such as prospective DRM, corrective DRM, and residual DRM (Zodrow & Hendel-Blackford, 2020). Prospective DRM is considered an activity that seeks to avoid developing or increasing DR (Zodrow & Hendel-Blackford, 2020). For example, restructuring urban development policies to reduce the effects of possible flooding. Or planting trees to reduce the effects of climate change. Corrective DRM seeks to reduce or remove existing DR. For instance, replanting parts of the rainforest to reduce or remove the risk of climate change. Or repopulate coral reefs to reduce or remove the risk of possible species extinction.

Residual DRM aims at strengthening the economic and social resilience of those faced with inevitable risk (Zodrow & Hendel-Blackford, 2020). Inevitable risk includes monsoon flooding and annual drought. Clark-Ginsberg (2020) states that DR is understood as a CAS that originates from complex interactions between people, institutions, and infrastructure. Resultantly, managing and reducing DR calls for a systemic and complex theoretical approach that analyse the interconnected efforts from different societal domains (Uusikyla, Tommila, & Uusikylä, 2020).

The key characteristics of CAS aid in better understanding the dynamics of disaster resilience (Coetzee, van Niekerk & Raju, 2016). Coetzee, van Niekerk and Raju (2016) found that the similarities between the concepts of disaster resilience and CAS provide sufficient theoretical and practical contributions to the field of DR studies. The complexity of disaster resilience plays a part in building it. Building resilience is different to each situation and requires extensive flexibility and adaption (Coetzee, van Niekerk & Raju, 2017). Adaption and flexibility are more likely to occur due to the interactions and interdependence of DRR in relation to other disciplines.

2.3.2.2 Interdisciplinary approaches

DRR can be seen as a vehicle connecting various disciplines and domains (Van Niekerk, 2011). Its primary function is to find means of reducing risk effectively. These means stretch from risk assessment and early warning systems to government involvement and education. Ultimately

DRR uses various autonomous agents (institutions, governments, technology, organizations, and corporations) to work towards reducing DR. DRR is a facilitator for connecting and growing a network of various entities. It is aimed at managing role-players for producing sustainable risk reduction. DRR is known as a complex systemic process of connecting organizations, administrative directives, operational capacity and skills (Van Niekerk, 2011).

This is done to implement policies, strategies, and improved coping capacity for reducing hazards (Van Niekerk, 2011). Reducing DR is a complex process whereby interdependent networks and adaptation become key to its functioning. DRR calls for systemic and complex theoretical approaches to analyse and help establish best practice initiatives (Uusikylä, Tommila, & Uusikylä, 2020). True DRR is only possible by tapping into other practical and scientific disciplines for access to underrepresented knowledge (Van Niekerk, 2006). Therefore, DRR can be conceptualized as a CAS attempting to use and manage complex systems for reducing DR.

2.3.2.3 DRR as complex adaptive system (CAS)

Self-organization and emergence in DRR are evident in the autonomous formation of communities and organizations working towards enforcing it. For instance, self-organising community groups are often the foundation of DRR measures (IFRC, 2019). DRR is an interdependent complex system with non-linear effects. These effects are influenced by minor changes to the system. Building code adaption, for instance, may aid in reduced casualties when faced with an event. Indicating that small changes have significant effects on DRR efforts (UNDRR, 2015). DRR can be seen as evolving through using climate change adaptation (CCA) in its activities.

Climate change poses a great risk to DRR efforts and causes the accumulation of previously unknown hydrometeorological hazards. Climate change adaptation (CCA) aims to adapt to the changing environment and prevent the development of climate-related hazards (SANBI, 2024). Through the incorporation of CCA into DRR, more residual DR is addressed and future risks that originate therefrom can be prevented. CCA entails climate smart agriculture, natural landscape restoration and protection, early warning systems, reinforcing infrastructure, and climate resilient livelihoods (SANBI, 2024).

DRR is extensively complex as its design is based on matching the complexity of the hazards it aims to reduce. Hydrometeorological hazards for instance are complex hazards that involve multiple interrelated components. These hazards cause the world's most devastating and most frequent disasters. Its enormous response and recovery costs put extreme pressure on affected populations and slow developmental efforts (Marra *et al.*, 2024).

2.3.3 Hydrometeorological hazards

Hydrometeorological hazards are devastating to thousands of people each year (USAID, 2021). Its effects are exponentially becoming worse due to climate change, pollution, deforestation, and environmental degradation (to name a few) (Debele *et al.*, 2019). Hydrometeorological risk is determined by analysing the interplay between vulnerability, exposure, and participating environmental and human domains (Merz *et al.*, 2010). Hydrometeorological hazards are events that result from the interaction between the earth's surface and the atmosphere, mainly with the presence or absence of the basic elements: wind and water.

The process of developing different hydrometeorological hazards primarily relies on the variations in interaction between water and wind. In addition, abnormal weather and climatic change further affect hydrometeorological hazard formation and contribute to its severity and impact (Jayawardena, 2015).

2.3.3.1 Conceptualisation

Precipitation causes most water-related hydrometeorological hazards to occur (Jayawardena, 2015). Alternative forms of precipitation can cause landslides (excessive rainfall) and avalanches (excessive snowfall) (Jayawardena, 2015). Flooding for instance is an extremely complex hydrometeorological hazard that develops due to many interdependent factors. Viglione and Rogger (2015) indicate that eight different types of flooding can occur. These include river, flash, dam-break, ice-jam, glacial-lake, urban, coastal, and cyclone-related floods (Viglione & Rogger, 2015).

The large variation in flood hazards shows the level of systemic mismatches within the environment. The reasons for floods are vast and range from rapid rainfall to the melting of snow or ice masses (Luino, 2016). The extensive sub-systems of flood hazards indicate that they are difficult to predict and manage (Pringle, 2022). Drought is no different, its onset is complex, and its persistence is difficult to reduce. The National Drought Mitigation Centre (NDMC) (2020) states that there exist five types of drought measures. These include meteorological, agricultural, hydrological, socio-economic, and ecological drought (NDMC, 2020).

The different types of measures indicate that their causes are widespread, and that systemic mismatch is due to a division of scales. For example, causes range from a lack of rainfall, human mismanagement of water, and climate change (Mekonnen & Gökçekuş, 2020). Wind-related hydrometeorological hazards involve systems affected by differential heating between poles and the equator which create various forms of cyclones (Jayawardena, 2015). It is important to

understand that wind and water interactions and dependence on one another form different variations of hydrometeorological hazards.

For example, wildfires can be linked to both water and wind as drought causes the probability of fires and, gushing winds spread the fires to large areas (Guion *et al.*, 2022). Droughts may be seen as a water-related hazard but can be influenced by wind (such as heatwaves), worsening its degree of intensity and probability (Derouin, 2021). The elements of water and wind are much more dangerous when interacting with one another and the environment. CAS are well known for being more prominent when interacting as it heightens the unpredictability of emergent behavior and levels of systemic uncertainty. All the aspects that make researching this phenomenon extremely challenging and elaborate.

2.3.3.2 Hydrometeorological hazards as CAS

Components of hydrometeorological hazards require consistent interplay between various sub-systems and are highly dependent on changes to the environment (McBean, 2016). These disruptions cause autonomous organization that directs the emergence of hazards such as floods, drought, landslides, wildfires, storms, extreme weather, tidal waves, and cyclones (Juvonen *et al.*, 2023). These hazards influence other systems dependent on the balance maintained in hydrometeorological processes. These systems include (amongst others) agriculture (Juvonen *et al.*, 2023), ecosystemic health (Caretta *et al.*, 2022), and socio-economic sectors (Ebedi-Nding, Tamoffo & Mouassom, 2024).

Changes to the hydrometeorological environment produce a domino effect of unpredictable non-linear behaviour. Complex and unforeseen hazard behaviours include rapid hazard intensification and secondary hazard development (Emanuel, 2013). The non-linearity of these hazards can be seen through examples such as rainfall-runoff relationships (Milly *et al.*, 2002). The extreme interdependence of these hazards intensifies the comprehension and management of their cascading effects (Smith & McCarthy, 2014). With new challenges such as global warming and climate change, hydrometeorological hazards are becoming more prominent than ever.

Climate change is considered a degree of adaption that sustains and escalates the occurrence and intensity of hydrometeorological hazards (Wang *et al.*, 2022). They are also sustained by rapid growth in population (Wu, *et al.*, 2016a), unregulated urbanization (Feng, Zhang & Bourke, 2021), pollution (Caretta *et al.*, 2022), and environmental degradation (McBean, 2016). Therefore, hydrometeorological hazards are prominent in vulnerable environments and flourish under challenging environmental conditions. Furthermore, hydrometeorological hazards are sustained by environments that cannot recover from their devastating effects.

Countries showing difficulty with these hazards primarily consist of financially restricted and underdeveloped areas which lack resources for reducing them (Caretta *et al.*, 2022). Consequently, the need for AI in DRR is extremely relevant and desirable for addressing hydrometeorological hazards in developing countries (Maragno *et al.*, 2018; McVittie *et al.*, 2018).

2.4 Conclusion

In this chapter, the theoretical lens of the study and its components was extensively defined and explored. It established the phenomenological approach to the research and the extent of its complexity. This chapter was used as a starting point in exploring AI for reducing hydrometeorological hazards in Africa. Additionally, it addressed the first research objective which aims to establish a framework for CAS theory and conceptualize the complexities involved in AI reducing hydrometeorological hazards in Africa. First, CAS was defined and discussed to establish a working framework for research analysis. CAS characteristics were identified in this research as self-organization and emergence (Carmicheal & Hadzikadic, 2019); interdependence and non-linear systems theory (Pype *et al.*, 2018); connectivity and network theory (Sayama *et al.*, 2013); and adaptation and evolution (Tzafestas, 2018).

Additionally, this research identified the fundamental challenges to CAS as the presence of uncertainty and the mismatches in systemic complexity. Secondly, the chapter explored the complex components that make up the phenomenon of AI combatting hydrometeorological hazards in Africa. These components were identified by the research as AI, DRR, and hydrometeorological hazards; and were conceptualised to provide an overview. Conceptualisation was done through using the framework of CAS theory.

AI was conceptualised by using algorithmic examples such as ML and NN. Furthermore, AI was explored as a CAS by considering models related to RL and evolutionary algorithms. DRR was conceptualised through its evolution from DRM. It was identified as a CAS through the components of resilience and CCA. Lastly, hydrometeorological hazards were conceptualised by considering floods, droughts, landslides and climate change. Additionally, hydrometeorological hazards were explored in terms of their interactions with each other and the environment. Therefore, establishing these hazards as CAS through their complex interconnected nature and non-linear structure.

AI combatting hydrometeorological hazards in Africa is considered a CAS made up of various CASSs. Keeping in mind that CAS is a difficult concept to define and fully comprehend, and therefore, difficult to conduct research on. The chapter explored the inherent complexity of the topic and the inevitable restrictions to its understanding.

The most prevalent characteristics of all the systems discussed in the chapter is that their components are interdependent and interrelated to one another. This makes defining and understanding the phenomenon increasingly difficult as not one of the systemic components can be defined without the other. Emergent behaviour is therefore also difficult to properly explain. The only certainty to these systems is the inevitable uncertainty associated with their functioning. It is important to explore the components associated with AI reducing African hydrometeorological hazards in relation to the characteristics of CAS.

This can only be achieved through considering the general applications of AI in DRR. This may aid in establishing specific emergent behaviours associated with AI in DRR. In the following chapter, AI is explored according to its general applications in DRR. This is done due to a lack in existing research on AI projects specifically reducing hydrometeorological hazards in Africa. Therefore, exploring the general uses of AI reducing hazards should prove to further conceptualise the research phenomenon and better identify the preferred applications of AI in DRR.

CHAPTER 3 AI IN DISASTER RISK REDUCTION (DRR)

3.1 Introduction

Kuglitsch and associates (2022) state that the methodological potential of AI is strengthened in DRR by novel techniques that allow parallel and heavy-duty data processing. AI methods present opportunities in applications for pre-processing observational data and post processing forecast model outputs (Kuglitsch *et al.*, 2022). According to the 'Second Workshop for AI in Natural Disaster Management', ML is most popular in communication, modelling for forecasting and prediction, and data monitoring and detection (ITU, 2021).

AI in DRR aims to efficiently strengthen the knowledge about natural hazards; better the effectivity of emergency communication; advance lead times and accuracy in forecasts; and improve timely detections (Kuglitsch *et al.*, 2022). AI applications exhibit many techniques used to combat DR. Various studies have been done on the different AI applications used for DRM purposes. The accumulative rise in the number of publications presents an opportunity to identify popular uses of AI for various DRR purposes. This chapter aims to explore and identify different AI uses for natural hazard and general DRR.

Although the studies done on AI in DRM focus on the previous categorisation thereof (mitigation, preparedness, response and recovery), this chapter aims to re-envision and re-structure the processes involved in disaster centred models, towards more risk reductive approaches. Therefore, AI reducing DR is examined by re-structuring various systemic literature reviews. This is done by using the categories of prospective, corrective and residual DRM. It is important to note that although the literature is structured according to specific categories (prospective, corrective, and residual DRM) it is impossible to completely isolate these systems from one another. They are interconnected and interdependent systems, functioning in constant flux. Therefore, certain categories may overlap or seem extremely similar/repetitive.

Firstly, AI applications in DRR are explored according to prospective DRM. It investigates AI uses related to environmental monitoring, simulated DR data, research and development (R&D), environmental resilience and adaptation, and proposed AI ethics and governmental policy development. Secondly, AI applications in corrective DRM are explored through considering hazard mapping, risk assessment, and mitigation strategy comparisons. Lastly, AI applications used for residual DRM is discussed according to preparedness, response and recovery processes.

Preparedness measures include early-warning systems and evacuation planning. AI uses for response are identified by the research as real-time event mapping, damage assessment, situational tracking, and robotic assistance. Recovery measures explored in this section are tracking progress, estimating repair costs, and evaluating damages. DRR's most prominent process involves reducing prospective risk. As DRR is focused on moving away from a disaster centered approach, prospective DRM becomes one of its most important facilitators, focused on reducing the development of potential risk.

3.2 Prospective DRM

Prospective DRM is the part of DRR which aims to address and avoid the development of new or increased DR (Manyena, Machingura & O'Keefe, 2019). Reducing prospective risk is extensively complex as these include unknown risks that may occur due to changes to/in the system. These unknown or uncertain risks need to be governed through prior interventions in systems prone to vulnerability. Examples include but are not limited to policy frameworks, education, community involvement and infrastructure.

As stated in Chapter 2, the performance of AI is largely dependent upon the availability of quality data (Mikalef & Gupta, 2021). The accumulation of valid and reliable data can, therefore, be considered prospective DRM as it avoids a lack of information and inconsistent model development. Global digitisation is increasing readily available data (Manyika & Sneider, 2018) and aids in AI systems becoming more reliable and comprehensive. AI applications, along with geospatial information systems (GIS), have become highly developed and show the potential for great effectivity in environmental monitoring (Nunavath & Goodwin, 2018).

3.2.1 Environmental monitoring

Geospatial data has been used as a technique for understanding and monitoring DR and hazards for decades. According to Sun and colleagues (2021) geospatial data collection is integral to learning and understanding natural systems; forecasting consequences and trends in human activity; and assessing hazards in relation to environmental and societal interactions. GIS has become heavily reliant on computational power, especially when considering three dimensional computations, route calculation, and map rendering (Li & Ning, 2023).

The advancement of AI has procured advancements in geospatial analysis which has made it possible to re-envision geospatial data at scale (Qin *et al.*, 2022). As GIS data is used for most hazard assessments and analysis, its amalgamation with AI presents great potential. Promising results emerge from combining GIS and AI such as cleaning data in subterranean utility networks;

simplifying interpretations of utility drawings; and more efficient asset recognition in images (Li & Ning, 2023).

Qin and associates (2022) stipulate that AI advancements, specifically in DL and ML, have created innovative geospatial data analysis methods. For instance, it enhances remote sensing image classification, change detection and time-series analysis; and determines semantic segmentation of 3D models, geographical text analysis, and environmental sensor data analysis (Qin *et al.*, 2022). Through modern computing, storage and cyberinfrastructure, geoscientists have bridged the gap between geospatial data and AI models to create systems that automatically monitor and forecast changes in nature (Sun, Bocchini & Davison, 2020).

An example of such a system is the 'spatial data analysis algorithm' named GeoAI. It uses high resolution geographic data and high-performance computing techniques such as deep learning (DL) to fuel rapid and accurate object detection (Janowics *et al.*, 2019). Projects by GeoAI includes information extraction from historical maps (Janowics *et al.*, 2020), terrain feature detection (Li *et al.*, 2021), semantic classification (Guo & Feng, 2020), densely distributed building footprints (Xie *et al.*, 2019), new methods for spatial interpolation (Zhu *et al.*, 2019), and traffic forecasting advancements (Ren, *et al.*, 2022).

Natural language processing (NLP) and ML algorithms are similarly extracting geographic information from textual (unstructured) data such as news articles and websites (Janowics *et al.*, 2019). Earth observational data has grown immensely through instrumental networks (such as seismic-, meteorological-, and hydrological- observation stations), remote sensing (drones and satellites), and crowdsourcing (surveys and IoT) (Kuglitsch *et al.*, 2022). Although data are becoming more readily available with global digitization, vulnerable environments still need historical data used for AI model generation. This problem is being addressed through simulated data.

3.2.2 Simulated data

AI applications thrive on vast amounts of quality data of which there are still limited amounts (Rashid & Kausik, 2024). The most obvious solution to this problem is probably the most difficult one: creating models that can function with limited data and collect it without the need for human input (Kelly, Kaye & Oviedo-Trespalacios, 2023). More challenging is executing it without any prior bias or lack of consideration, which in the current stages of AI is still relatively far-fetched (Chen, 2023). With the remaining scarcity of observational data, AI can generate simulated data using unsupervised algorithms (Tan *et al.*, 2020).

Various computational models are used to generate data, estimate disaster-induced impact, and identify vulnerable structures (Sun, Bocchini & Davison, 2020). Examples of these models include PRAISys (Bocchini *et al.*, 2015) and In-Core (van de Lindt *et al.*, 2016). PRAISys (Probabilistic Resilience Assessment of Interdependent Systems) platform aims to combine individual infrastructure models with their systemic interdependencies to assess infrastructural resilience under extreme event uncertainty (Bocchini *et al.*, 2015).

The platform aims to classify uncertainties whilst devising mathematical and computational tools to capture their characteristics. This is done to enable better design and management in creating next generation infrastructure that is more resilient to component failures and extreme events (Bocchini *et al.*, 2015). In rainfall-runoff process modelling, for instance, AI is used to simulate river flow using hydrological data (Dawson *et al.*, 2000). Water runoff process projects include water runoff simulations (Liu *et al.*, 2014) and estimation of downstream flow (Pramanik & Panda, 2009).

In-Core is a simulation platform enabling users to model the impacts of natural hazards on communities and the resilience present in those communities (Bocchini *et al.*, 2015). Like PRAISys, In-Core enables users to identify prospective risks and overlooked hazards which aids in addressing DR and enhances resilience. For these platforms to materialize the need for educated and expert developers are essential. Therefore, investment in AI research and development (R&D) is integral to facilitate its DRR opportunities.

3.2.3 Research and Development (R&D)

Training future developers and empowering individuals who are interested in AI can aid in more versatile and effective model development. Institutions such as AI4PEP (Artificial Intelligence for Pandemic, Epidemic, Preparedness & Response) provide funding, grants and awards to prospective AI innovators set on developing responsible AI. AI4PEP applicants should adhere to themes such as early warning systems, early detection, early response, mitigation and control of early disease outbreaks (AI4PEP, 2023).

Funding innovations and research in AI may contribute to reducing prospective risk. Institutional funding creates an environment where individuals can contribute to the AI DRR body of knowledge and enforce best practice initiatives (Vasileiou, Barnett & Fraser, 2022). This may prevent ineffective means of AI implementation and encourage further development of sustainable models. Additionally, reducing prospective risk involves building a resilient and interconnected network of active agents that direct various disciplines towards a common goal (Mitchell, 2013).

For example, the AI platform 'MOBILIZE' is used for building resilient communities that employ multi-agent collaborations (MOBILIZE, 2019). This user-friendly API (Application Programming Interface) allows agencies to interactively explore and upload hazard, exposure, and vulnerability information (Abid *et al.*, 2021). The MOBILIZE goal is to establish a common understanding of local risk and implement DRR procedures. The Azure cloud-based service offers a virtual reality technology interface which allows users to visualize 3D representations of hazards and their prospective effects (Abid *et al.*, 2021).

The visualization of real-time data supports information such as rainfall predictions, flood-prone areas and drainage lines (Abid *et al.*, 2021). 'AI for Good' is another example of a digital platform created to connect various autonomous agents (governments, corporations, developers, researchers etc.). These agents are interested in using AI for advancing towards the United Nations (UN) sustainable developmental goals (SDG) (ITU, 2021). It facilitates interdisciplinary and interagency collaborations, novel AI development, and research innovations.

Further reduction of prospective risk can be accomplished by more extensive and meticulous urban and environmental planning. Most hazards develop due to a lack in structural adaptation. With the rise in climate change and extreme weather, urban and infrastructural planning should prioritize adaptation and sustainability measures.

3.2.4 Environmental resilience and adaptation

AI assists in DRR through ensuring measures are in place for building more resilient and sustainable structures (Kaswan & Dhatteval, 2021). Therefore, the prospect of more sustainable and resilient architecture aids in facilitating less fatalities during emergency events. Urban land use planning can benefit from the use of AI and ensure spatial engineering proficiently makes use of environmental resources (Chaturvedi & De Vries, 2021). In China, for example, urban planners and scientists have developed an AI-based urban planning system that can outperform human planners (Ghisleni, 2024). The project aims to define the ideal urban planning system, using the '15-minute city' concept (Ghisleni, 2024). This relates to building cities in such a way that most daily services and needs are located within a 15 min walk or bike ride (Schauenberg, 2023).

In existing literature there is limited research on urban resilience (Tan *et al.*, 2020). Resilience aids in the capacity to absorb against disaster damage and loss (Rose & Liao, 2005). Consequently, its inclusion in research can help effected environments reduce the risk of systemic and structural failures whilst encouraging speedy recovery (Xie *et al.*, 2018). Agricultural adaptation is vital to building environmental resilience. Agricultural systems use AI for crop and soil health monitoring, automated weeding, intelligent spraying, insect and plant disease

detection, livestock health monitoring, harvesting, ploughing, pruning, grading, sorting, and energy security (Mana *et al*, 2024).

Water resource management can also be considered an environmental resilience and adaptation measure in prospective DRM. Hubert and others (2020) indicate that there is need for a digital transformation in water management systems. They indicate that AI management of water resources will aid in enhancing service delivery, cost reduction, and reduce unaccounted for water problems (Hubert *et al.*, 2020). AI shows strategic advantage to applications in water management, namely operational efficiency, multiple processing abilities, sustainable practice, and quality assurance (Lunani, 2023).

With the rapid rise in DRR AI applications, ethical governance has become a concern. Therefore, to further reduce prospective risk in DRR efforts, policy development is integral to AI implementation.

3.2.5 Policy development

Encouraging the ethical use of AI in DRR avoids developing novel risks that may cause unpredictable emergent behaviors. AI may also help assess climate risk and assist in development of policies, strategic frameworks and facilitate appropriate operational approaches (Kaack *et al.*, 2021). One of the first institutions to formulate international guidelines on ethical AI use is the United Nations Educational, Scientific and Cultural Organisation (UNESCO).

Their human rights approach to AI facilitates key guidelines to ethical AI use namely proportionality and 'do no harm'; safety and security; right to privacy and data protection; multi-stakeholder and adaptive governance and collaboration; responsibility and accountability; transparency and explainability; human oversight and determination; sustainability; awareness and literacy; and fairness and non-discrimination (UNESCO, 2023). The ethical conduct of AI use can only be governed by concrete policy development. UNESCO (2023) developed key policy recommendations that need to be implemented for ethical use of AI by Member States.



Figure 3.1: Responsible AI policy area development recommendations (UNESCO, 2023)

As there is still a long way to go before actionable resources are provisioned to Member States, implementing the recommendations in Figure 3.1 can be accomplished through using two methodologies (UNESCO, 2023). The Readiness Assessment Methodology (RAM) and the Ethical Impact Assessment (EIA). RAM is designed to aid Member States in determining their preparedness for implementing the proposed recommendations. RAM aids in addressing requirements such as the presence of laws that regulate AI and the ability of national infrastructure to support AI technology.

Through determining RAM, UNESCO can custom tailor its capacity-building support and help Member States create a roadmap towards the ethical use and development of AI. EIA is a structured process that operationalizes the proposed recommendations. By aiding project team collaboration with affected communities, EIA helps identify and assess the impacts of AI systems. EIA also aids in identifying those most affected by AI, the form of its impacts, preventing harm, and eloquent resource allocation.

These methods provide an opportunity to reflect on the potential impacts of AI and identify the prevention measures needed to reduce them (UNESCO, 2023). Reducing prospective disaster risk cannot be confined to single activities or processes. It is a combination of various interconnected and interdependent actions set on reducing DR in different domains. Gender

inequality, poverty, mismanagement, corruption, violence, environmental degradation and climate change are among the drivers of prospective DR.

Therefore, addressing prospective DR should start by looking at underlying systems that enforce vulnerability and possible exposure of a population. The above-mentioned examples only touch the surface of reducing prospective DR in AI DRR and can only be adequately examined by relating to a specific context. In general, the application of AI in DRR should consider various prospective DR such as data generation and collection, infrastructural adaptation, R&D investments, facilitation of multiagent collaborations, ethical conduct, and policy development.

Although the literature (Abid *et al.*, 2021; Sun, Bocchini & Davison, 2020; Tan *et al.*, 2020) includes limited accounts of AI reducing prospective risk, the reviews themselves can contribute to this goal. Through research on AI and the applications thereof in DRR, these studies broaden prospective avenues for better understanding DR, enabling multi-agent collaborations, raising awareness and ultimately facilitating resilient development.

Although the discussed systemic reviews can be considered part of limiting and preventing prospective risk, much of its content still focuses on corrective and residual DRM. Corrective DRM is different from prospective DRM as its focus is on understanding a specific existing risk and not on the possibility of it.

3.3 Corrective DRM

Corrective DRM activities seek to remove or reduce current DR and require immediate attention (UNDRR, n.d.). In other words, corrective DRM primarily relates to mitigation measures. Mitigation consists of forecasting, assessing, monitoring, and evaluating existing hazards, through considering the vulnerability and exposure of a community. Sun, Bocchini and Davison (2020) found that although there is limited literature on AI in mitigation, AI projects can be derived from plans executed in response and restoration efforts.

Their findings state that supervised and unsupervised AI models are mostly used in mitigation for forecasting hazards and assessing risks (application area 1) (see Figure 3.2). Supervised and unsupervised models are also used in evaluating impacts due to hazards (application area 2) and assessing vulnerability (application area 3) (Sun, Bocchini & Davison, 2020). The publications found on mitigation indicate fewer applications of AI methods in application areas 2 and 3 compared to those in application area 1 (Figure 3.2) (Sun, Bocchini & Davison, 2020). Application area 4 (comparing mitigation strategies) has the least publications in mitigation (Sun, Bocchini & Davison, 2020).

ML models are popular in forecasting, mapping, situational tracking, event awareness, and division support (Sarker, 2022). Through utilising AI for impact and vulnerability analysis, role-players can gain situational awareness and develop efficient mitigation strategies (Schwartz, 2018). For example, mitigation strategies include disaster risk related policy development (Sun, Bocchini & Davison, 2020a; 2021), retrofitting vulnerable structures (Karamlou *et al.*, 2016), using underground cables, and elevating electric substations (Duffey, 2019). Corrective DRM involves predicting and mapping hazards and risks to reduce their effects and prevent their accumulation.

3.3.1 Hazard mapping

The development of hazard maps is integral to establishing terrain characteristics, meteorology, lithology, and human activity for mitigation efforts (Sun, Bocchini & Davison, 2020). Traditional methods of developing hazard maps have shown to produce high volumes of false alarm rates and prove labour intensive (Bellaire *et al.*, 2017). AI techniques rapidly analyse extensive amounts of data to accurately assess hazard risk in a timely manner (Pradhan, 2009; Yilmaz, 2010). Therefore, AI is a vital tool used by various scholars to develop spatial dispersal and susceptibility maps (Arinta & Andi, 2019; Chen *et al.*, 2020).

AI's timely processing capacity uses different methods to help develop maps for various hydrometeorological hazard reduction purposes. For instance, AI mapping projects involve snow avalanche predictions (Choubin *et al.*, 2019; Dekanova *et al.*, 2018; Rauter & Winkler, 2018; Gauthier *et al.*, 2017), landslide susceptibility (Goetz *et al.*, 2015; Zhou *et al.*, 2018; Xu *et al.*, 2012; Dou *et al.*, 2015), forecasting precipitation (Huang & Xiang, 2018), fire susceptibility (Sachdeva *et al.*, 2018), and fire size prediction (Mitsopoulos & Mallinis, 2017).

Structural damage from natural hazards is predicted by using fragility curves (analysis of historical and simulated data) in various projects (Mangalathu, Jeon & DesRoches, 2018; Mahmoudi & Chouinard, 2016). Hazards causing infrastructural service disruptions are also predicted using historical data (Cerrai *et al.*, 2019; D'Amico *et al.*, 2019; Wanik *et al.*, 2015). Whereas community and structural vulnerabilities are mapped by using AI in conjunction with social and physical sensors (Yoon & Jeong, 2016; Wang *et al.*, 2019a; Nabian & Meidani, 2018).

Abid and colleagues (2021) found, through analysing 52 studies on flood vulnerability mapping, that ANN is mostly used for analysing input data. This includes rainfall, slope, elevation, flow accumulation, and geographical data gathered by remote sensing techniques. Furthermore, in 53 landslide disaster exposure mapping studies, Abid and others (2021) found that AI classifier algorithms were most frequently used on data from satellite spatial images and field surveys.

Indicating that corrective DRM mapping is primarily achieved through using ML techniques accompanied by sensors, satellites and surveys.

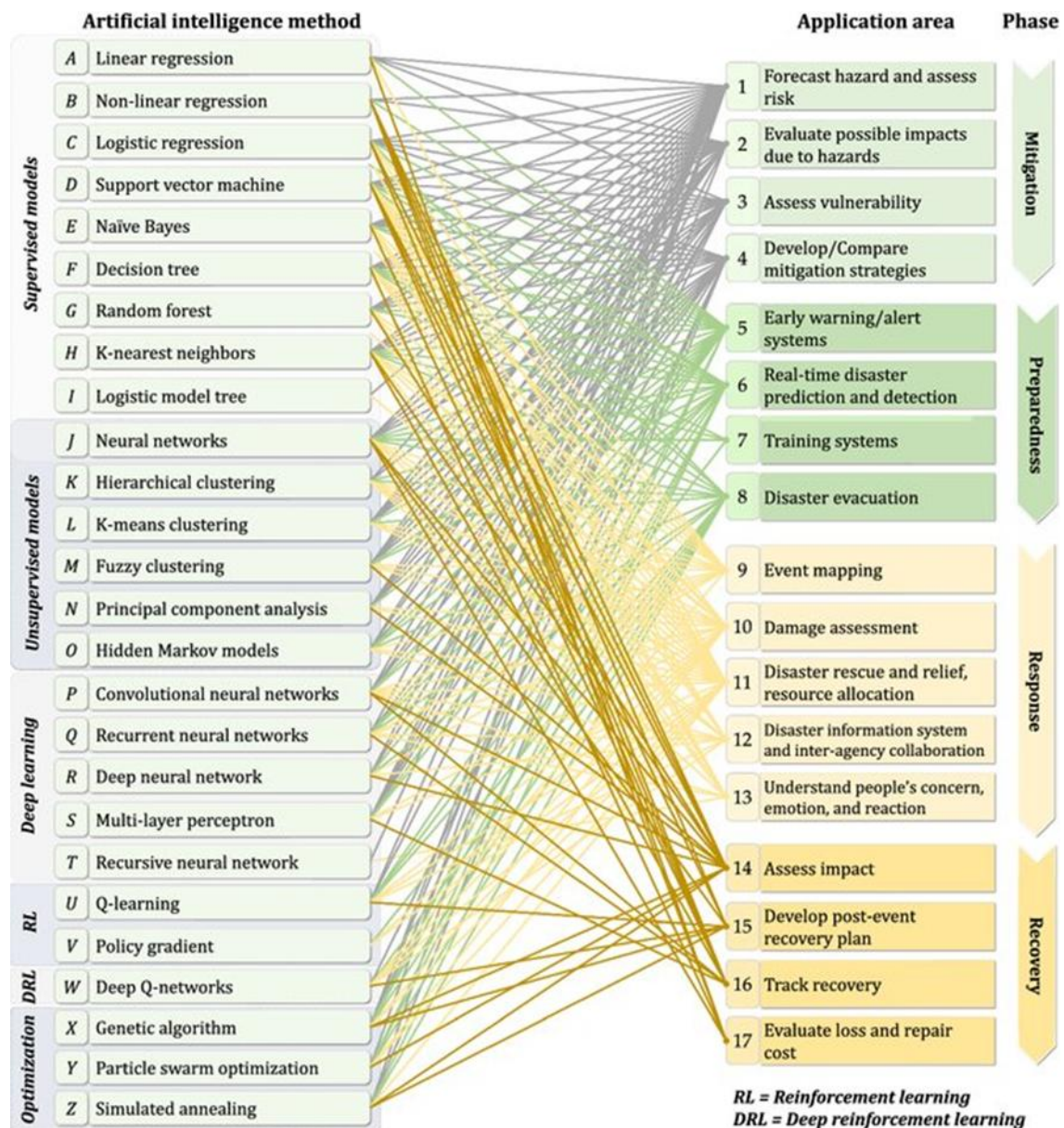


Figure 3.2: Artificial Intelligence in Disaster Risk Management (Sun, Bocchini & Davison, 2020)

Assessing risk is also vital for corrective DRM, as tracking and monitoring various hazards assist in developing early warning systems. Prevention and preparedness strategies are largely based on risk assessment and are vital for effective DRR efforts.

3.3.2 Risk assessment

Risk assessment entails determining the nature and extent of DR (UNDRR, n.d.). It can be used to forecast and predict possible DR. Various projects are present in AI risk assessment (Xia *et al.*, 2019) consisting of emergency resource demand prediction (Liu, Hu & Li, 2012) and emergency warning systems (Kang & Choo, 2016). Real-time identification of impending hazards and early warning indicators are practical solutions to mitigation efforts (Sun, Bocchini & Davison, 2020). AI algorithms such as linear, non-linear, and logistic regression are used to forecast risks and hazards and predict their possible impacts (Abid *et al.*, 2021).

AI can serve as a cost-effective way to forecast events, such as floods (Yaseen *et al.*, 2015), ice jams (Zhao, Hicks & Fayek, 2012), fires (Muhammad *et al.*, 2018), and cyclone trajectories and storms (Ghosh & Krishnamurti, 2018). According to Tan and associates (2020) flood mitigation can be divided into six objectives namely: risk assessment, water level prediction, streamflow forecasting, rainfall-runoff process modelling, and flood frequency analysis. AI projects in flood risk assessment are used for regional flooding (Tan *et al.*, 2020), flash flood modelling (Ragettli *et al.*, 2017), flood risk graphs (Darabi *et al.*, 2019), and flood disaster prediction (Tayfur *et al.*, 2018; Zhou, Guo & Chang, 2019).

Moreover, water level prediction AI projects involve forecasting hydrological data (Jiao, Guo & Ding, 2016), water level prediction (Seo *et al.*, 2015), and streamflow forecasting (Badrzadeh, Sarukkalige & Jayawardena, 2015; Hadi & Tombul, 2018). Furthermore, risk assessment studies on landslides depend on reliability assessments (Tan *et al.*, 2020) and involve a vast amount of AI projects (Shirzadi *et al.*, 2017; Chen *et al.*, 2017). Other AI projects discussed by Tan and others (2020) include rainfall risk assessment (Choi *et al.*, 2018; Sulaiman *et al.*, 2021) fire risk assessment (Sayad, Mousannif & Moatassime, 2019; JaaFari *et al.*, 2019), drought risk assessment (Achour, *et al.*, 2020), assessing the risk of a collapse (Hoang & Pham, 2016), debris flow (Pai *et al.*, 2014), risk of ice (Wang *et al.*, 2019a), and storm risk assessment (Hart *et al.*, 2019).

Risk assessment is important for determining the extent and possible impacts of hazards. It aids in developing strategies for effective DRR. A vital part of corrective DRM is considering and re-evaluating mitigation measures. Mitigation measures are not absolute and can present flaws in management. Therefore, to ensure the most effective measures are in place, mitigation strategies need constant comparison and development.

3.3.3 Strategy development and comparison

AI methods can be utilised to develop and compare mitigation strategies (Sun, Bocchini & Davison, 2020). Re-evaluation of mitigation strategies creates a feedback loop of revised measures. It ensures measures are always up to date and adapted to novel risk formation. This can be achieved by using an estimation of needs (Nguyen *et al.*, 2017), recognising human activity (Sadiq, Selamat & Ibrahim, 2018), and identifying priorities in management (Canon, Satuito & Sy, 2018). AI is also used to develop climate change adaptation measures which aims to advance accurate prediction tools for assessing and estimating extreme environmental events (Sahil *et al.*, 2023).

Additionally, AI is used in developing mitigation strategies specifically concerned with falling hazards on construction sites (Bigham *et al.*, 2018). The project considers hazard identification at the pre-construction phase and suggests enforcing applicable building codes to reduce risk (Bigham *et al.*, 2018). Analysing remote images and developing emergency plans are also possible through AI (Dou *et al.*, 2014). AI is used in comparing and developing mitigation strategies to efficiently train systems and plan disaster evacuation procedures (Sulistijono & Risnumawan, 2016; Ci, Liu & Wang, 2019).

Reducing existing hazards and preventing them from developing new or increased DR is an extensively complex venture. Therefore, developers of AI models must consider various interventions and their effects for bettering mitigation practices. By comparing mitigation strategies AI techniques can learn from past executions and become more efficient. Corrective DRM focusses on existing hazard reduction whereas residual DRM deals with existing hazards that cannot be reduced, only managed.

3.4 Residual DRM

Residual or compensatory DRM aims to strengthen the economic and social resilience of societies and individuals faced with risks that cannot be reduced (Wagner *et al.*, 2021). Residual DRM is composed of preparedness, response and recovery measures. Additionally, a mixture of various financing instruments including contingency credit, national contingency funds, social safety nets, insurance, and reinsurance (UNDRR, n.d.). Residual DRM is composed of preparedness, response and recovery.

Most DRM systems are focused on residual DRM which indicates the disaster centred approach of previous DRM models. In DRR focused models, residual DRM deals with inevitable hazards

by reducing their impact. When faced with these hazards it is best to have effective preparedness measures in place.

3.4.1 Preparedness

In preparedness the primary measures are to formulate emergency plans, carry out emergency drills, and enhance capacity such as early warning, monitoring, resilience and recovery rates (Ahmadi, Seifi & Tootooni, 2015; Mashi, Oghenejabor & Inkani, 2019). The preparation phase is categorised by Sun and partners (2020) in Figure 3.2 as early warning/ alert systems (application area 5); real-time disaster prediction and detection (application area 6); training systems (application area 7); and disaster evacuation (application area 8).

According to the various publications reviewed through Sun and associates (2020), most AI methods are applied to application areas 5, 6, and 8, whereas limited applications are ascribed to area 7 (Figure 3.2). The limited publications on application area 7 (disaster training systems) may be due to a lack in human response data (Sun, Bocchini & Davison, 2020). On the other hand, Tan and others (2020) categorise the use of AI for preparedness as mainly consisting of emergency warning systems. Hydrometeorological risk assessment is made easier through using AI models to help monitor hazards and ensure more effective early warning systems (Fortes de Meira & Bello, 2020).

3.4.1.1 Early warning systems

AI helps to speed up the process of early warning systems by communicating relevant information to role-players and distributing accurate decision-making tools (Lamsal & Kumar, 2020). Accelerating the process of early warning contributes to more efficient response measures and less necessity for damage control. Through improved monitoring systems, AI presents the opportunity for more comprehensive hazard understanding and initiates cross-border and comprehensive solutions (ITU News, 2022).

For instance, early warning systems by Gizaw and Gan (2016) uses AI to determine the number of possible regional floods in Columbia and Canada. Additionally, the UrbanFlood project uses an internet platform to communicate abnormal dike behaviours using various sensor streams for early warning (Noymanee, Nikitin & Kalyuzhnaya, 2017). Also, the mobile application called DHARA utilises AI to anticipate the likelihood of floods and aid in early warning systems implementing preparedness and restoration plans (Kumar & Sud, 2020).

Early warning models derive data from satellite imagery and social media applications. For example, cloud services (using IoT) can aid in rapidly and accurately sharing information on

disaster events for more efficient early warning systems (Chung & Park, 2015). One of the most pertinent algorithms used in AI prediction models is DL (Kabir, Gruzdev & Madria, 2020). DL aids in limiting threat of hazard (Abid *et al.*, 2021), and solving prediction problems (Yang & Chervone, 2019; Yao *et al.*, 2020). Additionally, an important part of preparedness is having evacuation plans in place and ready for execution.

3.4.1.2 Evacuation planning

AI is used in various projects for emergency evacuation (Tissera, Printista & Luque, 2012) and emergency behaviour (Innocente & Grasso, 2019). Some disasters require immediate evacuation whereas others may give people a few days to prepare (Sun, Bocchini & Davison, 2020). During evacuations, large crowds move in different directions which makes it necessary to identify effective routes (Peng, Li & Hu, 2019), develop support systems (Higuchi *et al.*, 2014) and estimate crowd dynamics (Zheng & Liu, 2019). Sun and associates (2020) indicate that preparing for an evacuation means preparing for possible problems and requires developing carefully considered countermeasures.

For example, to move more traffic inland during an evacuation, AI can be used to activate and regulate contraflow lane reversals (Burris *et al.*, 2015). Preventing the risk of traffic jams and car accidents during an evacuation. Furthermore, AI can predict cyclone evacuation decisions by using ML methods (Sun, Huang & Zhao, 2024). The project by Sun, Huang & Zhao (2024) predicts household-level evacuation decisions by using accessible demographic and resource related indicators. Rather than focus on psychological indicators of predicting evacuation behaviour, its focus is directed on physical access to relief stations.

Preparedness is vital to reducing DR in residual DRM efforts. However, areas that remain lacking in preparedness literature include the significant role of preparedness, planning, management, and its impact on disaster response (Tan *et al.*, 2020). Preparing response and rescue plans benefit advancements that reduce the impacts of DR and ensure efficiency of efforts (Tan *et al.*, 2020). Response entails reacting to hazard impact and aims to reduce its effects on livelihoods and infrastructure (Ouma, 2020).

3.4.2 Response

The main purpose of disaster response is to maintain stability in socio-economic systems (Caunhye, Nie & Pokharel, 2012; Wu & Cui, 2018). AI techniques aid response efforts by improving the exchange of information, real-time support, and simulated scenarios on multi-agent platforms (Abid *et al.*, 2021). Efforts in this stage include implementing preparedness measures,

analysing disaster locations, deploying rescue teams, enabling transportation of materials, and enforcing evacuation procedures (Anaya-Arenas, Renaud & Ruiz, 2014; Poblet, Garcia-Cuesta & Casanovas, 2018).

Sun and others (2020) note in Figure 3.2 that ML and DL are frequently applied to event mapping (application area 9) and damage assessment (application area 10). Most AI models are applied to disaster rescue and resource allocations (application area 11). Whereas ML and DL are used for disaster information systems, inter agency collaborations (application area 12), and understanding people's concerns, actions and emotions (application area 13) (Sun, Bocchini & Davison, 2020). Tan and others (2020) similarly find that disaster response in AI application mostly consists of disaster environment analysis, emergency rescue procedures, and personnel evacuation.

Furthermore, they find that disaster response AI projects can be divided into six categories namely search and rescue (Geng *et al.*, 2019), emergency response decision (Han & Deng, 2018), emergency evacuation (Na, Son & Hong, 2019), environmental analysis (Zhao *et al.*, 2018), website application (Alam, Ofli & Imran, 2018) and emergency materials transportation (Liu & Xie, 2017). To support efficient disaster response efforts, it is essential to determine situational awareness through applying models to live area maps (Ramchurn *et al.*, 2016).

3.4.2.1 Real-time event mapping

Real-time event mapping is crucial to effective response behaviour. Damage information and event maps provide extensive information for resource deployment, the formulation of short-term housing needs, and the development of search and rescue procedures (Kim *et al.*, 2018; Rizk *et al.*, 2019). Hydro One for instance uses AI in real-time predictive analysis to position crews at service stations and reduce service restoration time (McConnon, 2018).

DL and ML techniques are commonly used for mapping emergency events (Abid *et al.*, 2021). Disaster related data are continuously generated from unmanned aerial vehicles (Aljehani & Inoue, 2018), satellites (Eguchi *et al.*, 2008), social media (Cervone *et al.*, 2016), and sensors (Park *et al.*, 2019). Satellite data is used to generate maps of damaged bridges and buildings (Balz & Liao, 2010), post-impact disaster regions (Casagli *et al.*, 2017; Rosser, Leibovici & Jackson, 2017), and infrastructural inventory (Eguchi *et al.*, 2008). Moreover, hazard data is analysed through computer vision methods which represent emergency situations using 'live maps' (Valkaniotis *et al.*, 2018; Xiao, Li & Gong, 2018).

Classifier algorithms are often used to analyse images and maps (Vetrivel *et al.*, 2016), compare pre- and post-event results, and extract discrepancies that indicate damages and prioritise response (Cervone *et al.*, 2016; Nguyen *et al.*, 2017). Assessing damage in response is vital to planning and risk reduction procedures. Damage assessment informs responders of blockages, unfit routes, and unstable environments, facilitating more effective response planning and behaviour.

3.4.2.2 Damage assessment

Various databases are established to support the assessment of damages from different hazards and structures (Sun, Bocchini & Davison, 2020). Databases include FEMA NFIP (Federal Emergency Management Agency National Flood Insurance Program) Redacted Claims Data Set (FEMA, 2019), the HOWAS 21 (Kellermann *et al.*, 2020) general assessment of flood damage data set, and the XBD (External Benchmarking Device) building damage assessment data set (Gupta *et al.*, 2019).

Supporting disaster response through crowd-sourced information is becoming increasingly popular (Sun, Bocchini & Davison, 2020). Information in situational awareness and damage assessment is being generated by volunteers focused on increasing the speed at which data is analysed. This aids in processing valuable crowdsourced information based on disaster damage maps (Ghosh *et al.*, 2011; Butler, 2013). For instance, the Humanitarian OpenStreetMap Team produced devastation maps of the Philippines after Typhoon Haiyan hit. These maps assisted in swift damage assessment and effective response actions (Butler, 2013).

Rescue and relief efforts are supported through utilising robotics, mobile phone data and social media platforms attempting to support time efficient and effective decision-making tools (Sun, Bocchini & Davison, 2020). The use of social networking sites and digital technologies provide the public with suitable and operative means of consuming and distributing information (Villodre & Criado, 2020). With the rise in information communication technology, large amounts of data are becoming available through telecommunication and social media tracking (Novellino *et al.*, 2018).

3.4.2.3 Social-media tracking

Social media is a powerful tool used by governments to distribute information and aid local communities in accessing assistance (Takahashi, Tandoc & Carmichael, 2015). ML is vital for analysing large amounts of social media data, turning volumes (during a crisis) into credible and comprehensive results (Oakley *et al.*, 2020). Data derived from social media are efficient sources

for building disaster information systems as it embeds time, geo-location and other disaster related information (Laylavi, Rajabifard & Kalantari, 2017).

Evidently, social-media tracking supports decision-making regarding resource allocation and disaster relief priorities (Castellanos, Marti & Sarkaria, 2018). Understanding the victims' psychological needs and emotions should prove helpful for disaster rescue efforts (Lin, Margolin & Wen, 2017; Li *et al.*, 2019). As humans are emotional beings, their thoughts and decision-making abilities become influenced in a time of crisis (Greifeneder, Bless & Pham, 2011). Social media data embeds emotional images to text which makes it possible to determine public psychological and healthcare needs (Wilson *et al.*, 2016; Kuang & Davison, 2017).

As an information source, social media does raise concern in terms of reliability, credibility, verification of information, and deriving actionable knowledge from big data (Acar & Muraki, 2011; MacEachren *et al.*, 2011; Tapia *et al.*, 2011). The effects of hazards usually hinder human intervention, as rescue efforts are limited by extreme environmental damage (Sun, Bocchini & Davison, 2020). Due to the increase in computation and censorious technology, robots have evolved to automated artificially intelligent machines (Darapureddy, Kurni & Saritha, 2021).

During an emergency the telecommunication volume increases drastically which causes a jump-delay pattern (Bagrow, Wang & Barabási, 2011). Due to the large number of calls for help, agencies need to classify vast amounts of time sensitive information and distribute it from public to institutional domains (Sun, Bocchini & Davison, 2020). ML is used to automatically recognise key words with a high priority and rapidly process verbal data from different areas (Ramchurn *et al.*, 2016). Sentiment mining through ML algorithms can aid disaster managers in executing crisis management and increase efficiency of disaster relief efforts (Sudha & Dhanalakshmi, 2024).

Additionally, mobile phone data is used to determine population displacement and movement immediately after a disaster through location-based algorithms (Bengtsson *et al.*, 2011). Frequently hazards destroy base stations and disable mobile communication. Therefore, alternative stations must be equipped with countermeasures that support emergency communications (Suriya & Sumithra, 2019; Wang *et al.*, 2019; Samir *et al.*, 2019). Sharing hazard information across organisations and agencies are done through collaborative GIS (Sun & Li, 2016; Abdalla & Esmail, 2018; Li, Batty & Goodchild, 2019a), decision tools (Moskowitz *et al.*, 2011) and information management platforms (Bunker, Levine & Woody, 2015; Rasouli, 2018).

Real-time data can be extracted from social media, remote sensors, mobile phones and aerial imagery using DL and ML algorithms (Sun, Bocchini & Davison, 2020). Disaster information systems include UN-SPIDER (United Nations Space-based Information for Disaster Management

and Emergency Response) (Subik *et al.*, 2010), MADIS (Multimedia-Aided Disaster Information Integration System) (Yang *et al.*, 2012), CrowdHelp (Besaleva & Weaver, 2013), Sahana (Careem *et al.*, 2006), and DMCsim (Disaster Management Coordination Simulation) (Hashemipour, Stuban & Dever, 2017).

With high sensory data popularity, AI collaboration with various robotics have shown promising for DRR. Robotics assist in mobility and extensive data gathering techniques. The technology forms a crucial part of AI effectivity and development.

3.4.2.4 Robotic assistance

The use of robotics in response enables role-players to intervene from a physically safe distance (Murphy, 2014; Axel & Van Aardt, 2021). Robotics can be utilised to serve as remote sensing platforms that map and interact with the environment (Stefanov & Evans, 2014). It can be used for fighting fires in dangerous conditions (Schneider & Wildermuth, 2017; Ando *et al.*, 2018), inspecting damaged areas (Lattanzi & Miller, 2015; 2017), and executing search and rescue activities (Hu *et al.*, 2019). In storm hazard reduction AI models, environmental analysis is a popular function and makes use of robotics for its execution (Murphy *et al.*, 2008).

In fire response AI is used with robotics in an advanced unmanned aerial system named Fotokite Stigma (Pizzuto, 2023). The fully autonomous robot is engineered to provide aerial overviews of an environment during search and rescue ventures, fire response, or traffic jams (Pizzuto, 2023). Another example of robotics used in AI response is called Colossus, a fire-fighting robot (Pizzuto, 2023). The high-risk operative robot is designed to withstand thermal waves of up to 900 degrees Celsius with heavy duty capabilities (Pizzuto, 2023).

ML is mostly used for robotics to aid in environmental adaptation and acquiring new technological skills (Lenz, 2016). DL, for example, is popular in robotic manipulation (Gemici & Savena, 2014; Lenz, 2016), handling multiple input data sources (Noda *et al.*, 2014), and visual detection (Giusti *et al.*, 2015). AI is predominantly used in response efforts for real-time event mapping, damage assessment, social media tracking, and robotics. Consequently, response efforts depend on the effectivity and availability of resources and facilities. According to the literature review by Tan and associates (2020), AI in response efforts have various limitations.

Disaster managers' ability to make emergency decisions need to be improved and must consider different stakeholder conditions such as time pressure, risks, and uncertainty (Tan *et al.*, 2020). Additionally, the limited data on response makes it difficult to conduct extensive studies and calls for designing AI models to generate simulated data (Tan *et al.*, 2020). After an emergency event,

DRM aims to recover from the impact of the hazard. The complex and multifaceted recovery process involves various role-players such as public authorities, governments, and private organizations (Sun, Bocchini & Davison, 2020a). All of which play a vital role in its execution.

3.4.3 Recovery

The main purpose of recovery is to shorten the time it takes to achieve it. This is facilitated by measures such as the formulation of recovery and reconstruction plans, available resources, post-disaster data analysis, restoration of infrastructure, and disaster assistance (Sahebjamnia, Torabi & Mansouri, 2015). In Figure 3.2, Sun and colleagues (2020) identify AI in recovery as part of assessing detailed disaster induced impact (application area 14), developing recovery plans (application area 15), tracking and recovery progress (application area 16), and loss estimation and repair cost (application area 17).

Hazard studies in AI recovery include damage evaluation, website application, post disaster reconstruction and assistance (Tan *et al.*, 2020). Tan and others identify different recovery AI projects related to damage evaluation (Rodriguez *et al.*, 2011; Kou, Ergu & Shi, 2014, Vetrivel *et al.*, 2016; Bai, Mas & Koshimura, 2018), website application (Shan *et al.*, 2019; Ahmad *et al.*, 2017), and reconstruction (Nejat & Damjanovic, 2012). Additionally, relevant AI projects include assistance in general recovery (Singh, 2007), flood recovery (Jiang *et al.*, 2018), and tsunami damage evaluation (Sublime & Kalinicheva, 2019).

In recent years there have been an increase in publications related to AI projects in disaster recovery (Sun, Bocchini & Davison, 2020a). Focus is primarily on determining the impact of disasters as detailed as possible (application area 14) (Sun, Bocchini & Davison, 2020). Accurate and rapid damage assessment is necessary for ensuring fast disaster recovery (Sun, Bocchini & Davison, 2020a). Initially, environmental damage was assessed by doing a visual inspection. However, the labour of visiting post disaster sites has become tedious, time consuming, and report unreliable (Sun, Bocchini & Davison, 2020). Therefore, AI aids in damage evaluation for disaster recovery ventures.

3.4.3.1 Damage evaluation

Damage assessment is greatly dependent on GIS data. GIS and AI are used in comparing pre and post disaster maps for determining environmental damages (Schultz & Perez, 2023). Building footprints are used as a reference for comparing post-disaster imagery (Schultz & Perez, 2023). To recognize objects in an image requires AI components in classification, localization, detection, and segmentation to be utilised (Pi, Nath & Behzadan, 2020). According to Zhu and Ye (2022),

AI spots damage by identifying high risk areas automatically, rapidly finding anomalies over large areas, and determining areas of spectral change.

Post-disaster damage mapping is useful in damage assessment as it helps track the impact of cyclones, earthquakes, and tsunamis (Sublime & Kalinicheva, 2019). For example, automatic post-disaster damage mapping uses DL techniques after the Tohoku Tsunami in Japan (Sublime & Kalinicheva, 2019). Additionally, changes in satellite images are detected using AI reconstruction errors of joint autoencoders (Kalinicheva, Sublime & Trocan, 2019). Change-detecting AI algorithms are increasingly popular for post-disaster satellite imagery assessments (Kalinicheva, Sublime & Trocan, 2019).

Satellite mapping for damage assessment is used to rapidly pinpoint cyclone damage and locate trapped people (Zhu & Ye, 2022). The AI model can provide images of large, damaged environments at a rapid pace (Zhu & Ye, 2022). Although great progress has been made by AI projects in damage assessment; image resolution, evaluation speed, and information quality still need to be upgraded (Tan *et al.*, 2020). Tan and others (2020) indicate that disaster loss assessment accuracy needs improvement.

The challenge is to increase speed and accuracy whilst identifying and mapping large amounts of data in real-time, as there is often a trade-off between accuracy and speed (Pi, Nath & Behzadan, 2020). Damage assessment AI models primarily consist of satellite imagery assessment and change detection. With damage assessment comes another important process in recovery known as estimating repair costs. After the proper assessment of damages to the environment, reparation costs can be estimated.

3.4.3.2 Repair cost estimation

Due to the limited publications on loss estimation and repair cost, Sun and associates (2020a) found that DR recovery is still in its infancy. Loss and repair costs are estimated in practice based on personal loans, insurance claims, assistant grants, and post-disaster assessments (Kim *et al.*, 2015). Although big data and vast development of data analytics offer an opportunity to push AI applicational growth; the lack in standardized methods recording and collecting data may cause a variety of economic impacts (Ladds *et al.*, 2017).

After an emergency there is an urgent need to assess loss and estimate the cost of repairing damage (Ladds *et al.*, 2017; Deryugina, 2017). Various AI techniques calculate loss and repair costs in an affected environment (Sun, Bocchini & Davison, 2020; Polvara *et al.*, 2020). AI algorithms, such as NN and regression, rapidly process images to identify structural damage,

repair needs, and repair costs. Additionally, analysing historical dispersion data from recovery funds; budget allocations, and insurance claims can be determined using AI assistance (Zagorecki *et al.*, 2013; Stojadinovic *et al.*, 2017).

Disinformation after an emergency can be a problem as rumours and fraud may impact governmental and victim vigilance (Sun, Bocchini & Davison, 2020). Data mining AI assists in tracking trends of information flow (Hong *et al.*, 2011; Badmus, 2020), recognizing potential fraud (Dutta, Dutta & Raahemi, 2017), and identifying untrue rumours (Wu, Yan & Zhu, 2015; Zubiaga *et al.*, 2018). ML for example can eradicate false insurance claims by examining a before-and-after comparison of high-resolution satellite imagery (Gilmour, 2019).

AI is also used in assessing loan risk in post-disaster recovery victims (Liu, Li & Zheng, 2022). Using smart disaster relief efforts, AI can assist those needing finances with credit scoring and personal loan approval (Liu, Li & Zheng, 2022). AI is also assigned fraud scores, anomaly detection, and consumer identity incoherence (Hovsepyan, Mosinyan & Kotolyan, 2023). After the reparation of environments have begun, tracking the progress of these recovery efforts are essential to confirming their effectivity. Therefore, AI can also be used for tracking recovery efforts and establishing their progression.

3.4.3.3 Tracking progress

AI methods can speed up recovery through processing data from social media, aerial images, and sensor information (Khaloo *et al.*, 2017; Khoshnoudian, Talaei & Fallahian, 2017). The analysis of social media data can therefore help track human recovery rates (Resch, Uslander & Havas, 2018). In addition, survey administration can aid in determining psychological distress levels post-disaster (Sun, Bocchini & Davison, 2020). ML and NN algorithms are usually adopted to analyse survey results through identifying prevention and risk factors presented by the data (Rosellini *et al.*, 2018).

AI methods are used to estimate the economic impact from hazards using ML to establish relations between the economy, critical environmental factors, and possibilities for growth (Zhang & Peacock, 2009; Cheng & Zhang, 2020; Qiang, Huang & Xu, 2020). Post event recovery plans are often carried out in hostile environments that limit the time of its execution (Sun, Bocchini & Davison, 2020a). Various AI techniques are used to identify efficient recovery and restoration planning (Hackl, Adey & Lethanh, 2018; Karamlou & Bocchini, 2016; Sun, Bocchini & Davison, 2020).

To measure a community's recovery over time, practitioners need to use efficient tools and metrics to determine their resilience (Curtis *et al.*, 2007). AI algorithms such as sentiment analysis (SA) and image classification methods (IC) come in handy when evaluating social media data and tracking disaster recovery rates (Malawani *et al.*, 2020; Mihunov *et al.*, 2020). For example, valuable insights may be drawn from assessing the spatial intensity of electric light during nightly hours, to indicate economic recovery rates in specific regions (Qiang *et al.*, 2020).

Another example is Google Street View, which is popular in remotely tracking disaster recovery rates over time (Curtis, Duval-Diop & Novak, 2010; Mabon, 2016). Comparing street view data over time will show environmental improvement or decay. Tan and others (2020) note that disaster recovery requires extensive study on the role of resource allocation. Additionally, the design of resource-sharing mechanisms between adjacent facilities also requires further exploration. Whilst including the necessity for transportation modes comprised various functions and capabilities (Tan *et al.*, 2020).

Utilising innovative AI technology in DRR presents with it more accurate risk assessment, forecasting improvement, better early warning systems, reconstruction strategies, and building resilience (Fortes de Meira & Bello, 2020). Furthermore, it uncovers various ways of collaboration, identifying tools, data collection, management methods, risk communication, and approaches for sharing knowledge (Fortes de Meira & Bello, 2020). AI assists in creating evacuation procedures and routes (Ci, Liu & Wang, 2019), mapping events (Diack, 2021), assessing impact (Sun, Bocchini & Davison, 2020), and estimating repair costs (Deryugina, 2017).

In recovery, the role of efficiency in DRR evaluations are neglected, as each hazard brings with it a unique complexity that may affect emergency management (Tan *et al.*, 2020). Grasping the dynamics of AI used for DRR is undoubtedly complex and versatile. This Chapter explored the various applications involved in AI DRR. It showed how the functions involved in AI DRR processes, overlap and interact with one another. For instance, damage assessment is vital to both response and recovery interventions. Early warning is beneficial for both corrective and residual DRM. Environmental monitoring is essential for each process in DRR, preventing, correcting and reducing various types of DR and hazards.

This is also true for hazard and risk mapping, as well as risk assessment. Social media tracking and robotic assistance can also be utilised in all the systems of DRR. Therefore, the sub-components in this chapter show versatility in application and strictly speaking cannot be confined to a particular sub-system in DRR. Consequently, the components of prospective, corrective and residual DRM overlap and interact with one another. Making their categorisation purely for

structuring purposes devoid of functioning reference. The systemic structure indicates, once more, the ever-present complexity involved in DRR and AI ventures.

3.5 Conclusion

This Chapter explored the various functions of AI in DRR efforts. These efforts were explored to create a generalised picture of DRR AI applications in different countries. This Chapter addresses the second research objective which aims to explore the use of AI in DRR, and the research done on the applications of it in various countries.

This approach helps facilitate the reader with a better orientation to the research. Comprehension of the general uses of AI in DRR creates a foundation for understanding the later literature (in chapter 5) on AI projects used for HHR. Although the studies done on AI in DRM focus on the previous categorisation thereof (mitigation, preparedness, response and recovery), this chapter aimed to re-envision and re-structure the processes involved in disaster centred models, towards more risk reductive approaches.

Therefore, AI reducing DR was examined by re-structuring various systemic literature reviews. This was done by using the categories of prospective, corrective and residual DRM. It is important to note that although the literature is structured according to specific categories (prospective, corrective, and residual DRM) it is impossible to completely isolate these systems from one another. They are interconnected and interdependent systems, functioning in constant flux. Therefore, certain categories may overlap or seem extremely similar/repetitive.

Firstly, AI applications in DRR was explored according to prospective DRM. It investigated AI uses related to environmental monitoring, simulated DR data, research and development (R&D), environmental resilience and adaptation, and proposed AI ethics and governmental policy development. Secondly, AI applications in corrective DRM was explored through considering hazard mapping, risk assessment, and mitigation strategy comparisons. Lastly, AI applications used for residual DRM was discussed according to preparedness, response and recovery processes.

Preparedness measures were described according to early-warning systems and evacuation planning. The AI used for response was identified by the research as real-time event mapping, damage assessment, situational tracking, and robotic assistance. Recovery measures explored in this section included tracking progress, estimating repair costs, and evaluating damages. DRR's most prominent process involves reducing prospective risk.

In terms of DRR, AI presents numerous opportunities for its development and optimisation (Kuglitsch, 2022). Through its immense algorithmic speed and accuracy, it is deemed the perfect partner for assessing, reducing, managing, and avoiding disaster risk. AI presents tremendous opportunities for development and growth in high-risk environments. Its applications are flexible and encompasses many different domains that could reduce vulnerability and its many challenges. Unfortunately, these AI applications in DRR remains a general outline of AI capability and lacks specific contextual relevance. There remains a knowledge gap in the specific uses of AI for African DRR and consequently for the reduction of hydrometeorological hazards.

In the following chapter AI is considered for its African prospective DRM capabilities. The chapter explores AI presence in African DRR ventures, with particular focus on general prospective DRM efforts. Prospective DRM efforts are discussed to indicate the emergence of an African AI ecosystem comprised of multiple relationships and network connections. It argues that autonomous agents with interest in African AI invest in prospective DRM ventures to ensure less corrective and residual DRM is needed. The chapter is structured to consider key government sectoral AI applications, international collaborations, and the complexities of AI used for African DRR.

CHAPTER 4 THE STATE OF AI IN AFRICA

4.1 Introduction

AI efforts in Africa have bloomed through governmental ventures, key sectoral applications, and international collaborations. All of which can be considered part of prospective DR measures, reducing and avoiding future DR. For instance, governmental involvement facilitates platforms for growth, research, and collaboration in African AI ventures. Platform development helps increase the efficiency of AI models and their ability to effectively reduce risk. Key governmental sectors invested in AI elevate the systemic efficiencies of reducing hydrometeorological hazards in Africa.

For example, with more efficient healthcare systems, populations can avoid outbreaks and reduce disease caused by hydrometeorological hazards; and with more efficient transportation, accidents can be reduced and road safety increased during an event. Through building elaborate networks in the AI community, Africa can develop a sustainable AI ecosystem. Avoiding prospective risk entails understanding the environment where risk is likely to occur. The Global AI Readiness (GAIR) Index measures the readiness of countries to effectively adopt AI.

It assesses each country's environment and determines their ability to facilitate AI applications. The top five African countries are identified by the research as Mauritius (61st), South-Africa (77th), Rwanda (84th), Senegal (91st), and Benin (97th) (Oxford Insights, 2023). An analysis graph is available on each country showing their rank in various domains, which include vision, governance and ethics, digital capacity, adaptability, maturity, innovation capacity, human capital, infrastructure, data availability, and data representativeness (Oxford Insights, 2023).

Some results are incoherent, for instance, Mauritius, Rwanda, Senegal and Benin are considered to have ranked 100 for 'vision' where South Africa has ranked 0 (Oxford Insights, 2023). With no clear indication of what 'vision' entails, the index shows a lack in transparency. Although Rutenberg and others (2021) critique the AI readiness scale as Eurocentric and unfit for assessing Africa's true potential, it still indicates a certain level of validity in AI implementation ability held by various African countries. The key aspects included in the index (AI strategy, governance, skill development, data availability and infrastructure) are relevant to AI readiness and must be considered when evaluating Africa.

Strathmore University (2024) is also mapping the utilization of AI in Africa. It considers seventeen sectors of AI applications exclusively derived from ML and DL algorithms, AI developers

comprised of African entities and individuals, and companies and models that are operational by the time of data collection.

In all the regions of Africa, AI is most used for corporate services (14%), health (12%), education (12%), and farming (11%) (Strathmore University, 2024). The AI tools popular in these AI models consist of data analytics (26%), chatbots (23%), decision support (12%), and diagnostics (9%) (Strathmore University, 2024). The most African AI activity is reported to be in South Africa, Madagascar, Malawi, Tanzania, Kenya, Cameroon, Nigeria, Sierra Leone, Egypt and Tunisia (Strathmore University, 2024). As most AI activity in Africa is said to be unreported online, progress and development are difficult to fully determine.

Nevertheless, it is important to start building a database for developments reported on to create more legitimate record-keeping and increased accountability measures. AI is relatively new to Africa and needs further investigation relating to governmental and sectoral applications. As this technology brings with it revolutionary changes to African society, multiple factors must be considered. For instance, the role of African governments in its development, the involvement of specific African countries in sectoral applications, and international and institutional collaboration in African AI portray the complex dynamics associated with AI in Africa.

The purpose of this chapter is to explore the projects and collaborative efforts involved in prospective DRR efforts using AI in Africa. It considers African governmental involvement in creating platforms that facilitate AI use and encourage policy development. Firstly, the role of government is discussed in terms of implementing and developing AI in Africa. This section discusses AI-friendly environments consisting of data collection and availability, institutional support, and hosting networking events. Furthermore, it explores ethics and public policy related to responsible AI, strategy development, and policy and governance.

Secondly, key economic sector applications of AI are explored using examples related to various African countries. Key economic sectors are identified in this research as: agriculture, health, finance, transportation, and education. Consequently, the technological sector is not included in this discussion as it overarches the discussions of each sector. As with all the categorisation efforts in this study, it is important to note that these sectors are not isolated from one another and are constantly interacting and overlapping. The complexity and interdependence of economic sectors make it difficult to explain one without the other. Nevertheless, this section aims to structure the versatility of AI in various key economic sectors.

Lastly, multi-agent stakeholders facilitating an African AI ecosystem is explored with relation to national and international role-players. Enforcing the development of such an ecosystem

contributes to the resilience and sustainability thereof as collaboration and interaction between various entities foster AI growth. Therefore, the section explores networking and collaboration opportunities, funding and investments, research and development, university involvement, and public-private partnerships. Governmental participation is integral to the development of an African AI ecosystem, as it sets the tone for AI implementation and development.

4.2 Government Participation

Government involvement in African AI can be considered prospective DRM as its processes include accessing quality data, policy development, facilitating better service delivery, sectoral improvement, and accommodating autonomous agent involvement. Research by the University of Pretoria indicates that international organizations support governments through multilateral commitments, policy analysis, and dialogue (Access-Partnership, 2018). Government participation in AI development consists of facilitating AI-friendly environments, ethics, and policy development.

Governments facilitating AI-friendly environments involve encouraging data availability and collection, establishing governmental AI institutions, and hosting networking events in African AI (AU, 2024). It includes discussions on data collection and availability, National AI agencies and task forces, and hosting conferences, workshops and seminars on AI (Gwagwa, 2020). Ethics and policy development is discussed with reference to responsible AI, strategy development, and AI policy (Plantinga *et al.*, 2024). All of which are interdependent on one another and difficult to separate.

The involvement of African governments in AI integration and development, sets the tone for its utilisation and application in various African countries. Government involvement and participation in African AI are vital to its legitimization and integration (Effoduh, 2020). A modest acceptance of AI adoption into various institutions and structures, facilitates an “AI normative emergence in Africa” (Effoduh, 2020), meaning that African government adoption of AI results in the normalization of the technology. Before normalization of AI applications can occur, development and facilitation of AI-friendly environments must first take place.

4.2.1 AI-friendly environments

African governments can be held responsible for setting the overall appeal, growth, and accessibility of AI development in their country (Mehr, 2017). They also encourage stakeholder funding and participation (Access-Partnership, 2018). Therefore, it is integral that African governments show their interest in developing AI friendly spaces to lure future investors and

stakeholders (Akileswaran & Hutchinson, 2019). AI-friendly environments include data availability and collection, institutional support, and networking events. Data availability and collection provides an environment where AI models can thrive and function efficiently.

Institutional support is necessary for establishing AI agencies, task forces, and commissions. Governments must put various measures in place to ensure AI use in the country is efficient, monitored, and effective. Lastly, facilitating an AI-friendly environment also requires collaboration and networking platforms. Hosting conferences and seminars develop strategic partnerships between African governments and enhances the versatility of the AI ecosystem. AI's dependence on data makes its application in Africa somewhat troublesome. With limited data available to train African AI models, government institutions largely contribute to this scarcity by limiting access to governmental data.

4.2.1.1 Data collection and availability

Various African countries have committed to open and transparent governmental data (Excell, 2012). However, data availability and access in Africa is still increasingly challenging due to data scarcity (Marwala, 2024), lack of clear policies and guidelines (Mbego, 2023), and ethical and privacy concerns (Ade-Ibijola & Okonkwo, 2023). Unfortunately access to governmental data is the best way to access and identify needed levels of intervention (Bvuma & Josph, 2019). Data can indicate the state, activity and impact of specific environments and aid in developing mapping, monitoring, and predictive models. Many African governments integrate open data initiatives in their country to promote transparent governance.

African governments attempt to make data available through platforms such as Data Science Nairobi (Eventbrite, 2022), the Machine Intelligence Institute of Africa (MIIAfrica, 2019), and Data Science Lagos (Tech365 Team, 2021). All of which aim to develop and encourage multi-stakeholder participation and access AI potential in Africa (Brandusescu, Freuler & Thakur, 2017). Additionally, the Kenyan Government was the first African country to implement an open-data information portal in 2011. The portal accesses details about water, sanitation, population, energy, poverty, and health; previously difficult to come by in Kenya (Kenya Data Portal, 2023).

Ghana also has an open data portal, providing information on various topics (NITA, 2020). Unfortunately, after the portal was established in 2020 it was never updated again. This is also true for South Africa (African Development Bank, 2024), Nigeria (Nigeria Data Portal, 2018), and Ethiopia (Ethiopia Data Portal, 2014). The City of Cape Town, however, has an up-and-running open data portal. Consisting of city budgets, residential utility services, greener living, personal

health, and research materials amongst others (City of Cape Town, 2024). The portal is a one-stop website for extensive and versatile data on Cape Town.

Rwanda provides open access to updated data on governmental policies and strategies (Government of the Republic of Rwanda, 2024). The governmental mandate is to monitor and evaluate the implementation of national policies, strategies and programs that promote communication and technology (Government of the Republic of Rwanda, 2024). The African Development Bank Group (2024) permits access to African data relating to governance, social topics, the environment, finances, debt, infrastructure, and prices. It provides statistical summaries of the above-mentioned topics relating to any African country (African Development Bank Group, 2024).

Even though the African data portal is technically managed by a bank, its data accessibility must be authorised by African governments involved in the research. The former South African Department of Trade and Industry formed the division of 'Future Industrial Production and Technologies' to identify the impact of emerging digital innovations on trade and industry (The Department of Trade, Industry and Competition, 2017). Moreover, participation from leading African economies such as South Africa, Ghana, Tunisia, Mauritius, and Kenya have meticulously documented past digital changes in their technological sector (Gwagwa *et al.*, 2021).

Through African governments collecting and digitizing data, they establish the norm of data documentation onto other entities such as businesses, NGO's, institutions, and individuals. Although data availability is extensively useful for training AI models, the time of collection also plays a vital role in time-sensitive analysis ventures. With the rise of AI technology in Africa, governments require institutional support and must prioritise establishment of task forces, agencies, and AI commissions (Effoduh, 2020).

4.2.1.2 Institutional support

African AI development faces various institutional challenges influencing the growth, control and direction of its development. These challenges include, but are not limited to, a lack of infrastructural support for digital technologies (Bon, Saa-Dittoh & Akkermans, 2023), scarcity of skilled AI workforces (Adetiba *et al.*, 2024), and political instability (Tinarwo & Babu, 2023). With institutional support, African governments can gain control of the direction, growth and development of AI in their country. Kenya, for example, assigned a taskforce to provide a roadmap contextualising the application of blockchain and other emerging technologies (Kenyan Wallstreet, 2018). Another task force is deployed by the government of Uganda to advise on domesticating technological advancements to propel the county's economic development

(Xinhua, 2019). They require the task force to provide solutions to existing issues, especially those related to agriculture (Xinhua, 2019).

Furthermore, the Nigerian government has revealed plans to enlist 120 experts to develop an AI adoption framework for the country (Ekhaton, 2024). The government aims to use AI applications to improve the lives of Nigerians and help grow the economy (Ekhaton, 2024). Governmental agencies also provide support in AI adoption. For example, the Egyptian government, formed the National Council for Artificial Intelligence comprising of prominent academics, governmental institutions, and leading business practitioners (Ministry of Communications and Information Technology, 2023).

Additionally, the Ethiopian government established an AI institute for creating innovative AI solutions at national and international levels (Ethiopian Artificial Intelligence Institute, 2022). The National AI Research and Development Centre is a state-of-the-art research facility playing a crucial role in Ethiopian governmental AI integration (Ethiopian Artificial Intelligence Institute, 2022).

The South African military academy has formally launched the Defence Artificial Intelligence Research Unit (DAIRU) as the centre for AI excellence (Wingrin, 2024). The motivation is that AI can be used for shaping geopolitics and conducting more efficient warfare (Wingrin, 2024). Mozambique uses AI for institutional support by utilising it for political elections. The platform was developed by the UNDP for use in member countries, and has been used in Lebanon, Tunisia, Libya, and Peru (MozParks, 2023). Its primary function is to ensure information integrity and transparency during political elections.

Furthermore, government of Tunisia has launched its first public AI institute at the University of Tunis (Sawahel, 2024). Its aim is to broaden the knowledge of AI integration in the country and encourage its ethical applications (Sawahel, 2024). Along with using AI for institutional support, participating African governments facilitate AI networking and collaboration events in their country. They present Africans with opportunities in AI R&D efforts as well as deployment ventures. Making networking vital to the growth of an African AI ecosystem. The following section focus on identifying and exploring various AI networking events hosted by African countries.

4.2.1.3 Host networking events

Hosting AI networking events indicate that governments have an interest in building strategic partnerships with other countries. Networking events in African AI can be seen as a way governments show their investment in future AI development (Access-Partnership, 2018;

Gwagwa *et al.*, 2020). These events include conferences, workshops, summits, expos, gala's, conventions and seminars. Networking enforces interaction and knowledge sharing platforms between AI enthusiasts and professionals whilst enabling the use of novel technology in Africa (Orlic, Taylor & Siminyu, 2020).

Governments meaning to communicate their willingness towards AI integration must create an environment where AI development and collaboration is encouraged. The Nigerian government is actively promoting stakeholder partnership engagement in AI and robotic research (Effoduh, 2021). For instance, they hosted an AI workshop in Abuja, centred around educating individuals not only on how to use AI, but also on how to use it for contextual relevance (Arise News, 2024). In other words, using their newfound knowledge to make practical changes and invest in future ventures such as, job creation, employment, and self-empowerment.

Partnering with UNESCO, the Namibian government hosted a forum encouraging sustainable development-orientated and ethical use of AI in Windhoek (UNESCO, 2022). The Algerian government hosted an AI for Africa (AIFA) Conference (AIFA, 2023). It comprised of a vast range of AI topics, namely: generative AI, computer vision, NLP, AI startups, and industry applications (AIFA, 2023). The main objective of this conference was to bring together Algerian practitioners, researchers, and entrepreneurs open for discussing the latest advancements in generative AI and computer vision (AIFA, 2023).

The Benin government hosted a West African conference on digital infrastructure and cybersecurity (Carnegie Mellon University, 2023). The conference motivated the need for diversity and inclusion in digital infrastructure and cybersecurity developments (Carnegie Mellon University, 2023). Additionally, the government of Botswana intends to prioritise the digital infrastructure in the country (Xinhua, 2023). With investment in high-speed connectivity, cybersecurity measures, and data centres, Botswana is showing extensive support for AI institutionalisation in Africa (Xinhua, 2023).

Furthermore, the Cameroonian government hosted a conference aimed at assessing the readiness of African media for adopting AI models and developing responsible uses thereof (TRT Afrika, 2024). The African Union of Broadcasting (AUB) organised the conference to assess the readiness of Africa media for using AI, strategy development for its effective adoption, promotion of stakeholder collaboration, and advocate coherent regional AI policies (TRT Afrika, 2024). Furthermore, AI networking events are hosted by many African governments. These events usually aid in AI strategy and policy framework planning and recommendations.

Although an AI-friendly environment is essential to its development in a country, its ethical and policy approaches in a country is just as important. To reduce prospective DR associated with AI implementation in Africa, it becomes vital to establish ethical and policy related frameworks and strategies. Through the utilisation of networking events, AI can help develop more efficient government service delivery systems and promote responsible use of the technology. Policy development in African AI makes use of data, institutional support, and strategic partnerships to determine the most practical and relevant AI policies.

4.2.2 Ethics and public policy

Ethics play a fundamental role in policy development and govern the perimeters set by rules and legislation. There exist exceptions to this statement, as ethics do not necessarily equal policy and vice versa. Nevertheless, for policy to be accepted and complied with, it should be deemed fair and responsible, in other words, ethical. Ethics is a widely debated and ever-changing concept. Consequently, 'ethical' AI use can be called responsible AI use. Responsible AI (RAI) guidelines ensure that all AI systems abide to democratic values (Sadek *et al.*, 2024).

4.2.2.1 Responsible AI

AI is complex and difficult to define as a policy concern, therefore, ensuring the responsible use of it is challenging (Adams, 2022). The Global Index on RAI is based on a human rights approach and acknowledge that the impact of AI on certain societies is still uncertain (Adams, 2022). There are clear limitations to the human rights approach, such as enforceability and accountability (Adams, 2022). RAI is still emerging in AI governance and is an umbrella term covering democratization and ethics (Gillis, 2023). The goal of RAI is to develop and deploy AI models within both ethical and legal parameters (Gillis, 2023). RAI systems increase reliability, transparency, and fairness of AI implementation (Gillis, 2023).

Okolo, Aruleba & Obaido (2023) identify the principles of RAI as accountability, transparency, explicability, and bias evaluation. This assists in deploying AI models that are safer, more efficient, and sustainable. The African Union Development Agency (AUDA) and the New Partnership for Africa's Development (NEPAD) published a White Paper on the regulation and responsible adoption of AI in Africa towards achieving the AU (African Union) Agenda 2063 (AUDA White Paper, 2023). It explores human capital development for AI, infrastructure and data, environments for development and deployment, AI economy, and building sustainable partnerships (AUDA White Paper, 2023).

It is worth noting that the RAI in the White Paper does not refer to 'ethical' AI but rather responsible ways of incorporating the technology in Africa. The South African government plans to regulate AI and misinformation (Illidge, 2024). They believe the increased use of generative AI can boost the spread of misinformation in South Africa (Illidge, 2024). Additionally, the Nigerian Communications Commission (NCC) advocates for responsible AI to ensure consumer rights are respected (Onyedika-Ugoeze, 2024). RAI aims to build trust, minimize negative effects, and empower consumers (Onyedika-Ugoeze, 2024).

Therefore, AI developers must be transparent about using algorithms, models, and data (Onyedika-Ugoeze, 2024). Egypt created a charter for RAI that includes human-centredness, fairness, security and safety, accountability, transparency, and explainability (Ministry of Communications and Information Technology, 2023a). Additionally, Kenya passed a robotics and AI society Bill in 2023. Its purpose is, amongst others, to promote responsible and ethical development and application of robotics and AI in Kenya (The Kenya Robotics and Artificial Intelligence Society Bill, 2023).

The Ghanaian healthcare sector is navigating the ethical landscape of AI to ensure its responsible integration (IIPGH, 2024). RAI is seen as important for Ghanaian healthcare data protection, avoiding biases and discriminations, and transparency and accountability (IIPGH, 2024). RAI requires a strategy and framework to ensure the development of AI policy in Africa. Various African countries have invested in developing strategies for AI use and integration, facilitating opportunities for experts to produce solutions and recommendations for AI growth and deployment in Africa.

4.2.2.2 Strategy development

A small number of African countries have started to implement strategies for improving AI policies with regards to data protection laws, depiction of legislation, ethical guideline development, and launching centres for AI excellence (Adams, 2022). Intra-governmental entities are collaborating with the New Partnership for Africa's Development (NEPAD) to support the African Union High Level Panel on Emerging Technologies (APET) (Gwagwa *et al.*, 2021). The Pathfinder Think Tank provides recommendations to the African Union on harnessing emerging technologies for economic development (AUDA-NEPAD, 2022).

Mauritius introduced various frameworks on the development of AI, for example Digital Mauritius 2030 (World Profile Group, 2017), the Digital Government Transformation Strategy 2018-2022 (The Commonwealth, 2018), and The Artificial Intelligence Strategy (Working Group on AI, 2018). The latest strategy (Mauritius Artificial Intelligence Strategy) is comprised of AI applications in

various sectors namely manufacturing, healthcare and biotechnology, fintech (financial technology), agriculture, ocean economy, and transportation (Chung-Tick-Kan *et al.*, 2018). Its focus is on skill development and the avoidance of job losses in Mauritius.

Egypt developed a strategy that consist of four pillars, namely AI for government, development, capacity building, and international activities (The National Council for Artificial Intelligence, 2022). The strategy aims to utilise AI for achieving the SDG's, facilitate regional cooperation, and establish Egypt as a prominent AI role-player (The National Council for Artificial Intelligence, 2022). Additionally, TFS (The Future Society) developed a National AI strategy for 2023-2033 for Ghana (Lannquist & Mialhe, 2022). The strategy contains in-depth AI policy mapping, local stakeholder consultations, high-level workshops, and SWOT analysis of Ghana's AI ecosystem (Lannquist & Mialhe, 2022).

The purpose of the strategy is to ensure RAI adoption in Ghana for sustainable and inclusive growth (Lannquist & Mialhe, 2022). This includes partners such as Smart Africa, Ghana's Ministry of Communications and Digitisation and Data Protection Commission, and GIZ (German Agency for International Cooperation) Fair Forward (Lannquist & Mialhe, 2022). Furthermore, Algeria has adopted an AI national strategy on research and innovation for driving skill development and AI tool application on key sectors (The GIP team, 2021). The strategy aims to build a foundation in AI research, apply novel AI techniques to different sectors, and utilise available material and human resources in Algeria (The GIP team, 2021).

Tunisia developed a national AI strategy in 2018, using a workshop hosed by UNESCO in collaboration with the National Agency for Scientific Research Promotion (ANPR, 2018). The strategy facilitates objectives and goals associated with AI implementation in Tunisia and creates the environment for an AI ecosystem. Lesotho developed a strategy on the national digital transformation in 2021 (Lesotho's National Digital Transformation Strategy, 2021). This strategy aims to transform various areas of Lesotho's society, such as government, infrastructure, population, and business (Lesotho's National Digital Transformation Strategy, 2021).

In association with autonomous agents such as Genesis and Digital Pathways, the strategy is set on integrating AI in structural domains and encouraging AI literate populations (Lesotho's National Digital Transformation Strategy, 2021). AI strategies are vital to the development of AI policies. All of which involve governing efforts. AI policies and governance are also relevant to DRR; as both involves the process of making decisions for the public good (Torjman, 2005). AI policy and governance is vital to prospective DRR efforts in Africa and reduce the potential of irresponsible AI use.

4.2.2.3 Policy and governance

Policy and governance in African AI use cover a multitude of areas and are applied in various ways. Both are complex systems comprised of various bureaucratic processes driven by fairness and accountability. Policy and governance go hand in hand, as policy is the result of governance and vice versa. For example, Sierra Leone has developed a policy on children's rights for AI use in education (UNICEF, 2019). Through the collaboration of UNICEF and DSTI (Directorate of Science, Technology, and Innovation), lessons from Sierra Leone will help contribute to global child rights policy development (UNICEF, 2019).

Additionally, the Republic of Rwanda, partnered with the Ministry of ICT and Innovation, developed the national AI policy to leverage economic growth, quality of life, and Rwanda as innovator of RAI (MINICT, 2022). The policy aims to position Rwanda as Africa's official AI lab and RAI champion, building skills and AI literacy, quality data ecosystems, public sectoral transformation, and RAI in the private sector (MINICT, 2022). Tanzania is using AI to create an e-government platform that aims to build capacity, ethical AI adoption, public awareness, research and collaboration, and policy framework development (DA4TI, 2024).

Policy framework development involves working closely with multiple stakeholders to create comprehensive AI policies (DA4TI, 2024). These policies must align with international standards whilst considering local nuances (DA4IT, 2024). Ethiopia has announced the finalisation of a draft national AI policy (Bilali, 2023). It aims to harness the potential of AI and promote sustainable and responsible implementations in Ethiopia (Bilali, 2023). The development of the policy involved extensive collaborations from governmental, institutional, and private sector entities (Bilali, 2023). It encompasses various key sectors, such as, data management, human resource development, infrastructure, ethics and law, assistance and encouragement, and R&D (Bilali, 2023).

South Africa is developing an AI national plan to establish regulatory framework and AI policy (Bhagattjee, 2024). The national AI strategy guiding principles include guarding against and mitigating any harm from AI deployment in South Africa (Bhagattjee, 2024). Harm involves anti-competitive behaviour, AI model monopoly between small number of technological players, risks in autonomous device and robotic AI, job losses, existential risk of loss of purpose, enhanced criminal risk, and uncontrolled military use (Bhagattjee, 2024).

Although the efforts in African AI policy development are few, they do seem to show some progress for the region. This is also true for the rest of African governmental AI participation efforts. African AI policy helps determine the country's readiness to adopt AI into regulatory systems. The quicker policy implementation takes place the quicker AI regulation can be achieved

in Africa. The regulation of AI in Africa ensures the decrease of potential DR developing from avoidable risk enhancing behaviours. As stated by Ngila (2022), efforts adopting AI in African governments show promising.

Government involvement is vital to developing and deploying AI projects in Africa. They ensure AI-friendly environments through data availability and collection, institutional support, and hosting networking events. They are also responsible for ensuring ethical policy development through using responsible AI approaches, developing AI strategies, and driving growth in AI policy and governance. Governments usually have some degree of control over sectoral uses for AI models. Brandusescu, Freuler and Thakur's (2017) research on AI and policy development in Africa states that AI participates in numerous key economic sectors.

It is important to note, once more, that all the sectors discussed here are interdependent and overlapping. In this research, specific categories are assigned to an otherwise fluid and complex system. Key economic sectors in the following section are not limited to agriculture, healthcare, finance, transportation and education. These sectors were merely selected due to their relevance in DRR efforts and their contribution towards prospective hydrometeorological DRM efforts.

4.3 Key Economic Sectors

The African continent wrestles with economic issues such as high unemployment, sluggish GDP growth, and over-reliance on conventional industries (Boison & Fiatui, 2024). Africa's economic issues are complicated institutional deficiencies such as, limited access to education, infrastructural deficits, and underdeveloped technology (Boison & Fiatui, 2024). AI can reduce these existing inefficiencies in the African economy and advance private and public services (Brandusescu, Freuler and Thakur, 2017).

The AI market is projected to expand and benefit the global economy with \$15 trillion by 2030 (Boison & Fiatui, 2024). The projected economic benefits of AI in Africa should aid in some of the continent's most pervasive problems namely poverty, rapid urbanisation, eradication of disease, healthcare service delivery, sustainability challenges, and growth in equality (Microsoft, 2018). AI emerges as a transformative force, reshaping Africa's economic landscape (Boison & Fiatui, 2024); yet could create serious risks of job market polarisation, structural unemployment, rising inequality and undesired industrial structures (Trabelsi, 2024). Transitioning towards an AI-driven economy presents with it extensive challenges, many of which include the risk of job displacement (Boison & Fiatui, 2024).

Nevertheless, AI is used for reducing prospective risk through various key economic sectoral involvements in Africa (Mienye, Sun & Ileberi, 2024). Key economic sectors in various countries usually involve the government, however, not all the AI applications mentioned in this section are being used for governmental purposes. Even though, AI can be useful in strengthening various areas of governmental service delivery. Additionally, and most importantly, AI may have the potential to contribute to the reduction of possible economic risks and help build resilience to natural hazards in Africa.

In this section, AI is explored with relevance to its prospective DRR applications in key African economic sectors. Key economic sectors are identified in this research as agriculture, healthcare, finance, transportation, and education. Each sector is briefly discussed in this section and related to AI applications and its relevance to DRR in Africa. African agriculture is at the heart of its global economic participation and therefore, its investment is vital for future growth and effective DRR. AI can be utilised to reduce various agricultural challenges in Africa and provide great opportunities for developing DRR strategies.

4.3.1 Agriculture

Agriculture is vital to African growth and development (Odusola, 2021). Although agricultural projections seem promising, Africa is burdened with drops in water tables, dependence on inorganic fertilisers, soil fertility depletion, emerging pest immunity, degradation of land, and the increase of unpredictable vulnerability to global climate change (Access-Partnership, 2018). The effects of climate change elevate the level of hazard entropy (2.2.3.2) which prove increasingly difficult to reduce (see section 2.2.2).

The agricultural sector in Africa accounts for more than 50% of its populations employment (Rutenberg, Gwagwa & Omino, 2021); and more than 70% of their livelihoods (Biteye, 2016). Therefore, efficient DRR is essential to decreasing the effects of climate change and natural hazards in the African agricultural sector (UN, 2019). African agriculture can be optimised through modern farming methods (Rutenberg, Gwagwa & Omino 2021). Modern farming methods can facilitate Africa's efforts in adapting to climate change; and building more resilient and sustainable agricultural systems (Shilomboleni, Epstein & Mansingh, 2024).

ML, advanced analytics, and satellite imagery can help improve agricultural productivity (Talaviya *et al.*, 2020). Additionally, AI can aid small-holding-farmers increase crop yield and manage price regulation; as well as make use of drones to plant and fertilise seeds at a faster pace (UN, 2021). Various African countries are utilising the potential of AI in African agriculture for DRR purposes. For instance, in Kenyan agriculture, the app Vital Signs estimates drought and rainfall patterns

(Herrick *et al.*, 2016) and the Agrio application provides detailed and curated information about crops to farmers (Agrio, 2019).

In Nigeria, applications such as Zenvus helps farmers make decisions about their crops based on sensory data (Turner, 2019), and Aerobotics uses smart drones to identify problematic crops in South Africa (Aerobotics, 2022). AI used for DRR in African agriculture can empower many African people and equip them with tools that help develop sustainable practices (Gikunda, 2024). Healthy agriculture reduces the risk of hunger, malnutrition, illness, increased mortality rates and decreased life expectancy rates in most developing countries (Manamela & Choung, 2024).

Efficient agriculture is essential to efficient healthcare; as these sectors share a complex and dynamic relationship (Hawkes & Ruel, 2006). The healthcare sector is an important part of DRR, not only for its role in response efforts (see section 3.3.2), but also for its importance to prevention and recovery rates (see section 3.1.4).

4.3.2 Healthcare

The public healthcare system has been one of the most worrying domains in Africa (Manamela & Choung, 2024). It faces challenges such as a lack of accessibility to qualified professionals, insufficient healthcare supplies, and uncertainty for patients in need of specialized help (Maphumulo & Bhengu, 2019). There exist various AI interventions for this sector such as supplementing staff, improving healthcare policies and service delivery, more effective diagnostics and interventions, and improved accessibility (Access-Partnership, 2018).

AI is rapidly becoming a prominent part of the healthcare sector in Africa and shows great potential for improving DRR efforts. For example, the AI application, Numberboost, is used in South Africa to aid people in locating mobile healthcare clinics (Carew, 2019). Numberboost increases healthcare access in environments deprived of quality healthcare facilities (Carew, 2019). Corti, the Danish ML company, assists in African diagnostic report accuracy and is used by emergency responders to make life-saving choices (Corti, 2020).

Njei and associates (2023) conducted a scientometric analysis on twenty-six articles regarding AI use for healthcare in Africa. They found limited publications and concluded that AI use in African healthcare is in its infancy (Njei *et al.*, 2023). One of the most pressing problems in this sector is the limited access to funds allocated towards proper healthcare services and addressing certain healthcare issues (Azevedo, 2017). AI in the financial sector can help people in Africa access opportunities and grow towards more resilient environments (Marwala, 2024a).

4.3.3 Finance

The African financial sector is a developing and profitable system that facilitates AI innovations (Ngugi, 2018). This may be true; however, Africa faces extreme challenges in its financial sector, mainly related to faulty banking systems (Abor *et al.*, 2022), large amounts of debt (Filocca, 2023), corruption (Hope, 2023), and mismanagement of funds (Rangongo, Mohlakwana & Beckmann, 2016). The African financial sector has extensive influence on DRR ventures especially in terms of AI investment and funding (UNDRR, 2020a) (see section 4.3.2), insurance (Maslo, 2022), and loan allocations (Liu, Li & Zheng, 2023).

AI may significantly reduce natural hazards in Africa through applications in the financial sector. For instance, the program DataProphet, uses ML solutions for small businesses in South Africa focused on insurance and accurate risk assessments (DataProphet, 2022); the insurance company Santam (in South Africa), uses AI to help mitigate natural disaster risk (Moodley, 2024), the application Farmdrive, offers credit to Kenyan farmers in need of financial support (FAO, 2017); and the program, Tala, distributes loans to Kenyan citizens devoid of credit histories (Tala, 2022).

Utilising AI in the financial sector creates an opportunity for efficient distribution of funds and the development of more resilient environments (Bahoo *et al.*, 2024). Creating resilient environments in Africa requires the facilitation of climate resilient transportation initiatives (Cinderby *et al.*, 2024). The transportation sector is integral to any developing country as its functioning drives efficient mitigation, prevention and response measures in DRR.

4.3.4 Transportation

The African transportation sector can present many opportunities for potential growth (African Development Bank, 2024a); however, it is deemed unsafe, inefficient and inaccessible to the public (Harrisberg, 2020; Akin & Kona, 2021). AI offers solutions for African transportation through increasing the safety of transportation, improving traffic flow, expanding infrastructural capacity, facilitating greater accessibility, and lowering carbon emissions (Access-Partneship, 2018). For example, AI aids in time efficiency and occupancy of public transport through tracking and monitoring transportation systems (Ernest, 2021).

In Uganda and Tanzania for instance, AI technology assists in building large data sets for the mapping of over 18 million streets and building footprints (UN, 2019a). This ML driven project is made possible by the amalgamated efforts of autonomous agents (see section 2.1.4.1) such as Bing maps, Microsoft Philanthropies, and Humanitarian Open Street Maps (HOTSM) (UN,

2019a). With previously unmapped areas clearly defined, both Uganda and Tanzania can reduce DR with improved architectural and agricultural planning and better-informed response rates.

Additionally, the automotive industry makes use of an AI based platform named DRIVE, developed by Nvidia (Nvidia Corporation, 2024). It enables trucks, automakers, start-ups, and tier-one suppliers to speed up the production of autonomous vehicles (AV) (Nvidia Corporation, 2024). These vehicles have surround vision capable of real-time understanding and precise HD map positioning for planning safer routes (University of Pretoria, 2020). Additionally, research by Ackaah, Leslie & Osei (2022) explore the adoption of self-driving vehicles in Ghana. Using an adapted version of the Technology Acceptance Model (TAM), Ackaah and others (2022) found that the dominant determining factor for using autonomous vehicles came down to attitude, subjective norm, and awareness.

Furthermore, Ackaah and associates (2022) recommend that governments educate the public on AV's, facilitate a positive mindset towards its use, and create awareness under older community members. Many AI challenges in Africa stem from a lack in knowledge. Education on AI is therefore extensively important for prospective DRR efforts. The education sector is gaining tremendous strides through its implementation of AI and shows promise in terms of assisting students and teachers alike (Access-Partnership, 2018). Additionally, AI is considered a key R&D field in need of more exploration.

4.3.5 Education

Africa has the fastest growing child population in the world and the demand for education is surpassing its capacity (The World Bank, 2024). AI has the potential to act as a transformative power in addressing African educational challenges (Chisom, Unachukwu & Osawaru, 2024). For example, The Counsel for Scientific and Industrial Research (CSIR) primarily makes use of AI in education through Natural Language Processing (NLP). This is done to recognise speech for facilitating learning support in South Africa (CSIR, 2022).

The Digital Humanities Association of Southern Africa (DHASA) provides university scholarships and mentorship to those who are interested in amalgamating humanities and digital data science (DHASA, 2022). DHASA provides an educational platform for members to participate and expand their understanding of data science. AI used for educational purposes show great advantages for transforming learning environments in Africa (Chisom, Unachukwu & Osawaru, 2024). However, this requires policy that can strategically and systematically integrate the use of AI for educational purposes (Chisom, Unachukwu & Osawaru, 2024).

Kiemde and Kora (2022) indicate that AI in education should actively work towards facilitating ethical uses and behaviour in Africa. By forming the ethical beliefs of students and educating them on rules of AI use may reduce the amount of future unethical AI utilization (Kiemde & Kora, 2022). Leading African countries show supportive yet cautious implementation of AI and report underfunding in R&D efforts (Gwagwa *et al.*, 2021). The lack of funding for the development of AI in Africa may delay the future of its integration (Access-Partnership, 2018).

Institutions and international collaborators are therefore vital to AI's growth in Africa and become key to accessing its potential (Travaly & Muvunyi, 2020). The University of Pretoria (UP) finds that effective key sector development is fuelled by a "vibrant AI ecosystem" compiled of policy makers, stakeholders, innovative start-up projects, civil society groups, and international institutions (Access-Partnership, 2018).

Gwagwa and associates (2021) note that the pockets of AI activity in Africa may fuel an effective AI ecosystem if it be properly funded, prioritized, and coordinated to produce an effective and driven AI infrastructure. African AI R&D efforts are built upon vast and versatile collaboration efforts. The largest and most active efforts in African AI are compiled of a network of collaborating autonomous agents. The greater the collaborative versatility, the more resilient DRR efforts become in African AI.

4.4 Collaboration in African AI

Some of Africa's prospective DRR promise lies with investors and stakeholders seizing the opportunity for mutual interest in developing and deploying AI technology. International collaborations with African countries indicate the prospective growth of an African AI ecosystem (Asiegbu & Okolo, 2024). An AI ecosystem which can enforce adaptive and evolutionary systemic behaviours through emergent synergetic activities. Entity involvement and collaboration in African AI development encourages an increase of reliability and validity in AI implementation. This fosters a sustainable and resilient system centred around best practice initiatives and adaptive efforts driving future AI applications in Africa (AU, 2024a).

Gwagwa and colleagues (2021) state that funding AI in R&D calls for more collaboration between governments, international development partners, and industry. The greater the collaboration efforts, the more resilient the African AI ecosystem becomes. Multiple entity support not only ensures stable funding and fewer retractions but also encourages multi-stakeholder participation (Belhadi *et al.*, 2021). International involvement in African AI facilitates AI collaboration opportunities, funding and investment, research and development, university involvement, and public-private corroborations.

The themes discussed in this section derives from literature related to international involvement in African AI and facilitates its applications in prospective DRR. The themes overlap and interconnect in some instances as many of the efforts in African AI encompass multiple functions. Collaboration opportunities explored in this section include the conference of Deep Learning Indaba, UN Global Pulse Labs, and AfriLabs. Each consists of vast international involvement driven by the growth of AI in Africa. Funding and investment examples include the XL Africa collaboration platform, international governments, capital industry, and UN agencies.

International funding and investment in AI should provide a sufficient push towards more of its implementation in African DRR. R&D support is shown through international industry support, research facilities, and research platforms and centres. The most effective way of ensuring R&D efforts materialize is by creating an environment where research can commence, and development of AI models are funded. University involvement in AI collaboration efforts is identified in this research as African university project development, research collaboration efforts, and AI research accessibility. Encouraging the development, research, and accessibility of AI in African universities enable extensive growth opportunities for the continent (Access-Partnership, 2018).

4.4.1 Collaboration opportunities

Collaboration opportunities in Africa are becoming integral to the implementation of African AI. The effectivity of AI applications in African DRR greatly depends on the exposure and opportunities presented by collaborative platforms (Eke, Chintu & Wakunuma, 2023). For example, Deep Learning Indaba is ideal in describing international collaboration efforts. It is focused on facilitating an environment where AI can be effectively developed (Rutenberg Gwagwa & Omino, 2021). It aims to spread knowledge and capacity of ML more widely across the continent by connecting AI-centred communities and individuals (Deep Learning Indaba, 2023).

The conference has been held all over Africa for the last six years and have been sponsored by a multitude of entities including Google, Apple, Microsoft and DeepMind (Deep Learning Indaba, 2023). As some do not always have the resources to attend AI conferences in other countries, accessibility is essential for improving informed African developmental ventures (Rutenberg Gwagwa & Omino, 2021). Another great example of a collaboration platform is the Global Pulse network, consisting of four labs that connect partnership specialists, data scientists, academic experts, data engineers and technical experts.

The network is created to help address development challenges through AI (UN Global Pulse, 2022). The global pulse initiative strives towards addressing complex real-world problems using a network of AI experts and developers sharing best practice strategies to drive more efficient AI models. The Pulse Lab network is made up of Pulse Lab New York (USA), Pulse Lab Jakarta (Indonesia), Pulse Lab Kampala (Uganda) and Pulse Lab Finland (Finland) (UN Global Pulse, 2023). The locations of these labs are self-selected, and host countries must express an explicit interest in hosting a lab that shares lessons, findings and experiences with others (UN Global Pulse, 2023).

UN agencies involved in Pulse Lab Kampala aim to help the Uganda government achieve the 2030 SDGs. This is done through partnering with developers in Uganda and testing, developing, and exploring 17 innovative AI projects (Rutenberg, Gwagwa & Omino, 2021). Another, African AI platform for collaboration is AfriLabs, with more than 400 corporate members each contributing to an AI hub (AI research lab). These spaces serve as a facilitating environment for ecosystemic engagement and capacity building, R&D, corporate engagement/corporate services, and consulting and advisory opportunities (AfriLabs, 2024).

They include partners such as United Nations Development Programme (UNDP), Intel, African Union, Ant group, and Visa, to name a few (AfriLabs, 2024). Collaboration platforms are integral for AI development in Africa. However, funding and investment is just as crucial to ensuring African AI growth. International agents contribute to these efforts and ensure further development of AI is attained in Africa.

4.4.2 Funding and investment

Funding and investing in African AI ventures are crucial to attaining the goals of the SFDRR (UNDRR, 2024). Investment in African AI varies between international governments and private institutions which form an essential part of ensuring AI development and deployment is deemed successful (Asmal *et al.*, 2019). XL Africa, for instance, focuses on funding companies that use AI technology for financial and social gain (The World Bank, 2017). The Nigerian company aims to connect startups across Africa with mentorship and access to investors (The World Bank, 2017). Its corporate partners include Microsoft, Global System for Mobile Communications Association (GSMA) Ecosystem Accelerator, and Google to name a few.

Multiple key investors in African AI R&D are identified as international governments such as China (Global Times, 2021), Sweden (Bradshaw, 2022) and Canada (Wits University, 2021). And capital industry investors include Google (Kene-Okafor, 2022), Facebook (Shead, 2018), Amazon (Malinga, 2021), and Apple (Sun, Bocchini & Davison, 2020). 'AI for good' funders are identified

as Omdena (Omdena, 2023) (USA) and Element AI (Canada) (Access-Partnership, 2018). They contribute towards utilising AI in Africa for the benefit of others. The Swedish International Development Agency and Canada's International Development Research Centre attributed CA\$20 million to the AI for Africa program (Gwagwa *et al.*, 2021).

Additionally, UN agencies are extensively involved in African AI funding. They are identified as the International Telecommunications Union (ITU) (Ngila, 2022), the International Labour Organization (ILO) (Ernst, Merola & Samaan, 2018), the Interregional Crime and Justice Research Institute (ICJRI) (UNESCO, 2020), and the Commission on Science and Technology for Development (CSTD) (TEIMUN, 2022). All of which aim to shorten Africa's time in reaching the Sustainable Development Goals (SDGs) using AI (Access-Partnership, 2018).

All of which aim to shorten Africa's time in reaching the SDGs using AI (Access-Partnership, 2018). Furthermore, select projects in Africa are supported by GSMA's Ecosystem Accelerator Innovation Fund from China. It provides opportunities to help AI businesses become more sustainable (GSMA, 2019). Additionally, the Ghanaian seed fund for African Innovators, MEST incubator, helps build commercial tech companies and give them financial support (MEST, 2023). MEST includes an array of partners such as Amazon, Samsung, Microsoft, United Nations Children's Fund (UNICEF), UNDP, and Mastercard (MEST, 2023).

The Middle East and North Africa (MENA) has extreme water scarcity which is exacerbated by population growth and climate change (Perera, 2023). With a grant from Google's philanthropic arm, the International Water Management Institute (IWMI) unveils an AI tool for more efficient water reuse systems (Perera, 2023). The e-ReWater tool provides features that can add value to water management systems in MENA countries (WUN, 2024). Such as, a comprehensive information dashboard, public education, improved decision making, climate resilience, and policy development (WUN, 2024). Unfortunately, AI models used for this tool are not specified.

International involvement in African AI facilitates the growth of certain AI related domains. For instance, R&D is an integral part of effective AI deployment in Africa. With efforts from various industry players, R&D in African AI can ensure more efficient model distribution and efficient application.

4.4.3 Research and Development (R&D) support

The effectivity and growth of AI in African DRR depends greatly on R&D support (Gwagwa *et al.*, 2020). Private industry players retain access to resources governments do not necessarily have and can use them for R&D purposes (Access-Partnership, 2018). These industries include

Microsoft (who provide scholarships to support research in AI) (After School Africa, 2022), IBM (established AI research facilities in Kenya and South Africa) (ScholarshipSet, 2022), and Google (providing the African Developer Scholarship for AI R&D) (OFA, 2022). As academia is a platform for innovative AI development, experts can research and experiment with novel AI-variants and develop efficient models for the African context (Perdy & Daugherty, 2016).

Research facilitators are identified in this study as Google's research facility in Ghana (Matias, 2022), IBM's researchers developing AI in Nairobi (Molapo *et al.*, 2021), and Microsoft's whitepaper on the importance of research in African AI (Microsoft News Centre, 2020). These agents allow for addressing challenging questions and issues regarding African AI development (Access-Partnership, 2018). As AI becomes a more prominent theme, the fostering of skill-building and specialisation of the field drives its accessibility and growth towards a more capable future in Africa (Butcher *et al.*, 2021).

Consequently, the University of Pretoria (South Africa) collaborating with the Intelligent Systems Group (ISG) (Australia) aims to develop real-world systems that apply to the South African context (University of Pretoria, 2022). Also, Strathmore University in Nairobi established the @iLabAfrica research centre in collaboration with entities such as, but not limited to, Google, Samsung, and Clinton Health Access Initiative (CHAI) (@iLabAfrica Centre, 2023). The research centre promotes innovative research for achieving SDGs in Kenya's 2030 vision report (Kenya Vision 2030, 2008).

Furthermore, the Centre for Artificial Intelligence Research (CAIR) in South Africa actively contributes to the country's digital transformation through capacity building and cross-disciplinary research (CAIR, 2022). Universities play a crucial role in R&D efforts in African AI (Gwagwa *et al.*, 2021a). With experts, researchers, and funders already in place, universities have the capacity to improve AI applications for the African context.

4.4.4 University involvement

University involvement in AI encourages R&D efforts by addressing social and institutional challenges. The Dedan Kimathi University of Technology in Nyeri endorses entrepreneurship and job creation in AI and aid in intellectual property rights (Dedan Kimathi Science and Technology Park, 2021). The University of Lagos in Nigeria is the creator of AI Hub, which is focused on promoting the AI lifecycle in DL and youth inclusion (The Guardian, 2018). Rutenberg and colleagues (2021) identify university participation in African AI development as Carnegie Mellon University in Kigali and Makerere University in Uganda. These universities are identified as some

of the first institutions to offer a Master of Science degree in Electrical and Computer Engineering with courses in robotics, ML, and IoT.

The Makerere University AI research group (AIR Lab) received support from the UN Global Pulse Lab to develop an air quality monitoring and prediction system named AirQo (Rutenberg, Gwagwa & Omino, 2021). Furthermore, the Weather Information Management in East Africa-Information and Communication Technology (WIMEA-ICT) project, funded by The Norwegian Agency for Development Cooperation, aims to build research capacity between various universities in Africa (WIMEA-ICT, 2017). The project assists in improving weather information management in Eastern Africa using AI information and communication technology.

Additionally, the University of Dodoma in Tanzania seeks to strengthen public universities' responsible AI research capacity (AI4D, 2023). Similarly, the University Virtuelle du Burkina Faso, facilitates research in Burkina Faso through an interdisciplinary centre of excellence in AI for development (CITADEL) (IDRC & SIDA, 2024). The university aims to make AI research more accessible to French-speaking African students (IDRC & SIDA, 2024). AI development is substantially driven by university activity but also through public-private collaborations. Private corporations and entities are partnering with local African organisations to produce specific AI applications and initiatives.

4.4.5 Public-private corroboration

Global technology companies and international organisations have been using exponential technologies to alter the future of DRR in various African contexts (Rutenberg, Gwagwa & Omino, 2021). Examples of these efforts are Omdena (Omdena, 2023a) and Element AI (Access-Partnership, 2018) collaborating with local African non-governmental organisations (NGOs), R365 and Renewable Africa. Furthermore, the Canadian based Element AI has projects supporting African humanitarian uses for AI and robotics which help build a trusting relationship between humans and machines (Rutenberg, Gwagwa & Omino, 2021).

The steady increase of African geospatial initiatives is sponsored by public-private partnerships, UN agencies, international industry, organizations, and global technology companies (Rutenberg, Gwagwa & Omino, 2021). Further public-private partnerships are identified as the SA company Aerobotics that uses ML algorithms and aerial imagery to address industry specific problems such as agriculture and insurance. The South African DEA (Development of Environmental Affairs), the CSI (Committee on Spatial Information), and the broader GIS community support the project.

Furthermore, the Vodafone Foundation collaborated with the government of Ghana and the Flow Minder Foundation to track the real-time movement of populations. This AI model is used to control and prevent widespread outbreaks during an epidemic (Vodafone Foundation, 2018). Another South African project stems from IBM researchers partnered with various Chinese government researchers and the Green Horizons initiative (IBM, 2015). This project applies ML to address the challenge of air quality prediction in South Africa (IBM, 2015).

Kenya's Ushahidi software is an open-sourced crisis mapping system used for real-time mining of news articles, social media content, and time-stamped and geo-tagged data from multiple sources (Ushahidi, 2023). Furthermore, One Concern, inspired by Ushahidi, is a crowdsourced predictive model used in Kenya to map out AI response to humanitarian crisis (One Concern, 2024). African AI is developing at a rapid pace and needs further exploration. The different domains of AI implementation in Africa illustrates its versatility and interconnection.

4.5 Conclusion

The purpose of this chapter was to explore the projects and collaborations involved in prospective DRR efforts using AI in Africa. It considered African governmental involvement in creating platforms that facilitate AI use and encourage policy development. It addressed the third research objective that aims to investigate the state of AI in Africa and the advantages and challenges faced by its implementation. This was achieved by firstly discussing the role of government in terms of implementing and developing AI in Africa. This section discussed AI-friendly environments consisting of data collection and availability, institutional support, and hosting networking events. Furthermore, it explored ethics and public policy related to responsible AI, strategy development, and public policy and governance.

Secondly, key economic sector applications of AI were explored using examples related to various African countries. Key economic sectors were identified in this section as: agriculture, health, finance, transportation, and education. Consequently, the technological sector was not included in the discussion as it overarched each sectoral discussion. As with all the categorisation efforts in this study, sectors were not isolated from one another and constantly interacted and overlapped. The section aimed to structure the versatility of AI in various key economic sectors.

Lastly, multi-agent stakeholders facilitating an African AI ecosystem was explored with relation to national and international role-players. The section discussed networking and collaboration opportunities, funding and investments, research and development, university involvement, and public-private partnerships. Consequently, the state of African AI was discussed to provide an overview of various applications and developments present in different institutional domains.

Highlighting the complexity involved in general AI implementation and governance for reducing prospective DR.

Although AI projects in Africa can be identified by general applications towards prospective DRM, the question remains on how these applications are utilised for specifically reducing hydrometeorological hazards. The prominence of a knowledge gap between the general understanding of AI capabilities in African DRR and the specifics associated with AI project implementation for reducing hydrometeorological hazards remains. Therefore, this gap can only be addressed by exploring specific AI projects.

The following chapter explores AI for reducing hydrometeorological hazards in Africa. These AI projects are primarily focused on corrective and residual DRR as in most cases the hazard is already present and requires reduction or management. However, climate change adaptation projects are considered in Chapter 5 as aiding prospective hydrometeorological DRR and includes water management, and land use and cover. Furthermore, corrective and residual hydrometeorological DRR projects are discussed according to flood reduction, drought reduction, landslide reduction, wildfire reduction, and tropical cyclone reduction.

Although, technically, these hazards cannot be separated as they are inherently linked to each other (hence the name hydrometeorological hazard), AI projects in Africa often target the result of these hazards on the environment. Consequently, Chapter 5 explores specific AI projects involved in reducing prospective, corrective and residual hydrometeorological DR. Through focus on the project function, AI model, country of application, and autonomous agent involvement; the chapter explores the various AI efforts for reducing hydrometeorological hazards in Africa.

CHAPTER 5 AI IN AFRICAN HYDROMETEOROLOGICAL DRR

5.1 Introduction

The fluidity of AI project application and interaction facilitates DRR in environments that desperately require change. AI can be used for a multitude of purposes in African DRR, namely, to expand hazard understanding (ITU, 2021a), track events in real-time (Neuhofer, Magnus & Celuch, 2020), monitor areas of concern (Van Heteren, Hirt & Van der Veken, 2020), and forecast hazards (Joshi, 2019). Fundamentally, this chapter serves as a data base, documenting and describing various AI projects in African hydrometeorological DRR. This chapter is predominantly written in a narrative way, which aids in efficiently combining various pieces of literature from different fields and disciplines.

In this chapter different AI projects are discussed according to their specific contributions in hydrometeorological hazard reduction efforts in Africa. Each section includes various African countries participating in R&D efforts. AI projects discussed in this chapter is selected due to their relevance to the study perimeters and their subject to availability. The project examples mentioned in this section aims to be inclusive and representative of most African countries. Therefore, the mentioned projects are not the only projects available but represent an array of countries and their efforts in using AI for HHR.

All projects in this chapter are described according to the parameters of African country of use, primary function, specific AI model, autonomous agent involvement (such as universities, corporations, institutions, investors and funders), and their location. Autonomous agents can be defined as any computational or physical system that operates independently, observes its environment and interacts with it in pursuit of its own goals (Rouse, 2024).

Although this definition primarily relates to computer science, its use in this research refers to the various involved entities driving the development of African AI projects used for HHR. This is done to identify different involved agents and transform them into nodes connected by the AI projects for African HHR in Chapter 6. The various sub-grouped headings such as assessment, evaluation, detection, monitoring, mapping, prediction and or forecasting fundamentally indicate the function related to the project. In this research, these functions are considered interconnected and can occur simultaneously in projects (see section 2.1.2). Thus, the discussed projects are not necessarily exclusively one function but rather predominantly one function.

African countries included are vast and therefore, the discussed projects are limited by chronological deployment and relevance to the research. The mentioned AI projects are subjected to selection by relevance and reliability of academic publications between 2020 to 2024. This period is selected mainly because it presents an increased availability of credible African AI project publications. This does not suggest that there were no credible publications before 2020, just that recent publications are more fit for this research purpose.

Firstly, prospective hydrometeorological hazard reduction is explored in terms of climate change adaptation (CCA). This section considers water management projects and land use and land cover (LULC) efforts. Water management is discussed in terms of water-quantity and -quality projects. Water quality and quantity consist of projects focused on AI evaluating, monitoring and predicting efforts. LULC projects are explored through urbanisation & rural development, and environmental conservation. Both sub-categories are discussed with relation to AI evaluating, mapping, monitoring, and predicting efforts.

Secondly, corrective and residual hydrometeorological DRR projects are explored in terms of flooding, drought, landslides, wildfires and tropical cyclones. Flood reduction projects in Africa are discussed according to AI predicting, susceptibility mapping, monitoring and assessing various flood prone areas. Drought reduction projects are identified and discussed with relation to forecasting, predicting, and monitoring efforts. Landslide reduction projects are explored through considering AI assessing and evaluating, susceptibility mapping, predicting and modelling. Wildfire reduction projects are discussed in terms of AI mapping, prediction, and detection ventures. Also, tropical cyclone reduction is explored considering AI detection and prediction projects.

The sheer amount of project examples in this chapter and their detail filled explanations cause difficulties in keeping track of their complexities. Therefore, at the end of each section, a Table is formulated to summarise the mentioned African AI project examples. Tables enable the researcher to present large amounts of data in a comprehensible and efficient manner (APA Style, 2019). Furthermore, tables assist in structuring and enhancing the trustworthiness of qualitative data (Cloutier & Ravasi, 2020) and help increase transparency in findings and efficiency of data analysis (Cloutier & Ravasi, 2020).

The Tables are structured according to the headings of African country, project reference, AI model, assisting technology, project purpose, autonomous agents and agent country (see

footnote¹ for table layout). Additionally, these tables represent the codes used for Chapter 6. Moreover, a geographical map of Africa is included in each section to illustrate the involved project examples and their weights. The country weights are indicated by colour and includes a chart to help the reader understand the figure. Ultimately, this chapter aims to identify and explore AI projects used for CCA and HHR in Africa.

Creating disaster resilient environments is a fundamental contemporary challenge (Dias *et al.*, 2019). Combining CCA with DRR efforts should help decrease environmental vulnerability and facilitate more resilient environments (Dias *et al.*, 2019). Although traditionally CCA is considered a concept on its own, it is in the spirit of this research and its CAS approach to consider it a measure of prospective HHR. Purely because implementing CCA helps reduce uncertain hydrometeorological hazard formation (Debele *et al.*, 2019).

¹ In the summarising tables, the heading 'African country' refers to the context of the AI project application. African countries are listed alphabetically. When more than one country applies a project, they are listed according to the first alphabetical country following the rest in the same section. The heading 'project reference' indicates the author(s) of the publication, listed as an in-text reference. Different projects from the same country are listed alphabetically according to their project reference. The heading 'AI model' refers to the type of AI model used for the various projects. These projects include multiple AI models used in hybrid AI projects or single AI models when deemed the most efficient. For example, a project makes use of different AI models to do different tasks, using multiple models at once can be considered using AI in a hybrid manner. All these AI models are included in the table. On the other hand, some projects mention the use of many AI models for the same purpose and usually find that one model is more efficient than the others. In this case, only the most efficient model is included in the table. 'Assisting technology' is included because of its presence in the AI project literature. Mentions of sensors, IoT and GIS suggests the presence of assisting technology in some African AI projects. Assisting technologies are identified in the literature as statistical models (such as GIS), robotics (such as remote sensing), and AI products (such as IoT). The 'project purpose' heading describes the basic incentive of the project, including its function and application area. For example, predicting and forecasting groundwater quantity. As mentioned in Chapter 5.1, 'Autonomous agents' are usually defined in terms of computer science, however in this research it is identified as any entity contributing to AI used for reducing hydrometeorological hazards. Therefore, they are referred to in this research as any entity helping realise a project. This includes any institution, corporation, or organisation that aids African AI projects in funds, investments, and/or research and development efforts. All these autonomous agents inadvertently contribute to the complexity of the network formed between local African ventures and international corroboration (see Chapter 4.3). The last heading, 'Agent country' refers to the country of the autonomous agent. This is included to reduce the variation between specifics in autonomous agents and combine the nodes under common countries. This can help place the project nodes and their networks geographically, considering the country of AI project application and the countries helping develop them. Sometimes the AI projects only involve autonomous agents from the country of its application. This indicates that the project is locally fuelled. Whereas players such as the World Bank and the United Nations fuel African AI projects in HHR internationally. CCA was considered due to its extensive influence on the development and severity of hydrometeorological hazards. For the sake of research relevance, CCA was especially observed in terms of water management efforts and land use and land cover (LULC) activities. These subsections are summarised using a table. The table indicates details of the African projects used for water management in quantity and quality regulation.

5.2 Climate Change Adaptation

Climate change adaptation (CCA) fundamentally involves adapting to the climatic changes in various environments (Biswas & Rahman, 2023). Unlike mitigation, adaptation does not attempt to reduce existing hazards, it rather aims to adapt to the environmental changes that produce them (Biswas & Rahman, 2023). Efficient application of CCA should help avoid any possible formation of hydrometeorological hazards. CCA in hydrometeorological hazard reduction frequently involves the management of water resources (FAO, 2024), developing sustainable urban infrastructure (Reinwald *et al.*, 2024), and enhancing environmental conservation practices (Delgado, Nearing & Rice, 2013).

In this section CCA is explored according to African AI project examples related to water management, and land use and land cover (LULC). Water management is explored in terms of water quality and water quantity related projects. AI is particularly used for evaluating, monitoring, and predicting water quality and quantity levels. Water quality AI projects are discussed according to existing or prospective contamination and pollution levels. Water quantity is explored according to existing and prospective water levels.

LULC is discussed according to urbanisation and rural development, as well as environmental conservation. Land use refers to human activities such as urbanisation, mining, deforestation, and agriculture (Deka *et al.*, 2019). Whereas land cover refers to physical earth surface cover namely grassland, urban areas, agricultural land, forests, and lakes (Wang *et al.*, 2023). In this section, urbanisation and rural development projects are mostly comprised of agricultural and urban expansion. Environmental conservation is explored in terms of various African AI projects enforcing water body and forest conservation efforts. Water management sub-headings are structured according to AI project functions namely evaluation, monitoring, and prediction. In LULC sub-headings include evaluation, mapping, monitoring, and prediction.

It is important to note that the structure of the sub-headings is essentially interdependent and interconnected. For instance, evaluation of LULC changes require access to maps for monitoring and assessing output. Prediction requires mapping and monitoring data to train the selected AI models and identify emerging patterns. Although these projects are discussed under one model function it is imperative to remember that these functions usually overlap in the projects and cannot be considered rigid in their placement. Water management is essential to CCA and informs various strategies and planning for sustainability and hydrometeorological hazard reduction.

5.2.1 Water management

Water management assists in reducing the risk of water scarcity and pollution (Cosgrove & Loucks, 2015). It is vital to climate change adaptation ventures and provides a means of reducing and avoiding DR. Various African countries are encouraged to use AI in water management, as it has the potential to revolutionise the water sector (Ajayi, 2023). Water management mainly entails evaluating, monitoring and predicting the states of water resources and following procedures in accordance with those results. Water management AI is discussed in this research according to water quality evaluation, monitoring and prediction, as well as water quantity assessment, monitoring and prediction.

AI water quality management is identified in this research as evaluating, monitoring, and predicting water class and contamination levels. On the other hand, AI water quantity management is identified in this research as evaluating, monitoring, and predicting water table levels and resource distribution. Regulating and sustaining water quality and quantity is vital to efficient water management. It facilitates stable and reliable systems that provide consistency in output. Water quality can establish the availability of drinking water and affect consumption.

5.2.1.1 Water quality

Water quality management in Africa is explored in this section according to various AI project examples. Evaluating, monitoring and predicting water quality is vital to ensuring water-related risks don't become hazards and trigger the development of other hazards such as contamination, disease, and famine. Identifying the water quality in Africa is important for the general health of the environmental ecosystem (Tampo *et al.*, 2023).

The African countries discussed in AI water quality evaluation includes Algeria, Burkina Faso, South Africa, Sudan, and Tunisia. These countries require constant water quality evaluations due to poor waste management systems causing extensive contamination (Poulet, 2019; Sanfo *et al.*, 2022; Gani *et al.*, 2021; Awad, 2024; UNEP, 2024). Also, these countries are vulnerable to unregulated mining techniques resulting in groundwater pollution (Moulahoum, 2022; Bretzler *et al.*, 2017; Khomo, 2024; Awad, 2021; Yahyaoui & Amor, 2024).

In water quality monitoring, African countries such as Cote d'Ivoire, Ghana, Mauritius, and Zambia are discussed. These countries have all experienced damages to natural environments due to extensive water contamination (UNEP, 2015; Awewomom, Ashie & Dzeble, 2024; Fakim, 2021; Muimba-Kankolongo *et al.*, 2022). Additionally, they experience ongoing challenges in providing

efficient water sanitation services (Ouattara *et al.*, 2022; Appiah-Effah *et al.*, 2019; Padaruth & Biranjia-Hurdoyal, 2015; Libanda *et al.*, 2024).

In water quality prediction, Algeria, Niger, Nigeria and South Africa makes use of AI to reduce and avoid irreversible contamination of their water resources. These countries are largely reliant on inorganic fertilizers that increase the risk of groundwater contamination (Fares, Naim & Bouadi, 2021; Numbere, Gbarakoro & Babatunde, 2023; Muza, *et al.*, 2022; Du Preez & Van Huyssteen, 2020). Also, they have rapidly developing industrial sectors which pose various risks to water quality (Eid *et al.*, 2024; UNIDO, 2021; Fashae & Obateru, 2021; Iloms *et al.*, 2020).

Water quality evaluation is essential to understanding water contamination and its severity level. With the rapid increase in aquatic environmental data, AI has become the ideal tool for evaluating water quality (Zhu *et al.*, 2022).

5.2.1.1.1 Evaluation

Water quality analysis and evaluation efforts have extensively improved the efficiency of water pollution reduction (Pan, Leng & Liu, 2012). Water quality evaluation is vital to the African context considering the regions limited access to clean water resources. AI has the potential to be utilised for evaluating poor-quality water resources and help monitor contamination (Zhu *et al.*, 2022). Although, still in its infancy, AI projects being used for water quality evaluation in different African countries are identified in this research. For example, an Algerian AI project evaluated groundwater quality for irrigation in deep aquifers (Eid *et al.*, 2023).

The study was carried out to determine the quality of water for agricultural irrigation purposes. It involved an array of autonomous agents from various institutes and universities. These agents include the University of Miskolc in Hungary, the Beni-Suef University in Egypt, King Khalid University in Saudi Arabia, Agricultural Research Centre in Egypt, Wroclaw University in Poland, the University of Sadat City in Egypt, Damanhour University in Egypt, and Kafrelsheikh University in Egypt (Eid *et al.*, 2023). In combination with GIS techniques, this project uses the ML algorithm Support Vector Machine (SVM) to determine groundwater quality.

Additionally, Burkina Faso uses ML techniques for nitrate identification in groundwater pollution in the National Mouhoun Basin (Ouedraogo *et al.*, 2023). AI evaluating and modelling techniques help determine the state and vulnerability of groundwater. For establishing the treatment of drinking water, the project made use of AI algorithms such as ANN, DL, PCA, SVM, RF, and Fuzzy Logic (FL) (Ouedraogo *et al.*, 2023). Autonomous agents involved in the project are Fada

N'Gourma University in Burkina Faso, Earth and Life Institute in Belgium, and the International Atomic Energy Agency in Vienna, Austria (Ouedraogo *et al.*, 2023).

Similarly, Tadesse and Dinka (2023) developed an ML model to identify the class of water quality of the Roodeplaat Dam in South Africa. The project used multiple ML algorithms but found the K-Nearest Neighbour (KNN) model to be the most efficient (Tadesse & Dinka, 2023). The study concluded that the quality of the Roodeplaat Dam water can be determined by ML models before its distribution and use (Tadesse & Dinka, 2023). The research from Tadesse and Dinka (2023) was made possible through autonomous agents from the University of Johannesburg in South Africa.

In Northern Khartoum State of Sudan, AI algorithms were used to model and evaluate an area groundwater quality index (Mohammed *et al.*, 2023). The primary source of drinking water in dry areas is reliant on groundwater; therefore, determining its quality is crucial to preventing health risks. The AI models used in this project includes MLP-NN and SVM algorithms (Mohammed *et al.*, 2023). Autonomous agents involved in this project are from the University of Miskolc in Hungary (Mohammed *et al.*, 2023).

Tunisia makes use of ML models in the Oriental Coast's shallow aquifer in Cap-Bon and is ranked by various levels of water irrigation quality (Yahyaoui *et al.*, 2023). Groundwater quality evaluation is considered a key parameter for improving water resource management efforts. Through comparing various ML algorithms to irrigation quality prediction; the study found that K-Nearest Neighbour (KNN) is the most accurate model (Yahyaoui, *et al.*, 2023). The autonomous agent involved in this project is the University of Sfax in Tunisia (Yahyaoui *et al.*, 2023).

Water class evaluation is important for detecting contaminants and is useful to countries with limited water resources. Water quality monitoring is also integral to water management efforts and is used in various African countries. Sensors are usually utilised in monitoring endeavours that aim to track the growth of certain contaminants in drinking water. AI for monitoring water quality is helpful for early detection and intervention activities.

5.2.1.1.2 Monitoring

AI monitoring water quality in Africa is useful for countries aiming to manage their water resources and maintain their water quality (Bangira *et al.*, 2024). Monitoring is essential to early warning systems and help minimise the level of contamination (UNEP, 2024a). For more efficient water management systems, monitoring water quality becomes essential.

For example, in Cote d'Ivoire, AI is used for modelling the spatio-temporal evolution of chlorophyll-a in three of its rivers (Soro *et al.*, 2020). The project involves the Cote d'Ivoire institutions known as the University of Félix Houphouët Boigny, the Research Centre for Oceanography, and the University of Péléforo Gon Coulibaly. The study found that ANN is the most efficient and cost-effective way of monitoring water eutrophication (excessive plant growth) of West African coastal rivers (Soro *et al.*, 2020).

Management of water pollution in the Ghana Pra River is achieved by using AI applications (Nti *et al.*, 2023). The Ghanaian project aims to uncover AI options towards environmental health protection, sustainability, and water security. It is utilised to monitor and track the river's pollution rates using remote sensors (RS). Agents involved in this project include the World Bank, Government of Ghana, the University for Development Studies in Ghana, and the University of Science and Technology in Ghana (Nti *et al.*, 2023). AI technologies used include ANN, ANFIS, MLR, Electro-Kinetic Remediation Technology (EKRT), Response Surface Methodology (RSM) and SVM (Nti *et al.*, 2023).

Mauritius utilises AI to monitor water quality and sanitation systems (Jogee *et al.*, 2024). Image classification techniques such as NN are used to detect the presence of pollutants in the water. Remote sensors (RS) are also used to detect major contaminants and are integrated with AI models to further predict water quality variations (Jogee *et al.*, 2024). Autonomous agents involved in this project includes the University of Toulouse in France, and the University of Mauritius in Moka.

Zambia uses of ML techniques and RS to monitor water pollution in the Kafue River (Mumbi & Phiri, 2023). The project aims to accurately predict water quality in rural areas using a model built upon the IoT and cloud computing systems (Mumbi & Phiri, 2023). ANN, with one hidden layer, is used to predict the Kafue River water quality index. The Autonomous agents involved in the project extends to the University of Zambia (Mumbi & Phiri, 2023).

A multitude of autonomous agents are involved in monitoring water quality in Africa. Monitoring water quality aids in reducing prospective hydrometeorological risk and possibly facing large-scale contamination, infection, and disease. Additionally, AI monitoring is used for predicting water quality in certain African countries. Susceptibility mapping and historical monitoring data make the prediction of water quality possible using various ML algorithms.

5.2.1.1.3 Prediction

Prediction of water quality is vital to efforts preventing contamination and severe dispersion (Miller *et al.*, 2024). The quality of water is predicted using various AI methods set on modelling prospective pollution risks. These risks are predicted using historical data on past area water contamination and environmental mapping to determine the level of susceptibility to possible hazards (Wang, *et al.*, 2024).

For example, Algeria uses AI for groundwater quality prediction in upper and middle Cheliff Plain (Elmeddahi *et al.*, 2023). The project involves an array of autonomous agents such as, the University of Benbouali in Algeria, the Vegetal Chemistry -Water-Energy Laboratory in Algeria, UK Centre for Ecology and Hydrology, University of Delhi in India, and the Zagazig University in Egypt. The project makes use of AI models namely Principal Component Analysis (PCA), Support Vector Machine (SVM), Multilayer Perceptron Neural Network (MLPNN), and Decision Tree Regression (DTR) (Elmeddahi *et al.*, 2023).

In Niger, AI is used for the assessment of aquifer susceptibility to contaminants, land pollution, groundwater quality degradation, and subsidence (Ojoboh, Ochie & Nwosu, 2020). The project uses a NN model set to determine the vulnerability of the Niger Delta. Which proved to be statistically efficient in predicting the aquifer susceptibility rating (Ojoboh, Ochie & Nwosu, 2020). Autonomous agents involved in the project includes Delta State University in Nigeria, ExxonMobil in the USA, and the Federal University of Technology Owerri in Nigeria (Ojoboh, Ochie & Nwosu, 2020).

In the southeastern parts of Nigeria, data-intelligent algorithms are combined for assessing and predicting groundwater resources quality (Egbueri & Agbasi, 2022). For spatial demarcation of water quality, K-means clustering (K-means), and agglomerative Q-mode hierarchical clustering (AQMHCC) is used. MLR and MLPNN models are used to predict and estimate water quality in this project (Egbueri & Agbasi, 2022). The project involves the Chukwuemeka Odumegwu Ojukwu University in Nigeria (Egbueri & Agbasi, 2022).

South Africa uses AI to predict the physicochemical characteristics of water quality in three Eastern Cape province District Municipalities (Setshedi, Mutingwende & Ngqwala, 2021). The project makes use of ANN that offers more accurate and comprehensive water prediction data. Autonomous agents involved in this project includes the Rhodes University and the Fort Hare University in South Africa and funding from the National Research Foundation of South Africa (Setshedi, Mutingwende & Ngqwala, 2021).

AI utilised for water quality evaluation, monitoring and prediction is important for prospective HHR in Africa. With many African countries experiencing water shortages, water quantity is also extremely important for reducing the risk of drought, flooding and agricultural production failures.

5.2.1.2 Water quantity

AI can be used in African countries to determine the amount of water available for distribution (Niyongabo *et al.*, 2024). It is used to assess, monitor, and predict water resource regulation (Gunasekaran & Boopathi, 2023). AI aids distributors and policy makers in making informed decisions for the efficient management of water resources (see Chapter 4), decreasing existing risk and avoiding the development of potential risk (see Chapter 3). Using AI to manage water quantity is useful for African countries and aid in dealing with sudden water drops. This research identifies literature themes in AI water quantity management projects in Africa as assessment, monitoring and prediction efforts.

AI evaluation of water quantity is mostly done in the African countries of the Democratic Republic of Congo, Ethiopia, Ghana, South Africa, Lesotho, and Rwanda. These countries all have difficulties in accessing drinking water and regulating its use (Inogwabini, 2020; Berhanu, 2020; Anim & Ofori-Asenso, 2020; Pryor, Zhang & Arias, 2021; Gasirabo *et al.*, 2019). Also, historically, each of them experienced damaging periods of inconsistent rainfall (Ndehedehe & Agutu, 2022; Abegaz & Mekoya, 2020; Owusu & Waylen, 2012; Roffe, Fitchett & Curtis, 2019; Tongwane & Moeletsi, 2014; Tuyisenge *et al.*, 2024).

AI monitoring water quantity projects in Africa involve Angola, Botswana, and Morocco. These countries can use AI monitoring projects as they all experience unexpected changes to reservoir levels (WBG, 2023; Perkins & Parida, 2022; Abdulla, 2024). Also, in various areas they struggle with water conservation due to an increasing demand (Cain & Baptista, 2020; Motho *et al.*, 2022; Taheripour *et al.*, 2020).

The African countries using AI for predicting water quantity includes Egypt, Libya, Kenya, Madagascar, Mali, Ghana, Mozambique, Uganda, Benin, Ethiopia and Senegal. All these countries aim to develop more sustainable water distribution systems and help minimise water waste (Gado & El-Agha, 2020; Elmnifi *et al.*, 2024; Mulwa, Li & Fangninou, 2021; Harifidy & Hiroshi, 2022; Sidibe & Minh, 2021; Adadzi, Coffie & Afetorgbor, 2019; Monteiro *et al.*, 2016; Huston *et al.*, 2021; Ollivier *et al.*, 2014; Beker & Kansal, 2023; Faye & Gomis, 2019).

Also, they all have a high risk of flash flood occurrences (Helmi & Zohney, 2020; Normand & Heggy, 2024; Barasa & Perera, 2017; Caimpalini *et al.*, 2018; Fofana *et al.*, 2022; Ahadzie *et al.*,

2017; Neves, 2024; Tibara, Wassa & Semakula, 2022; Zahiri *et al.*, 2016; Dejen & Soni, 2020; Soltesova, 2017) and could benefit from AI predicting water quantity. Evaluation is an important part of establishing water table levels. The use of AI for water quantity evaluations can aid in more effective water management efforts (Goyal, Kumar & Gupta, 2024).

5.2.1.2.1 Evaluation

Along with water quality evaluation, water quantity evaluation aids in implementing water resource management policies (Hwang, Park & Song, 2020). Therefore, determining the state of water quantity is important when creating strategies for hydrometeorological DRR (Bardossy & Hachem, 2021).

For example, in the Democratic Republic of Congo's Kinshasa area, AI is used to assess and evaluate the regulation of water resources by considering factors such as the community, economy, water consumption, and water availability (Amsini & Gozen, 2023). The autonomous agents involved in this project include the Near East University in Cyprus and the Near East University in Turkey. The AI algorithms used for this project include ANN, Adaptive Neuro-Fuzzy Interface Systems (ANFIS), and Multi-Linear Regression (MLR) models (Amsini & Gozen, 2023).

Ethiopia uses an integrated AI and GIS spatial evaluation tool to delineate groundwater potential zones in complex terrains (Tamiru, Wagari & Tadese, 2022). In other words, the tools aim to detect areas where groundwater could accumulate and potentially become a water resource. This project is an excellent example of the purpose fulfilling two functions namely: evaluation and prediction. The individual criterion was weighted and ranked using AI algorithms ANN and Analytical Hierarchy Process (AHP) (Tamiru, Wagari & Tadese, 2022). The project primarily includes the involvement of Wollega University in Ethiopia.

Ghana uses AI to evaluate land suitability for informal, small-scale irrigation development (Akpoti *et al.*, 2022). The model maps spatial explicit suitability for dry-season small-scale irrigation measures (Akpoti *et al.*, 2022). It is developed using Boosted Regression Trees (BRT), RF, and Maximum Entropy (ME). The agents involved include the University of Energy and Natural Resources in Ghana, the University of Manchester in the UK, and the International Water Management Institute in Ghana (Akpoti *et al.*, 2022).

Evapotranspiration is crucial to the management of water resources and in examining geo-temporal patterns of drought-prone areas (Mahasa, Xulu & Mbatha, 2023). AI is used in the characterization of evapotranspiration in the Orange River Basin of South Africa and Lesotho (Mahasa, Xulu & Mbatha, 2023). The study used RF and Wavelet Analysis (WA) algorithms to

identify variables and confirm coherence between them. The autonomous agents involved in the study include the South African institutions of the University of the Free State, University of KwaZulu-Natal, and the University of Zululand (Mahasa, Xulu & Mbatha, 2023). The study was funded by the University of the Free State and the National Research Foundation of South Africa.

Rwanda is using AI to evaluate rainfall quantities and climate change patterns in the city of Kigali (Bizimana *et al.*, 2023). Rainfall patterns have changed dramatically in Rwanda, ranging from water scarcity to flooding events. The project experiments found that the Geno Fuzzy Interface System (GENOFIS) model, a hybrid model of GA, NN and SVM, was the most efficient and accurate model for rainfall and related prediction patterns (Bizimana *et al.*, 2023). The project involves the autonomous agents from the Istanbul Technical University in Turkey, University of Strathclyde in Scotland, Rwanda Water Resources Board, Rwanda Meteorology Agency, and Sakarya University in Turkey.

Water quantity evaluation is an effective means of understanding the dynamics of a water system and considering external factors that may influence these systems (Mashaly & Fernald, 2020). Therefore, monitoring water quantity regulation and availability is important for creating a sustainable and reliable water supply. Monitoring assists in early warning systems, preparedness measures and response.

5.2.1.2.2 Monitoring

AI water quantity monitoring usually involves sensors or some sort of data collection mechanism aimed at feeding the model with real-time data (Chawla, Karthikeyan & Mishra, 2020). AI is pristine at monitoring water quantity and detecting the slightest changes in water tables.

For instance, Angola uses AI for 3D water saturation estimation models; facilitating inversion output and ANN algorithms (Hasen *et al.*, 2020). Using seismic datasets, the model conducts both reservoir characterisation and reservoir monitoring. The model uses ANN and Bayesian techniques (NB) to analyse seismic data and accurately estimate water saturation logs (Hasen *et al.*, 2020). The project was proposed in a conference paper at the Abu Dhabi International Petroleum Exhibition & Conference (Hasen *et al.*, 2020). It involves two companies, Schlumberger in USA and Sonagol in Angola. Both of which are involved in mining ventures for oil, petroleum and natural gas.

Botswana uses AI for a dam water level monitoring and prediction project (Ouma *et al.*, 2022). They found that based on climate factors and indices, MLPNN models provided the most accurate prediction results, and for improving those results, the use of VAR (Vector Auto-Regressive)-ANN

hybrid models was deemed most efficient (Ouma *et al.*, 2022). The autonomous agents involved are the University of Botswana, the Botswana International University of Science and Technology, and Michigan State University in the USA (Ouma *et al.*, 2022).

Morocco monitors water resources through AI-based systems that automate water meter data collection (Naim *et al.*, 2021). With the growing need for water resources, monitoring has become crucial for its sustainable and rational use (Naim *et al.*, 2021). The project offers consumption monitoring, water leak detection, water consumption visualisation, and portable water coverage (Naim *et al.*, 2021). It uses a Convolutional Neural Network (CNN) model with a 98.70% accuracy, that was tested and validated by the researcher's experiments. Those involved consist of entities from the Chouaib Doukkali University in Morocco (Naim *et al.*, 2021).

The African AI projects in monitoring water quantity primarily involves tracking and mapping water level fluctuations. This is useful for preparedness, early warning, intervention and crisis management behaviours. Prediction on the other hand is useful in prevention efforts and aims to avoid existing and developing novel risk. Monitoring data is used to train AI prediction models and forecasting models. This indicates the interdependent nature of these AI applicational sub-categories.

5.2.1.2.3 Prediction and forecasting

AI prediction models can be used to forecast possible outputs of a system (Markovics & Mayer, 2022). The functions of prediction and forecasting differ merely by type of data use. Prediction uses current data, and forecasting uses historical and current data. These outputs can be used for reverse engineering possible solutions to prospective hydrometeorological DR. AI aids in developing and implementing sustainable solutions to systemic risks in water quantity fluctuations (Galaz *et al.*, 2021).

For example, Egypt aims to move towards more sustainable water systems and uses AI to predict non-revenue water (NRW) resources (Elkharbotly, Seddik & Khalifa, 2022). The model aids in forecasting the NRW ratio before and after water network rehabilitation has taken place. Autonomous agents involved in the project includes the Ain Shams University in Egypt (Elkharbotly, Seddik & Khalifa, 2022). The AI models used for this project include ANN and MLP approaches, aiding in strengthening the accountability of water use in Egypt.

In Libya, AI is used to predict groundwater levels in Sarir Wellfield (Taher, 2020). ANN is used in this project and shows promise in predicting the confined aquifer water levels at Sarir Wellfield. The groundwater level prediction project involves the Libyan University of Benghazi (Taher,

2020). The project assists water resource managers and policymakers in developing groundwater resource distribution and regulation efforts.

Transboundary water management between Kenya and Egypt is done by predicting their water demand trends (Mumbi *et al.*, 2021). Using feed-forward NN (FFNN), the water demand along the Nile River in Kenya and Egypt can be forecasted. Aiding governing bodies in making timely provisions and constructing plans to meet the increasing demand for water (Mumbi *et al.*, 2021). The agent affiliations in the study consist of the College of Environmental Science and Engineering in Tongji University, China.

In Madagascar, AI is used to assess the future impact of climate change on the hydrology of the Mangoky River (Tanteliniaina, Rahaman & Zhai, 2021). The project aims being useful to CCA, managing water resources and water engineering in Madagascar. The future impact of climate change is established by making use of SWAT (soil and water assessment tool) and ANN algorithms (Tanteliniaina, Rahaman & Zhai, 2021). The project involves the Chongqing University in China, and the Jashore University of Science and Technology located in Bangladesh.

Mali uses AI for multiclass spatial predictions of borehole yields (Gomez-Escalonilla *et al.*, 2022). As much of the groundwater in Mali is used without regulation, it may cause problems such as unregistered use, widespread contamination, resource sustainability, and dropping water tables. Consequently, the project uses groundwater potential mapping to underpin groundwater resource exploration and planning.

The project found that ML algorithms; Extra Trees Classification (ETC), Logistic Regression (LR), and the Gradient Boosting Classifier (GBC) are the most suitable for groundwater potential mapping. Autonomous agent involvement includes Complutense University of Madrid in Spain, the Natural Superior School of Bamako in Mali, the University of Sciences, Techniques and Technology of Bamako also in Mali, and the University of Alcala in Spain (Gomez-Escalonilla *et al.*, 2022).

In Egypt, forecasting the water vapour pressure deficit of agricultural water management is done by using ML in semi-arid environments (Elbeltagi *et al.*, 2023). Researchers Elbeltagi and associates (2023) found that Random Forest (RF) algorithms outperform any other ML models used for forecasting in the study. The National Science and Technology Support Projects of China funded the research. Furthermore, the study includes autonomous agents Zhejiang University in China, Mansoura University in Egypt, Indian Institute of technology in India, University of the Chinese Academy of Sciences in China, Jiangsu University in China, Minia University in Egypt, and Shaqra University in Saudi Arabia (Elbeltagi *et al.*, 2023).

In Ghana, AI is used for rainfall forecasting and prediction efforts (Adjei *et al.*, 2021). Rainfall is considered a direct influence on landslides, flooding, drought, and avalanches. However, its prediction accuracy still needs to be improved in most techniques. Therefore, this project aimed to use DL, ANN, and LSTM models to produce an accurate rainfall predictor. The results show that the developed model outperformed existing models in various areas, but still requires improvement. The project involves the Nanjing University of Information Science and Technology in China (Adjei *et al.*, 2021).

Mozambique forecasts daily natural streamflow using AI at the Cahora Bassa Dam (Martinho *et al.*, 2020). Predicting streamflow seven days ahead is done using the hybrid approach of Extreme Learning Machine (ELM) and Genetic Algorithm (GA). The model uses past river flows, rainfall, humidity, and evaporation measures as input and has been shown to be a practical tool for predicting streams. Agents involved include Pungue-Tete University in Mozambique, and the Federal University of Juiz de Fora in Brazil. Essential support during this project came from the Cahora Bassa Hydroelectric Company in Mozambique, and financial support came from the Brazilian National Council for Scientific and Technological Development, and the Foundation for the Support of Research in the State of Minas Gerais in Brazil (Martinho *et al.*, 2020).

In Uganda, AI is used for logistic pipe failure prediction models in urban water distribution networks (Auma *et al.*, 2023). The study used two logistic regression models to predict waterpipe distribution failure. The Binomial Logistic Regression (BLR) model was shown to be the most accurate and has better performance in pipe failure management (Auma *et al.*, 2023). Autonomous agent involvement includes the Makerere University in Uganda, Moi University in Kenya, the Dar es Salaam in Tanzania, and Harvard University in the USA.

The project forms part of the Building Capacity in Water Engineering for Addressing Sustainable Development Goals in East Africa (CAWESDEA) project and is funded by the Canadian International Development Research Centre programme on Strengthening Engineering Ecosystems in sub-Saharan Africa (Auma *et al.*, 2023).

In Benin, monthly rainfall predictions are made using ANN models (Aizansi, Ogunjobi & Ogou, 2024). These models are developed by Multi-Layer Perceptron (MLP) approaches that predict rainfall two months in advance. They are used in six geographically diverse locations across Benin (Aizansi, Ogunjobi & Ogou, 2024). Autonomous agents involved in this project include the National Agency of Meteorology in Benin, WASCAL (West African Science Service Centre for Climate Change and Adapted Land Use) Competence Centre in Burkina Faso, and the d'Abomey-Calavi University of Benin (Aizansi, Ogunjobi & Ogou, 2024).

Ethiopia uses AI to develop models for predicting monthly rainfall without climatic data from meteorological stations (Abebe & Endalie, 2023). Due to limited rainfall data in Ethiopia, AI is utilized to produce rainfall predictions. Assessing both ANN and ANFIS models for long-term monthly prediction of precipitation, ANFIS outperformed ANN on all assessment levels (Abebe & Endalie, 2023). Autonomous agents in this project involve the Jimma Institute of Technology in Ethiopia.

In the Sahel Region in Senegal, ML regressors are utilised for daily rainfall predictions (Nyasulu *et al.*, 2023). The over-dependence on rain-fed agriculture in Sub-Saharan Africa has deemed unreliable with increasing climate change and unpredictable weather. The project explored various regression algorithms and found that GBC is the most efficient method for timely and long-term daily rainfall forecasting (Nyasulu *et al.*, 2023). Autonomous agents involved include the University of Gaston Berger in Senegal, and the French consulting company, Grenoble.

Prediction models are extensive in water management ventures and indicate the potential growth of an AI ecosystem in Africa. The regulation of water resources is vital to Africa's drive towards achieving water security and consequently water related SDGs (Mugagga & Nabaasa, 2016). Water management is at the heart of preventing devastating hydrometeorological hazards and reducing the effects of climate change (UNESCO, 2020).

Due to the vast number of projects mentioned in this section, Table 5.2.1 is compiled to help make the data more manageable. Below a summary of AI for water management project examples in Africa is presented in table format. After which a geographical map (Figure 5.2.1) illustrates the project examples across the region (MapChart, 2024).

Table 5.2.1: Summary of AI water management project examples in Africa.

African Country	Project Reference	AI Model	Assisting Technology	Project Purpose	Autonomous Agents	Agent Country
Algeria	(Eid <i>et al.</i> , 2023)	SVM	GIS	Evaluating groundwater quality in deep aquifer irrigation.	Beni-Suef University University of Sadat City Damanhour University Kafrelsheikh University University of Miskolc Wroclaw University King Khalid University	Egypt Egypt Egypt Egypt Hungary Poland Saudi Arabia
Algeria	(Elmeddahi <i>et al.</i> , 2023)	DTR MLPNN PCA SVM	Not specified	Predicting groundwater quality.	University of Benbouali Vegetal Chemistry -Water-Energy Laboratory Zagazig University University of Delhi Centre for Ecology and Hydrology	Algeria Algeria Egypt India UK
Angola	(Hasen <i>et al.</i> , 2020)	ANN NB	Not specified	Monitoring quantity of water saturation.	Sonagol Schlumberger	Angola USA
Benin	(Aizansi, Ogunjobi & Ogou, 2024)	ANN MLP	Not specified	Predicting monthly rainfall.	d'Abomey-Calavi University National Agency of Meteorology WASCAL Competence Centre	Benin Benin Burkina Faso
Botswana	(Ouma <i>et al.</i> , 2022)	MLPNN VAR-ANN	Not specified	Monitoring and predicting water level.	International University of Science and Technology University of Botswana Michigan State University	Botswana Botswana USA
Burkina Faso	(Ouedraogo <i>et al.</i> , 2023)	ANN DL FL	Not specified	Evaluating groundwater nitrate pollution.	International Atomic Energy Agency Earth and Life Institute	Austria Belgium

		PCA RF SVM			Fada N'Gourma University	Burkina Faso
Congo	(Amsini & Gozen, 2023)	ANFIS ANN MLR	Not specified	Evaluating water resources and water regulation.	Near East University Near East University	Cyprus Turkey
Cote d'Ivoire	(Soro <i>et al.</i> , 2020)	ANN	Not specified	Monitoring water eutrophication.	University of Félix Houphouët Boigny Research Centre for Oceanography University of Péléforo Gon Coulibaly	Cote d'Ivoire Cote d'Ivoire Cote d'Ivoire
Egypt	(Elbeltagi <i>et al.</i> , 2023)	RF	Not specified	Forecasting the water vapour pressure deficit.	Jiangsu University National Science and Technology Support Projects University of the Chinese Academy of Sciences Zhejiang University Mansoura University Minia University Indian Institute of Technology Shaqra University	China China China China Egypt Egypt India Saudi Arabia
Egypt	(Elkharbotly, Seddik & Khalifa, 2022)	ANN MLP	Not specified	Predicting and forecasting non-revenue water ratio.	Ain Shams University	Egypt
Egypt Kenya	(Mumbi <i>et al.</i> , 2021)	FFNN	Not specified	Predicting and forecasting trends in water demands.	Tongji University	China

Ethiopia	(Abebe & Endalie, 2023)	ANFIS	Not specified	Predicting monthly rainfall.	Jimma Institute of Technology	Ethiopia
Ethiopia	(Tamiru, Wagari & Tadesse, 2022)	AHP ANN	GIS	Evaluating potential groundwater quantities.	Wollega University	Ethiopia
Ghana	(Adjei <i>et al.</i> , 2021)	ANN DL LSTM	Not specified	Forecasting and predicting of rainfall.	Nanjing University of Information Science and Technology	China
Ghana	(Akpoti <i>et al.</i> , 2022)	BRT ME RF	Not specified	Evaluating land suitability for dry season irrigation.	International Water Management Institute University of Energy and Natural Resources University of Manchester	Ghana Ghana UK
Ghana	(Nti <i>et al.</i> , 2023)	ANN ANFIS MLR SVM	EKRT RSM RS	Monitoring river pollution.	University of Science and Technology Government of Ghana University for Development Studies World Bank	Ghana Ghana Ghana USA
Lesotho South Africa	(Mahasa, Xulu & Mbatha, 2023)	RF WA	Not specified	Evaluating drought prone evapotranspiration areas.	University of the Free State University of KwaZulu-Natal University of Zululand National Research Foundation	South Africa South Africa South Africa South Africa
Libya	(Taher, 2020)	ANN	Not specified	Predicting groundwater level.	Libyan University of Benghazi	Libya
Madagascar	(Tanteliniaina, Rahaman & Zhai, 2021)	ANN	SWAT	Predicting impact of climate change on water quantity.	Jashore University of Science and Technology Chongqing University	Bangladesh China
Mali	(Gomez-Escalonilla <i>et al.</i> , 2022)	ETC GBC LR	Not specified	Predicting groundwater quantity potential.	Natural Superior School of Bamako University of Sciences,	Mali Mali

					Techniques and Technology Complutense University of Madrid	Spain
					University of Alcala	Spain
Mauritius	(Jogee <i>et al.</i> , 2024)	ANN	RS	Monitoring water quality and sanitation systems.	University of Toulouse University of Mauritius	France Mauritius
Morocco	(Naim <i>et al.</i> , 2021)	CNN	Not specified	Monitoring quantity of water resources.	Chouaib Doukkali University	Morocco
Mozambique	(Martinho <i>et al.</i> , 2020)	ELM GA	Not specified	Forecasting and predicting natural streamflow.	Federal University of Juiz de Fora Foundation for the Support of Research National Council for Scientific & Technological Development Cahora Bassa Hydroelectric Company Pungue-Tete University	Brazil Brazil Brazil Mozambique Mozambique
Nigeria	(Ojoboh, Ochie & Nwosu, 2020)	ANN	Not specified	Predicting aquifer susceptibility to contaminants.	Delta State University Federal University of Technology ExxonMobil	Nigeria Nigeria USA
Nigeria	(Egbueri & Agbasi, 2022)	AQMHC K-means MLPNN MLR	Not specified	Predicting groundwater quality.	Chukwuemeka Odumegwu Ojukwu University	Nigeria
Rwanda	(Bizimana <i>et al.</i> , 2023)	GENOFIS	Not specified	Evaluating rainfall quantities and climate change patterns.	Water Resources Board Meteorology Agency University of Strathclyde Istanbul Technical University Sakarya University	Rwanda Rwanda Scotland Turkey Turkey

Senegal	(Nyasulu <i>et al.</i> , 2023)	GBC	Not specified	Predicting of daily rainfall.	Grenoble University of Gaston Berger	France Senegal
South Africa	(Setshedi, Mutingwende & Ngqwala, 2021)	ANN	Not specified	Predicting physiochemical characteristics of water quality.	Rhodes University Fort Hare University National Research Foundation	South Africa South Africa South Africa
South Africa	(Tadesse & Dinka, 2023)	KNN	Not specified	Evaluating class of dam water quality.	University of Johannesburg	South Africa
Sudan	(Mohammed <i>et al.</i> , 2023)	MLPNN SVM	Not specified	Evaluating groundwater quality index.	University of Miskolc	Hungary
Tunisia	(Yahyaoui <i>et al.</i> , 2023)	KNN	Not specified	Evaluating groundwater quality for irrigation.	University of Sfax	Tunisia
Uganda	(Auma <i>et al.</i> , 2023)	BLR	Not specified	Predicting logistic pipe failure in urban systems.	International Development Research Centre Moi University Dar es Salaam Makerere University Harvard University	Canada Kenya Tanzania Uganda USA
Zambia	(Mumbi & Phiri, 2023)	ANN	Cloud comp. IoT RS	Monitoring and sensing river pollution.	University of Zambia	Zambia

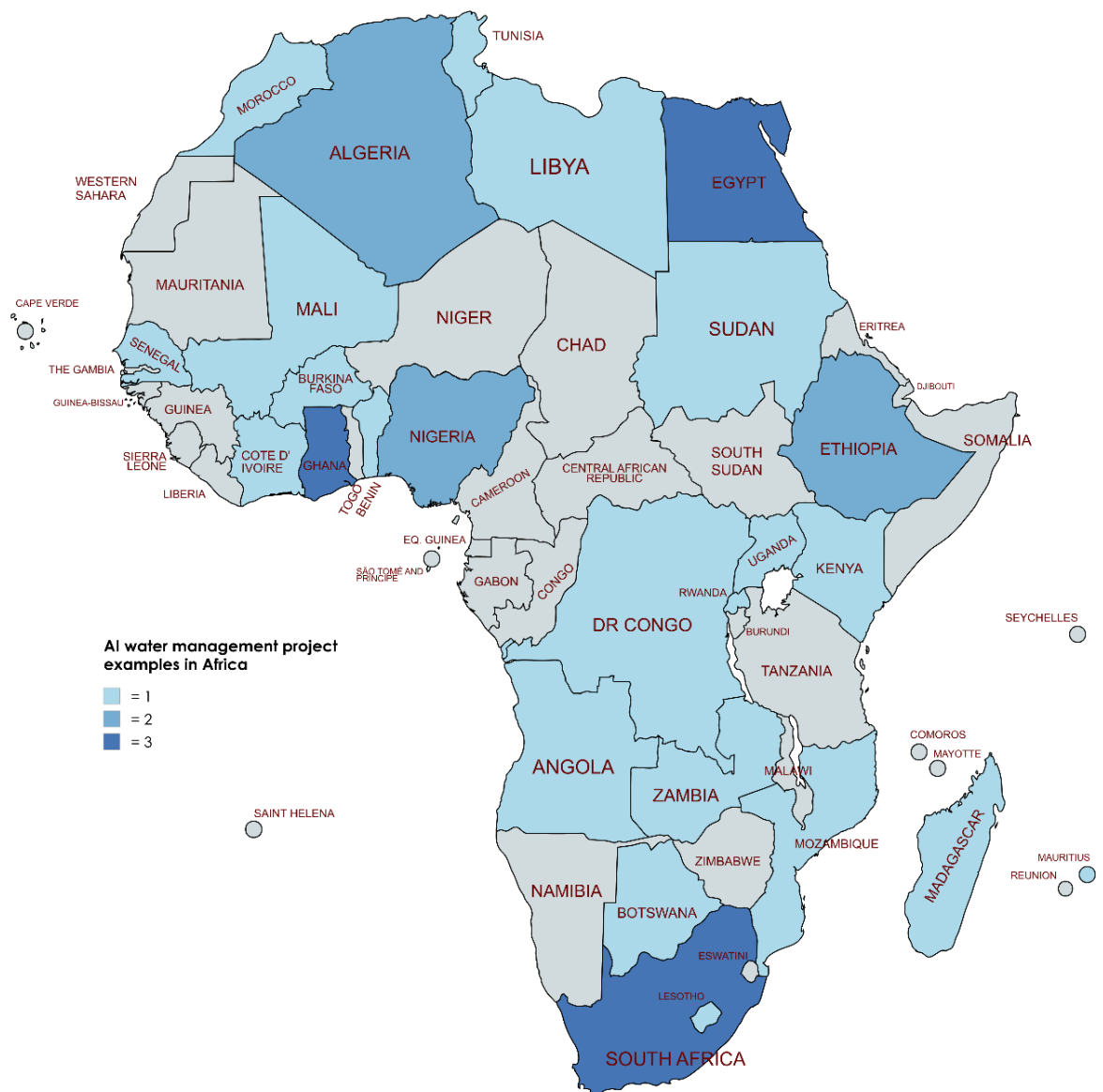


Figure 5.2.1: Map of AI for water management project examples in Africa.

Along with water management efforts, sustainable land use and land cover is also an efficient way of reducing climate related DR. (Xie, Zhang, Zheng & He, 2020). CCA uses environmental measures to build capacity against climate related hazards (Karki *et al.*, 2021). LULC AI projects are useful for reducing DR as it assists in planning iterative and systemic procedures for more sustainable development (Shrestha, Thapa & Manisha, 2021). It is crucial for Africa's development to consider LULC sustainability and resilience efforts.

5.2.2 Land use and land cover (LULC)

With the rapid increase in population and urban development, environments are suffering extreme degradation and causing the development of prospective risk (Annan *et al.*, 2024). Due to the dramatic changes in climate and global urbanisation, many studies have been conducted on Land Use and Land Cover (LULC) changes (Michel *et al.*, 2021). These changes are one of the primary factors involved in ecosystemic degradation and global climate change (Aka *et al.*, 2023). LULC information is essential to environmental research on agricultural sustainability, urban planning, environmental applications, and natural hazard assessment (Zaabar *et al.*, 2022).

In this section, LULC is discussed according to urbanisation and rural development, and ecosystemic conservation efforts. Urbanisation and rural development consist of urban and rural AI projects set on enforcing risk adaptation measures. LULC is extensively connected to urbanisation and agricultural development through environmental adaptation ventures. Additionally, ecosystemic conservation efforts are discussed involving mainly water body and forest conservation. Conservation of environments are essential to CCA and determines the level of ecosystemic resilience and sustainability.

Both, urbanisation and rural development, and environmental conservation projects are discussed under model functions such as evaluation, mapping, monitoring, and prediction. All of which are essentially interdependent functions and cannot truly be isolated from one another to fulfil the central task. As in the water management (section 5.1.1) discussion, the categories are for structuring purposes and by no means portray the complexities associated with AI model functioning. AI projects for urbanisation and rural development can be beneficial in implementing sufficient adaptation measures and policies.

5.2.2.1 Urbanisation and rural development

Urbanisation and rural development effects are highly divergent. Some assessments find that the demand for agricultural goods in growing urban areas increase agricultural development (Sakketa *et al.*, 2023). Whereas others find a loss of livelihoods relative to displacement and agricultural land conversion and may lead to low-density, discontinuous, inadequately planned, and automobile-dependant urban development (Sakketa *et al.*, 2023). Consequently, AI models are used to help evaluate, map, monitor, and predict urbanisation and agricultural development. Policy and planning are also greatly influenced by these outputs and help determine priorities.

In this research, various African countries are identified using AI for LULC changes in urban and rural environments. They primarily consist of urban and agriculturally related projects using data

to better understand and anticipate urban and rural development. AI projects identified in this section involves urbanisation and rural development evaluations in the African countries of Burkina Faso, Kenya, Cote d'Ivoire, Djibouti, and Malawi.

All these countries share a notable increase in urbanisation (Lee, 2022; Oiro *et al.*, 2020; Zahouli *et al.*, 2020; Chire, Tamru & Ismael, 2022; Nazombe & Nambazo, 2023) and can benefit from AI evaluation. Additionally, the livelihoods of many people in these countries depend on their agricultural employment (Sawadogo, 2022; Kogo, Kumar & Koech, 2020; ClaverKouakou & N'Zue, 2020; Chandrasekharam *et al.*, 2019; Bhatti *et al.*, 2021). Therefore, AI evaluating agricultural development in Burkina Faso, Kenya, Cote d'Ivoire, Djibouti, and Malawi might enable better understanding of land use and cover.

Countries concerned with mapping urban and/or rural development are identified as Ghana, Niger, and Mozambique. These countries have all experienced extensive urban expansion in recent years (Osumanu & Akomgbangre, 2020; Tiepolo & Galligari, 2021; Mottelson & Venerandi, 2023) and should find mapping urban areas useful for management and planning. Also, land use changes are becoming more rapid and prominent in these countries (Doe, Amoako & Adamtey, 2022; World Bank, 2023; Shannon *et al.*, 2020). Consequently, AI mapping vast amounts of area data can be useful in various DRR ventures.

AI projects monitoring urban and rural development are used in Angola, Cameroon, Egypt, and Somalia. These countries can benefit from AI monitoring efforts, as all of them are vulnerable to agricultural land degradation (Correia, Amraoui & Santos, 2024; Tawe, 2021; AbdelRahman, Afifi & Scopa, 2022; Mohamed & Nageye, 2020). Also, unregulated urbanisation in these countries create environmental damage to certain areas (Amado *et al.*, 2020; Enjema *et al.*, 2020; Saber *et al.*, 2020; Hassan *et al.*, 2024).

Lastly, countries using AI projects for predicting urban and rural LULC changes are Egypt, Morocco and Uganda. These countries all aim to become more sustainable in terms of urban and rural development (Saqr *et al.*, 2022; Beroho *et al.*, 2023; Bunyangha *et al.*, 2021). They can use prediction models to assist in planning efforts. Additionally, they all have experienced the problem of urban sprawl and could benefit from prediction models (Youssef, Mostafa & Amer, 2023; Boulmani & Saadane, 2023; Muchelo *et al.*, 2024).

Evaluation of LULC changes in African urban and rural development helps indicate various adaptation measures for decreasing or avoiding the impacts of climate change-related hydrometeorological hazards. Evaluation is crucial to understanding urban and rural development changes and making informed decisions towards sustainable growth.

5.2.2.1.1 Evaluation

Evaluating of LULC changes is essential for adapting to possible impacts of drought and flood vulnerability, environmental degradation, groundwater depletion, ecosystemic service loss, soil erosion, landslide hazards and many more (Talukdar *et al.*, 2020). Urbanization and agricultural development evaluation is important for planning policy procedures, and appropriate CCA requirements. Evaluation projects aim to understand the state of African urbanization and agricultural development.

For example, two major urban centres of Burkina Faso (Ouagadougou & Bobo-Dioulasso) makes use of AI to analyse and evaluate LULC dynamics between the years 2003 and 2021 (Ouedraogo *et al.*, 2023a). The project aims to evaluate the rapid urbanisation associated with Burkina Faso. The data can further be used for prediction models and evaluation efforts when extended to various AI algorithms. By making use of intensity analysis, LULC images are classified using RF, SVM and Gradient Tree Boost (GTB) algorithms. The project includes the autonomous agents of the Federal University of Technology in Nigeria, Competence Centre in Burkina Faso, and the Julius-Maximilians-University of Wurzburg in Germany (Ouedraogo *et al.*, 2023a).

In Kenya, AI is used for the evaluation of an iron mining site in Kishushe (Siljander *et al.*, 2020). The feasibility study between traditional and ML algorithms showed RF to be the most accurate model. The project involves the University of Helsinki in Finland, the Taita Taveta University in Kenya, the Taita Taveta Country Government in Kenya, and the Technical University of Bergakademie Freiberg in Germany. Funding is provided by the Ministry of Foreign Affairs in Finland under the Taitagis project coordinated by the Finnish National Agency for Education (Siljander *et al.*, 2020).

Cote d'Ivoire uses AI to understand and evaluate LULC changes and their effects on Land Surface Temperature (LST) in yam farming areas (Aka *et al.*, 2023). The project makes use of RF model GEE as its algorithm of choice and indicates that high-resolution images can be used for evaluating biophysical parameters in LST and vegetation. The project includes various autonomous agent involvement, namely the University of Lome in Togo, the Felix Houphouet-Boigny University in Cote d'Ivoire, the University of Energy and Natural Resources in Ghana, the company Environmental Solutions in Ghana, and Digital Earth Africa in Ghana (Aka *et al.*, 2023).

In Djibouti, AI is utilised to comprehensively analyse LULC dynamics (Pandit, Shimada & Dube, 2024). The project aims to quantify and evaluate the intricate interplay between land patterns and resource dynamics. It makes use of RF algorithms to classify land use and inform sustainable land management practices. It involves the Tokyo University of Agriculture in Japan and the

University of the Western Cape in South Africa. The project is funded by the Japan Science and Technology Agency and the Japan International Cooperation Agency under the Science and Technology Research Partnership for Sustainable Development (Pandit, Shimada & Dube, 2024).

Malawi uses AI to examine land-cover transitions based on drivers such as population density, slope, soil texture, elevation and demographical location (Mungai *et al.*, 2022). The project aims to understand short- to long-term shocks and landscape interactions. MLPNN was developed to examine and model anthropogenic and environmental drivers of land change (Mungai *et al.*, 2022). The agents involved in the project are the University of Alabama in the USA, Michigan State University in the USA, and the International Maize and Wheat Improvement Center in Mexico (Mungai *et al.*, 2022). Furthermore, the project was funded by USAID (Mungai *et al.*, 2022).

Evaluation efforts in LULC urban and rural development is essential to better understanding the patterns of population and production growth. It is also vital to creating prediction models and exploring the dynamics of LULC changes. Mapping is vital to evaluation efforts and provides historical and current illustrations of different LULC changes in urban and agricultural development efforts. In the following section, various African countries use mapping AI projects to observe urban and agricultural dynamics clearly.

5.2.2.1.2 Mapping

Urban sustainability concerns are centred around rapid urbanisation, environmental impacts, Urban Heat Island (UHI) development, and reduced urban security (Liu *et al.*, 2020). Accurate LULC data is vital to sustainable urban and agricultural planning, and further research efforts (Chowdhury, 2024). With an increase in the need for accurate LULC maps, various classification algorithms require comparison or amalgamation (Chowdhury, 2024).

For example, in the Sefwi Wiawso District of Ghana, AI is used to map and predict LULC dynamics due to its rapid urban expansion (Boateng & Aduah, 2022). The project uses data from 2010, 2015 and 2020 to predict LULC changes in 2025. And utilises MLC and CA-ANN algorithms to map and predict area changes. Autonomous agent involvement includes the University of Mines and Technology of Tarkwa in Ghana (Boateng & Aduah, 2022). Additionally, Ghana makes use of AI in the form of parametric and non-parametric classifiers, assessing LULC categories in the Juaboso and Bia West district's cocoa landscape (Donkor *et al.*, 2022).

The project aims to map the Ghanaian districts using various ML models (Donkor *et al.*, 2022). The highest overall accuracy model showed to be the SVM algorithm and was most efficient in

mapping and monitoring cocoa driven deforestation. The project involves agents from the Resource Management Support Centre of Forestry Commission in Ghana, the Kwame Nkrumah University of Science and Technology in Ghana, the Forestry Research Institute of Ghana, and the University of Energy and Natural Resources in Ghana (Donkor *et al.*, 2022).

In Niger, AI is used for land use mapping in a heterogeneous landscape known as Sahel (Schultz *et al.*, 2021). The project makes use of remote sensing imageries to produce accurate, high resolution land use maps. The AI models used for the project includes MLC, SVM and RF. Autonomous agents involved include the University of Bonn in Germany, Kent State University in the USA, and University Abdou Moumouni in Niger (Schultz *et al.*, 2021). Funding is provided by the German Federal Ministry of Education and Research, and the German Research Foundation (Schultz *et al.*, 2021).

Mozambique uses AI to map LULC classes between the years 2011 and 2020 (Macarrigue *et al.*, 2023). The project uses GEE platform's RF classifier to map the changes to the northern region. Autonomous agents include the State University of Campinas in Brazil, the Department of Research in Mozambique, the Brazilian Agricultural Research Corporation, and Kansas State University in the USA. The project was funded by the National Council for Scientific and Technological Development Grant (NCSTDG) from Brazil (Macarrigue *et al.*, 2023).

The mapping of urban and rural development becomes important for evaluation, monitoring and prediction efforts in LULC changes. Therefore, mapping has become a popular function associated with AI algorithms and assists in efficient and accurate map generation efforts. Monitoring urbanisation and rural development is fundamental to tracking changes in LULC, and for assessing progress and sustainable growth. Urban and rural monitoring in Africa increases the accountability and success rates of policy makers and stakeholders.

5.2.2.1.3 Monitoring

Monitoring is important in urban and rural development as it enables authorities and other stakeholders to leverage resources towards sustainable growth (Musakwa & Van Niekerk, 2014). Urban and rural LULC changes can be monitored using high-resolution satellite products and aid in up-to-date processing efforts (Lefulebe, Van der Walt & Xulu, 2022).

In Angola, for example, AI is utilised for monitoring urban expansion developments (Ngolo & Watanabe, 2022). By integrating GIS, remote sensing and ML techniques, Angola can map LULC changes and optimise satellite pixel classification. The project uses an unsupervised learning algorithm named Product Quantized K-means (PQk-means) for classification and an LR model to

monitor the urban expansion of Luanda (Ngolo & Watanabe, 2022). The agents involved in this project are from the Hokkaido University in Japan and is funded by the Government of Japan.

In Northern Cameroon, ML approaches are used for land cover monitoring (Yuh *et al.*, 2023). Due to coarse satellite imagery, ML models in Africa need help to function and influence the performance of these models. The project aims to monitor, map and quantify LULC changes in Cameroon (Yuh *et al.*, 2023). Using various ML models, RF was shown to be the most accurate model for monitoring land cover changes. The autonomous agents involved in the project are the University of Concordia in Canada and the Warsaw University of Life Sciences in Poland (Yuh *et al.*, 2023).

Egypt uses AI to model spatiotemporal LULC changes in the El-Fayoum Governorate area (Atef, Ahmed & Abdel-Maguid, 2023). The project uses GIS with AI algorithms such as MLC, RF, and SVM. Using high resolution Google satellite imagery, the models indicate various socioeconomic changes to the landscape over 20-years. Autonomous agents involved in the project include the Fayoum University and the Cairo University in Egypt, and funding from the Science, Technology & Innovation Funding Authority and the Egyptian Knowledge Bank (Atef, Ahmed & Abdel-Maguid, 2023).

In Banadir, Somalia, AI monitors urban expansion and LULC changes (Hamud, Shafir & Shaharum, 2021). Through using multi-temporal Landsat images from 1989, 2003 & 2018, the project monitors presented changes. The ML algorithms involved in the project include SVM and RF classifiers and the GEE cloud platform (Hamud, Shafir & Shaharum, 2021). The Monash University in Malaysia and the University Putra in Malaysia are autonomous agents involved in this project.

Urban and rural monitoring is used to determine the rate of urban expansion and spatiotemporal LULC changes occurring in an environment. Monitoring efforts help increase the implementation of effective CCA measures and track their progress. CCA measures also find urban and rural LULC prediction models useful. AI prediction models are essentially used to add time to adaptation measure development and implementation.

5.2.2.1.4 Prediction

Prediction of urban and rural development involves identifying spatiotemporal patterns in LULC changes and considering the driving forces of change (Mostafa *et al.*, 2021). With the rapid expansion of cities, urbanisation and agricultural growth is ensured. Prediction models enable

several applications such as microclimate modelling, urban planning, and policy development (Al-Dousari, Mishra & Singh, 2023).

For example, in the Gharbia Governorate area of Egypt, AI is used for monitoring and predicting urban expansion changes (Mostafa *et al.*, 2021). The project analyses the changes in LULC from 1991 to 2018 and predicts future changes between the years 2033 to 2048. It uses the LR-Markov chain model to monitor and predict LULC changes. Agents involved in this project include the Xi'an Jiaotong University in China and the Benha University in Egypt (Mostafa *et al.*, 2021). Funding is provided by the Ministry of Science and Technology of the People's Republic of China.

In Uganda, AI is utilised to predict LULC changes in semi-arid Lokere and Lokok catchments (Osaliya *et al.*, 2020). Change has been rapid in these areas due to change driven policies and efforts aiming at pastoral sedentarisation. The project uses the MLP-NN to develop empirical models based on historical change, and Markov chains for prediction efforts. Autonomous agent involvement includes the University of Nairobi in Kenya, the Makerere University in Uganda, and the Regional Universities Forum for Capacity Building in Agriculture in Uganda. The project received funding from a grant provided by the Carnegie Corporation of New York in the USA (Osaliya *et al.*, 2020).

The Mediterranean Watershed in Morocco is utilising AI to predict LULC scenarios (Beroho *et al.*, 2023). The scenarios were created using the CA-Markov model and showed efficient in forecasting efforts. The agents involved are Abdelmalek Essaadi University in Morocco, the National Institute for Agricultural Research of Rabat in Morocco, Institute for Systems and Robotics in Portugal, the Mohammed VI Polytechnic University in Morocco, the Centre for Management of Maritime Infrastructure in Italy, and the Hassan II University of Casablanca in Morocco (Beroho *et al.*, 2023).

Utilisation of prediction models for urban and rural LULC provides an opportunity for better planning and execution of adaptation measures. Prediction models in African urban and rural LULC changes primarily involve urban and spatiotemporal expansion ventures. Sustainable growth in LULC is determined by directed urban and agricultural growth and environmental conservation efforts. Expansion of various infrastructure associated with development requires space which is usually occupied by vital natural ecosystems. Keeping these environments in takt and functioning requires extensive environmental conservation measures.

5.2.2.2 Environmental conservation

Africa possesses an extensively diverse variety of natural resources and biomes; these can facilitate organic climate change adaptation measures (Rawlins *et al.*, 2023) and risk reduction efforts (Young *et al.*, 2019). Therefore, environmental conservation is imperative to sustaining complex eco-systems and the countless benefits provided by their wellbeing. AI is a useful tool for spatiotemporal analysis and provides a cost-efficient way of evaluating, mapping, monitoring and predicting the state of various areas. Efforts identified in African hydrometeorological environmental conservation largely include conserving different forests and water bodies.

LULC changes in various areas indicate a growing need for environmental conservation and the application of sustainable systems. The field of spatial ecology best describes the aim of AI models, which involves studying habitat loss and fragmentation due to human activity. This section discusses AI projects used for environmental conservation in LULC DRR efforts. This research identifies Egypt, Ethiopia, South Africa, Zambia, The Gambia, Mauritania, Togo, and Tunisia as countries involved in evaluating environments for conservation purposes.

These countries are relevant to the evaluation of LULC conservation efforts as all of them have expanding conservation areas (Shaltout & Bedair, 2022; Fashing *et al.*, 2022; Taylor, 2024; Lehner *et al.*, 2021; Dampha, 2021; UNEP, 2021; Wansi, 2023; Ayati, 2023). Additionally, all these countries have protected ecosystems in need of preservation (UNDP, 2021; Admasu, Scholte & Berhanu, 2023; Lewis & van Skalkwyk, 2019; UNEP, 2023; Gilruth *et al.*, 2021; Tregarot *et al.*, 2020; Akodewou *et al.*, 2020; Piras *et al.*, 2022).

African countries use AI to map LULC changes for environmental conservation efforts include Algeria, Benin, Botswana, Seychelles, Gabon, Guinea-Bissau, Madagascar, Senegal, the Gambia, Guinea, Sierra Leone, Liberia, Cote d'Ivoire, Ghana, Togo, and Nigeria. All these countries are actively digitizing environmental data to aid in more sustainable development (Loucif, 2023; WBG, 2019; Sebubi *et al.*, 2020; UNDP, 2021a; WBG, 2024; UNU, 2024; Devenish *et al.*, 2023; Cruz, Dutz & Rodriguez-Castelan, 2021; Dawda, 2022; Camara, 2021; Chukwu *et al.*, 2022; Jones, 2021; Kouton, Kakou & Okoua, 2024; Quarshie *et al.*, 2023; Abalo *et al.*, 2021; Ojakorotu, Olajide & Dunmade, 2020).

Additionally, these countries all experience vast LULC changes causing environmental damage (Bouzeria *et al.*, 2023; Tiando *et al.*, 2021; Mugari & Masundire, 2022; Etongo, Vel & Mendez, 2022; Biname *et al.*, 2024; Lopes *et al.*, 2023; Tiandraza *et al.*, 2023; Thiam *et al.*, 2021; Solly *et al.*, 2021; Traore, Mawenda & Komba, 2018; Barnieh *et al.*, 2023; De Sousa *et al.*, 2023; Abu *et al.*, 2021).

al., 2021; Taffour-Mills, Antwi-Agyei & Addo-Fordjour, 2020; Yono *et al.*, 2023; Obiahu & Elias, 2020).

African countries use AI for monitoring environmental conservation areas are identified in this section as Lesotho, Tanzania, Liberia and Nigeria. All these countries aim to increase their effectivity in sustainable spatial planning (Pasanisi *et al.*, 2021; Zhang *et al.*, 2020; Christensen, Hartman & Samii, 2021; Enoguanbhor *et al.*, 2021). Also, these countries experience environmentally degrading spatiotemporal LULC changes (Turpie *et al.*, 2021; Chilagane, Kashaigili & Mutayoba, 2020; Larmouth, 2024; Obiahu, Yan & Uchenna, 2021).

Various African countries use predictive models for environmental conservation, namely Cameroon, The Democratic Republic of Congo, Ethiopia, Libya, Morocco, Angola, Namibia, Rwanda, Senegal, Botswana, Sudan, Mauritius, & Zimbabwe. All these countries have various protected environments fuelled by eco-tourism (Harilal, Tichaawa & Saarinen, 2021; Musambaghani, 2023; Aseres & Sira, 2020; Saaed *et al.*, 2022; Lamnadi, 2020; Ezaquias, 2022; Mudzengi *et al.*, 2020; Sabuhoro *et al.*, 2017; Sene-Harper & Seye, 2020; Stone & Stone, 2020; Ismail, 2021; Mallinder, 2023; Warinda *et al.*, 2024). Therefore, economically these countries benefit from conservation efforts.

Additionally, they all experience exploitation of various natural resources (Gur *et al.*, 2020; Mukenza *et al.*, 2022; Wassie, 2020; Spittaels, 2022; Jamali, Namous & Amir, 2020; Awosanmi *et al.*, 2022; Kalvelage, Diez & Bollig, 2023; Bolson & Patzek, 2022; Faye *et al.*, 2021; Thakadu, Garekae & Lepetub, 2020; Wise, 2021; Seetah *et al.*, 2022; Macheka, Maharaj & Nzima, 2019). Through predictive conservation efforts, these countries can mitigate prospective DR (see Chapter 3.2). Prediction models can aid in understanding the urgency for DRR efforts in vulnerable and exposed environments. LULC evaluations are essential as changes to it impacts the land surface temperature (Das *et al.*, 2021).

5.2.2.2.1 Evaluation

Evaluating LULC dynamics indicates the complex interplay between the environment and human activities. Additionally, it shows far-reaching implications for biodiversity, climate change and sustainable growth (Abebe, Getachew & Ewunetu, 2022). Interdisciplinary approaches to LULC change evaluation aims to not only advance scientific understanding but also inform decision-making on evidence-based sustainable land conservation and management efforts (Issa *et al.*, 2020).

In Egypt, for example, AI is used for land cover classification along the Nile Valley and Delta regions (Gharbia, Khalifa & Hassanien, 2021). Using AI in remote sensing applications decreases the time required to classify Landsat imagery. Deep CNN is used to classify LULC via a multispectral Landsat dataset. The autonomous agents involved in this project are the Nuclear Materials Authority in Egypt, Cairo University in Egypt and the Scientific Research Group in Egypt (Gharbia, Khalifa & Hassanien, 2021).

In Ethiopia's Lake Haramaya Watershed, AI is utilised to perform in-depth quantitative evaluation and produce accurate land maps (Woldemariam *et al.*, 2021). The project uses various ML algorithms; however, it finds that SVM is the most accurate classifier. The autonomous agents involved in the project are the Entoto Observatory and Research Center in Ethiopia, the Addis Ababa University in Ethiopia, and the Haramaya University in Ethiopia (Woldemariam *et al.*, 2021).

In the Limpopo province of South Africa, AI is utilised to evaluate the LULC changes in the unprotected wetland ecosystems in arid-tropical areas (Thamaga, Dube & Shoko, 2021). Long-term Landsat archival data was used to evaluate the dynamics of LULC changes over 36 years (1983-2019). Analysis of multi-source satellite images was performed using SVM and advanced GIS tools. The project involves the two South African Universities of the Western Cape and Witwatersrand. Funding was provided by the South African National Space Agency (Thamaga, Dube & Shoko, 2021).

The Zambian Bangweulu wetland and surrounding areas use AI to model LULC changes (Chundu *et al.*, 2024). The project aims to evaluate the consistent growth of cropland and built-up areas from 1990-2020. AI models used for this evaluation includes SVM, Naïve Bayes (NB), Decision Tree Regression (DTR), and K-Nearest Neighbour (KNN). Agents involved include the University of Zambia Integrated Water Resources Management Centre, and funding from the O.R. Tambo Africa Research Chair Initiative from the AU (in Ethiopia), the EU (in Belgium) under the Wetlands Monitoring and Assessment project, and the joint efforts of the EU and AU, in the Global Monitoring for Environment and Security program (Chundu *et al.*, 2024).

The Gambia is utilising AI to evaluate and monitor the states and dynamics of mangrove forests in land cover transitions (Harou *et al.*, 2023). There are extensive environmental benefits to keeping mangroves healthy and flourishing, as they support multiple livelihoods in The Gambia. Landsat data is used for the training of the RF algorithms on the GEE platform. Autonomous agent involvement includes the Centre for International Forestry Research and World Agroforestry in Kenya, Kenyatta University in Kenya, and the Global Ever-Greening Alliance in Australia (Harou *et al.*, 2023).

In Southwest Mauritania, AI evaluates LULC changes (Diallo, Ewemoje & Abidine, 2022). Using GIS and remote sensing data from the years 1984, 2000, and 2022, an MLC model is applied to evaluate the changes between various years. This project involves funding from the African Union Commission grant through the Pan African University scholarship in Ethiopia. Furthermore, the University of Ibadan in Nigeria and the Diawling National Park in Mauritania are also involved (Diallo, Ewemoje & Abidine, 2022).

Togo makes use of AI for the characterization of land cover changes and forest-cover dynamics between 1985 and 2020 (Kombate *et al.*, 2022). Using a combination of earth observational data (EOD) and field inventories, the GEE platform is utilised with the RF algorithm. Evaluation of Togo contributes to forestry and territorial administration efforts. The project includes autonomous agents of the University de Sherbrooke in Canada and the University de Lome in Togo. The project funding comes from the Government of Canada, Department of Foreign Affairs, Trade and Development (Canadian Partnership Branch), and the Natural Sciences and Engineering Research Council of Canada (Kombate *et al.*, 2022).

In Tunisia, AI is used for analysing four decades of LULC changes in semiarid environments (Kadri *et al.*, 2023). The project investigates long-term drivers of change in the Rihana region making use of GEE and its RF algorithm. Autonomous agent involvement includes the National Research Institute for Rural Engineering, Water and Forestry in Tunisia, the National Agronomic Institute of Tunisia, the French Agricultural Research Centre for International Development, the Institute of Arid Regions in Tunisia, and the Lund University in Sweden. The project was funded by the Climate Change Adaptation Program for Vulnerable Territories of Tunisia (Kadri *et al.*, 2023).

Evaluation efforts in African LULC environmental conservation showed that they were mainly concerned with analysing, assessing, and characterising water bodies and forest-rich areas. Understanding various environmental changes involves seeing those changes occur over a period. Maps assist in this venture and are popular for identifying conservation needs and efforts. And is essential to identifying, monitoring, tracking and targeting environmental changes in conservation areas.

5.1.2.2.2 Mapping

Mapping efforts in African environmental conservation includes many AI projects. AI generation of spatiotemporal maps is shown to be very accurate and efficient in spotting detailed changes to landscapes (Li & Ning, 2023). These models are beneficial for environmental conservation efforts

and aid in finding significant environmental changes. Pinpointing where intervention is required and how it might take place.

For example, Algeria is making use of CNN with object-based image analysis (OBIA) for LULC mapping in coastal regions (Zaabar, Niculescu & Kamel, 2022). LULC mapping is fundamental to environmental monitoring and management. The Algerian project aims to map the coastal region of Ain Temouchent and monitor LULC changes. Autonomous agents involved in the project includes the University of Western Brittany in France and the MVRE (Mobilisation et Valorisation des Ressources en Eau) Laboratory in Algeria (Zaabar, Niculescu & Kamel, 2022).

The Oueme River Basin in Benin uses AI to map, assess, and quantify LULC changes (Annan *et al.*, 2024). It was found, using historical data, that the river basin experienced a steady decline in area from 1986 to 2023. The project makes use of the Google Earth Engine (GEE) to distinguish various environmental images using supervised classification models (Annan *et al.*, 2024). Keeping in mind that GEE is compiled of RF algorithms. Agent involvement includes the Collage of Engineering in Ghana, the Technical University of Munich in Germany, and WASCAL in Ghana and Benin (Annan *et al.*, 2024).

In Botswana's Ngamilandi District, AI maps the Boteti-Thamalakane River system (Gondo, Kolawole & Mfundisi, 2023). The project analyses the dynamics of LULC changes along the river and provides policy makers with information on water management issues. It makes use of ANN for land use evaluation and Maximum Likelihood Classification (MLC) is used for classification activities. The agent involvement only extends to the University of Botswana (Gondo, Kolawole & Mfundisi, 2023).

In the Seychelles, AI is utilised for mapping national seagrass area extent (Lee *et al.*, 2023). Seagrass is essential for environmental well-being and provides ecosystem services worth trillions. This project uses an RF model in mapping these extensive seagrass meadows. Agents involved include the Remote Sensing Technology Institute in Germany, German Aerospace, the University of Oxford in the UK, Ecospan Environmental Ltd. in the UK, the University of Seychelles, The Pew Charitable Trusts in the USA, Island Conservation Society in Seychelles, The Seychelles Conservation and Climate Adaptation Trust, and the University of Florida in the USA. The project funding is from The Pew Charitable Trusts (Lee *et al.*, 2023).

In Northwest Gabon, AI is used for mapping LULC specifically looking at forest cover and forest type (Wasniewski *et al.*, 2020). The project makes use of RF algorithms to classify spatial resolution imagery and map out the environment. Autonomous agents involved in this project includes the University of Warsaw in Poland, the Centre of Applied Geomatics in Poland, and the

University of Omar Bongo of Libreville in Gabon. The project received funding for publishing costs by the Polish Ministry of Science and Higher Education (Wasniewski *et al.*, 2020).

Another Gabon LULC AI project uses Landsat image data from 1988, 2000, 2013, and 2022 to map land use changes on the environment (Biname *et al.*, 2024). SVM is used for the project and found that urbanisation had rapidly increased, and vegetation had rapidly decreased. The autonomous agents involved are the Pan African University in Nigeria, the University of Ibadan in Nigeria, the Omar Bongo University in Gabon, the University of the Free State in South Africa, and the National Centre for Scientific and Technological Research in Gabon (Biname *et al.*, 2024).

The Cantanhez National Park in Guinea-Bissau is experiencing extreme levels of deforestation due to increased opment of cashew nut orchards (Pereira, Lopes & Pedroso, 2022). To counter the problem, mapping and monitoring efforts need to commence. Using SVM and RF algorithms, AI can map complex areas and create a base for monitoring deforestation. The project involves autonomous agents from the University of Porto in Portugal and the remote sensing consultant Lisboa from Portugal (Pereira, Lopes & Pedroso, 2022).

In Madagascar, AI is utilised in documenting the impact of climate change and human activities on the tropical rainforest in the Betampona Nature Reserve (Cota *et al.*, 2021). The project uses Fully Convolution Neural Networks (FCNN) and map the effects of conservation efforts in the Nature Reserve. Autonomous agents involved in the project include the Saint Louis University in the USA, the Madagascar Fauna and Flora Group in the UK, and funding from the Saint Louis University Geospatial Institute and NASA (Cota *et al.*, 2021).

Coastal mangrove forests are mapped using AI models along the West African Coast (Liu *et al.*, 2020). For the characterisation of mangroves, up-to-date extent mapping is essential. The project aims to evaluate the performance of ML models mapping 20m of mangrove forests across West Africa. The project uses RF, Gradient Boosting Classifier (GBC), NN and GEE. The study area includes Senegal, The Gambia, Guinea Bissau, Guinea, Sierra Leone, Liberia, Cote d'Ivoire, Ghana, Togo, Benin, and Nigeria (Liu *et al.*, 2020).

The project involves USA agents from Harvard University, the University of Maryland, the University of Delaware, East Carolina University, the California Institute of Technology, and the US Forest Service (Liu *et al.*, 2020). The funding is provided by the NASA Carbon Monitoring System Program Project Estimating Total Ecosystem Carbon in Blue Carbon and Tropical Peatland Ecosystems (Liu *et al.*, 2020).

The large variety of AI projects in Africa that map LULC changes for conservation purposes indicates an investment in environmental sustainability ventures. Maps form the base for any application, their use is greatly beneficial for forest and water body conservation and sustainability. Monitoring uses maps generated from various robotic systems such as satellites and drones. Using monitoring systems helps track LULC changes to vulnerable environments and inform more efficient decision-making.

5.1.2.2.3 Monitoring

Environmental conservation systems are assisting environmental conservation efforts in Africa. Environmental monitoring is crucial for assessing environmental trends and conditions, policy development and implementation, and information development for compiling reports to policymakers, the public and international platforms (UN, 2003). Various African countries utilise AI monitoring systems for LULC.

For example, Lesotho is building a land cover monitoring system that makes use of EOD and RF for determining national land cover statistics). The project aims to extract key information from environmental monitoring and land degradation identification for effective and sustainable spatial planning. The agents involved in the project includes the Government of Lesotho and the FAO from Italy. The project is funded by the EU for the establishment of the baseline for integrated catchment (De Simone, Ouellette & Gennari, 2022).

Tanzania's Ngorongoro world heritage site uses AI to monitor LULC pattern dynamics (Mwabumba *et al.*, 2022). Making use of remote sensing and GIS, AI model CA-Markov classifies are used to monitor ecosystem services and LULC pattern change. The project involves the Nelson Mandela African Institution of Science and Technology in Tanzania, the Indian Institute of Technology, the University of Environment and Sustainable Development in Ghana, and the Water Institute in Tanzania. Funding of this project comes from Arusha Tanzania (Mwabumba *et al.*, 2022).

In Liberia AI is used for LULC change detection and monitoring of two proposed protected areas (Jones, 2021). The areas consist of Zwedru & Gbi-Krahn Bassa, that cover roughly 1300 square kilometres of the Grand Gedeh Country. Both areas are in the Sapo-Tai West African forest complex which is becoming an increasingly fragmented ecoregion. Making use of satellite imagery data from 2016 and 2020, SVM based classification determines changes in Liberian LULC (Jones, 2021). The project involves the Johns Hopkins University in Baltimore, Maryland USA.

Zaria City in Nigeria uses AI to monitor and predict spatiotemporal LULC changes (Koko *et al.*, 2020). Making use of remote sensing data and GIS techniques to detect, monitor and map the LULC changes in Zaria City. The project then makes use of a CA-Markov model to validate, simulate and model those changes. The National Natural Science Foundation of China funded this project which further involves the Zhejiang University in China. The results found that barren land has decreased over the last three and a half decades; and that this will continue to happen as reforestation, urbanisation and vegetation efforts are underway (Koko *et al.*, 2020).

AI monitoring African LULC environmental conservation primarily involves ecosystemic and spatiotemporal changes. Monitoring environments are essential to the conservation of vulnerable and unique ecosystems in Africa. Through tracking changes, we can not only address emerging challenges but also identify patterns and trends. Pattern identification aids in developing and training prediction models. Prediction of environmental change in conservation areas gives rise to opportunities in preventing and avoiding the risk of hazards.

5.1.2.2.4 Prediction

Environmental conservation change predictions are crucial to help avoid the exploitation of natural resources, keep balance in environmental ecosystems, and prevent human-induced natural hazards (Earth Reminder, 2022). For example, in Cameroon, AI is used to predict LULC changes in the Santchou Wildlife Reserve (Fogang *et al.*, 2023). Due to its rapid degradation over the last three decades, satellite images are used for analysing and calculating the spatial distribution of biomes in the reserve. The Cellular Automata (CA)-Markov model is used to predict changes and identify potential patterns of evolution. The project involved the Cameroonian universities of Dschang and Yaounde (Fogang *et al.*, 2023).

In The Democratic Republic of the Congo, AI is used for examining LULC changes and its prediction (Michel *et al.*, 2021). With rapid demographic growth and urbanisation, the project aims at comprehensive analysis and prediction of the Luki Biosphere Reserve LULC changes. This was carried out using the Multi-Layer Perceptron Markov (MLP-Markov) model and revealed drastic changes to the region. The project includes the involvement of the Northeast Forestry University in China and the University of Kinshasa in the Democratic Republic of Congo. Additionally, the project receives funding from The Fundamental Research Funds for the Central Universities in China (Michel *et al.*, 2021).

The Upper Omo-Gibe River Basin in Ethiopia is making use of AI to predict and forecast future LULC changes (Lukas, Melesse & Kenea, 2023). The main objective of the study is to evaluate LULC changes from 1991-2022 and predict future changes from the year 2022 to 2067. Transition

potential modelling and prediction was computed using a CA-ANN model. The project involves the Abra Minch University in Ethiopia and the Florida International University in the USA. Funding was received from the Abra Minch University's water research centre (Lukas, Melesse & Kenea, 2023).

In Libya's Ajdabiya, AI forecasts LULC for modelling changes in land area (Aldileemi, Zhran & El-Mewafi, 2023). By using GIS and remote sensing data from 2016, 2020, and 2022, AI can help forecast 2030, 2040, and 2050 changes. The algorithmic model used for this project is CA-Markov and produces the most accurate results. The project involves the Mansoura University in Egypt (Aldileemi, Zhran & El-Mewafi, 2023).

In the transboundary Okavango basin, AI is predicting priority management of LULC changes (Kavhu, Mashimbye & Luvuno, 2023). The basin extends between Angola, Namibia, Botswana, and South Africa. AI models used for predicting changes to the basin include RF, Extreme Gradient Boosting (XGBoost), ANN, and DNN. The project involves autonomous agents from Stellenbosch University in South Africa and the Zimbabwe Parks and Wildlife Management Authority in Zimbabwe (Kavhu, Mashimbye & Luvuno, 2023). Funding is provided by USAID in the USA.

Rwanda uses AI for predicting LULC changes in the African Great Lakes Region (Kayitesi *et al.*, 2024). The project conducts analysis on historical data to determine prediction outputs. The classification, validation, change detection and prediction of data was achieved using RF and Multiple Decision Trees (MDT). The agents involved in the project are the University of Lausanne and the International Union for Conservation of Nature in Switzerland. The project is funded by the Swiss Government Excellence Scholarships for Foreign Scholars and the Schlumberger Foundation (Kayitesi *et al.*, 2024).

AI is used for two watersheds in the Senegal River Basin to predict LULC changes (Sambou *et al.*, 2023). The management of transboundary river basins are dependent on classification and prediction models. RF is used for data classification and the MLP-Markov chain model is used for prediction efforts. Autonomous agents are the University of Abomey-Calavi in Benin, the University of Montpellier in France, Potsdam institute for Climate Impact Research in Germany, European Space Agency in Italy, and the Cheikh Anta Diop University in Senegal. Funding is provided from the German Federal Ministry of Education and Research (Sambou *et al.*, 2023).

The Gedaref landscape in Eastern Sudan uses AI to monitor and predict LULC changes (Osman *et al.*, 2023). There exists limited to no knowledge of LULC size and structure, transition, degree of change, outlook, and intensity. Prediction efforts for the year 2028 and 2048 was achieved

using the CA-ANN model. The result from the study assists in managing natural resources and mitigating land fragmentation. The agents involved include the University of Gezira in Sudan, International Centre of Insect Physiology and Ecology in Kenya, and the University of Nairobi in Kenya (Osman *et al.*, 2023).

Mauritius uses AI for spatiotemporal analysis of the invasive plant species, *Vachellia nilotica* (Sunkur & Mauremootoo, 2024). The project makes use of ANN to predict the plant growth patterns and simulate the growth from the coast towards the central plateau. Data is collected using GIS and remote sensing and claim to be a cost-effective means of data gathering. The project involves autonomous agents such as the University of Technology in Mauritius and the consultant firm InSpiral Pathways in the UK (Sunkur & Mauremootoo, 2024).

Zimbabwe uses AI to model historic and future LULC changes and their impact on the Shashe sub-catchment wetland area (Sibanda & Ahmed, 2021). The project aim is to use current and historic data to predict LULC. AI algorithms used are the CA-Markov and RF classification models. The autonomous agents involved are Lupane State University in Zimbabwe and the University of Witwatersrand in South Africa (Sibanda & Ahmed, 2021). No funding was specified in the research paper.

In this research, AI projects aimed at predicting LULC changes in African environmental conservation involves nature reserves, landscapes, water basins, rivers, wetlands and lakes. Predicting changes in environmental conservation is essential to developing and deploying strategies for adaptation (CITE). All the various functions (evaluation, mapping, monitoring, and prediction) mentioned in LULC changes are important for adaptation to climate change.

To simplify and summarise the data gathered in this section, all LULC project examples are formulated into Table 5.2.2. Additionally, a geographical map (Figure 5.2.2) illustrates the various African countries involved in the project examples and their weights.

Table 5.2.2: Summary of AI LULC project examples in Africa.

African Country	Project Reference	AI Model	Assisting Technology	Project Purpose	Autonomous Agents	Agent Country
Algeria	(Zaabar, Niculescu & Kamel, 2022)	CNN	OBIA	Mapping LULC changes in coastal regions.	MVRE Laboratory University of Western Brittany	Algeria France
Angola Botswana Namibia South Africa	(Kavhu, Mashimbye & Luvuno, 2023)	DNN NN RF XGBoost	Not specified	Predicting river priority management of LULC changes.	Stellenbosch University Parks & Wildlife Management Authority USAID	South Africa Zimbabwe USA
Angola	(Ngolo & Watanabe, 2022)	LR PQk-means	GIS Remote-sensing	Monitoring urban expansion.	Government of Japan Hokkaido University	Japan Japan
Benin	(Annan et al., 2024)	RF	GEE	Mapping LULC changes in river basin conservation.	WASCAL Technical University of Munich Collage of Engineering WASCAL	Benin Germany Ghana Ghana
Botswana	(Gondo, Kolawole & Mfundisi, 2023)	ANN MLC	Not specified	Mapping LULC changes along the river.	University of Botswana	Botswana
Bukina Faso	(Ouedraogo et al., 2023a)	GTB RF SVM	Not specified	Evaluating rapid urbanisation.	Competence Centre Julius-Maximilians-University of Wurzburg Federal University of Technology	Burkina Faso Germany Nigeria
Cameroon	(Fogang et al., 2023)	CA-Markov	Sensor-images	Predicting LULC changes in wildlife reserve.	University of Dschang University of Yaounde	Cameroon Cameroon
Cameroon	(Yuh et al., 2023)	RF	Satellite-imagery	Monitoring land cover changes.	University of Concordia Warsaw University of Life Sciences	Canada Poland
Congo	(Michel et al., 2021)	MLP-	Not specified	Pedicting LULC changes in	Fundamental Research Funds	China

		Markov		nature reserve.	for the Central Universities Northeast Forestry University University of Kinshasa	China Congo
Cote d'Ivoire	(Aka et al., 2023)	RF	GEE	Evaluating LULC effects on vegetation.	Felix Houphouet-Boigny University Digital Earth Africa Environmental Solutions University of Energy and Natural Resources University of Lome	Cote d'Ivoire Ghana Ghana Ghana Togo
Djibouti	(Pandit, Shimada & Dube, 2024)	RF	Not specified	Evaluating changes in land patterns and resource dynamics.	International Cooperation Agency Science and Technology Agency Tokyo University of Agriculture University of the Western Cape	Japan Japan Japan South Africa
Egypt	(Atef, Ahmed & Abdel-Maguid, 2023)	MLC RF SVM	GIS Satelite- imagery	Monitoring socio-economic changes to landscape.	Cairo University Egyptian Knowledge Bank Fayoum University Science, Technology & Innovation Funding Authority	Egypt Egypt Egypt Egypt
Egypt	(Gharbia, Khalifa & Hassanien, 2021)	CNN	Landsat RS	Evaluating land cover classification.	Cairo University Nuclear Materials Authority Scientific Research Group	Egypt Egypt Egypt
Egypt	(Mostafa et al., 2021)	LR-Makov	Not specified	Monitoring and predicting urban changes in exapansion.	Ministry of Science and Technology Xi'an Jiaotong University Benha University	China China Egypt
Ethiopia	(Lukas, Melesse &	CA-ANN	Not specified	Predicting and forecasting	Abra Minch University	Ethiopia

	Kenea, 2023)			LULC changes to river.	Florida International University	USA
Ethiopia	(Woldemariam et al., 2021)	SVM	Not specified	Evaluating to produce in-depth land maps.	Addis Ababa University Entoto Observatory and Research Center Haramaya University	Ethiopia Ethiopia Ethiopia
Gabon	(Biname et al., 2024)	SVM	Landsat	Mapping LULC changes on the environment.	National Centre for Scientific and Technological Research Omar Bongo University Pan African University University of Ibadan University of the Free State	Gabon Gabon Nigeria Nigeria South Africa
Gabon	(Wasniewski et al., 2020)	RF	Spatial-resolution	Mapping forest cover and forest type.	University of Omar Bongo Centre of Applied Geomatics Ministry of Science and Higher Education University of Warsaw	Gabon Poland Poland Poland
Gambia, the	(Harou et al., 2023)	RF	GEE Landsat	Evaluating and monitoring the dynamics of mangroves.	Global EverGreening Alliance Centre for International Forestry Research and World Agroforestry Kenyatta University	Australia Kenya Kenya
Ghana	(Boateng & Aduah, 2022)	CA-ANN MLC	Not specified	Mapping and predicting rapid urban expansion.	University of Mines and Technology	Ghana
Ghana	(Donkor et al., 2022)	SVM		Mapping and monitoring deforestation in agriculture.	Forestry Research Institute Kwame Nkrumah University of Science and Technology Resource Management Support Centre of Forestry Commission University of Energy and Natural Resources	Ghana Ghana Ghana Ghana

Guinea-Bissau	(Pereira, Lopes & Pedroso, 2022)	RF SVM	RS	Mapping and monitoring deforestation.	Lisboa University of Porto	Portugal Portugal
Kenya	(Siljander et al., 2020)	RF	Not specified	Evaluating an iron mining site.	Ministry of Foreign Affairs National Agency for Education University of Helsinki Technical University of Bergakademie Freiberg Taita Taveta Country Government Taita Taveta University	Finland Finland Finland Germany Kenya Kenya
Lesotho	(De Simone, Ouellette & Gennari, 2022)	RF	EOD	Monitoring land cover and land degradation.	European Union FAO Government of Lesotho	Belgium Italy Lesotho
Liberia	(Jones, 2021)	SVM	Satellite-imagery	Monitoring and detecting LULC change.	Johns Hopkins University	USA
Libya	(Aldileemi, Zhran & El-Mewafi, 2023)	CA-Markov	GIS RS	Predicting land area changes.	Mansoura University	Egypt
Madagascar	(Cota et al., 2021)	FCNN	Not specified	Mapping the effects of conservation efforts in a nature reserve.	Madagascar Fauna and Flora NASA Saint Louis University	UK USA USA
Malawi	(Mungai et al., 2022)	MLPNN	Not specified	Evaluating population density and environmental state.	International Maize and Wheat Improvement Michigan State University University of Alabama USAID	Mexico USA USA USA
Mauritius	(Sunkur & Mauremootoo, 2024)	ANN	GIS RS	Predicting and simulating land cover changes.	University of Technology InSpiral Pathways	Mauritius UK
Mauritania	(Diallo, Ewemoje & Abidine, 2022)	MLC	GIS RS	Evaluating LULC changes.	African Union Commission grant	Ethiopia

					Diawling National Park University of Ibadan	Mauritania Nigeria
Morocco	(Beroho et al., 2023)	CA-Markov	Not specified	Predicting and forecasting LULC scenarios.	Centre for Management of Maritime Infrastructure Abdelmalek Essaadi University Hassan II University of Casablanca Mohammed VI Polytechnic University National Institute for Agricultural Research of Rabat Institute for Systems and Robotics	Italy Morocco Morocco Morocco Morocco Portugal
Mozambique	(Macarringue et al., 2023)	RF	GEE	Mapping land use changes.	Agricultural Research Corporation NCSTDG State University of Campinas Department of Research Kansas State University	Brazil Brazil Brazil Mozambique USA
Niger	(Schultz et al., 2021)	MLC RF SVM	RS	High resolution mapping of land use.	Federal Ministry of Education and Research Research Foundation University of Bonn University Abdou Moumouni	Germany Germany Germany Niger
Nigeria	(Koko et al., 2020)	CA-Markov	GIS RS	Monitor and predict spatiotemporal changes to LULC.	National Natural Science Foundation Zhejiang University	China China
Rwanda	(Kayitesi et al., 2024)	MDT RF	Not specified	Predicting LULC changes in the Great Lakes Region.	International Union for Conservation of Nature University of Lausanne Schlumberger Foundation	Switzerland Switzerland Switzerland

					Swiss Government	Switzerland
Senegal	(Sambou et al., 2023)	MLP-Markov RF	Not specified	Predicting LULC changes in a river basin.	University of Abomey-Calavi University of Montpellier European Space Agency Federal Ministry of Education and Research Potsdam institute for Climate Impact Research	Benin France Italy Germany Germany
Seychelles	(Lee et al., 2023)	RF	Not specified	Mapping national seagrass area extent.	Aerospace Remote Sensing Technology Institute Conservation and Climate Adaptation Trust Island Conservation Society University of Seychelles Ecospan Environmental Ltd University of Oxford Pew Charitable Trusts University of Florida	Germany Germany Seychelles Seychelles Seychelles UK UK USA USA
Somalia	(Hamud, Shafir & Shahrur, 2021)	RF SVM	GEE Landsat	Monitoring urban expansion and use changes.	Monash University University Putra	Malaysia Malaysia
South Africa	(Thamaga, Dube & Shoko, 2021)	SVM	GIS	Evaluating changes in unprotected wetland ecosystems.	National Space Agency Universities of the Western Cape University of Witwatersrand	South Africa South Africa South Africa
Sudan	(Osman et al., 2023)	CA-ANN	Not specified	Predicting and monitoring LULC changes.	International Centre of Insect Physiology and Ecology University of Nairobi University of Gezira	Kenya Kenya Sudan
Tanzania	(Mwabumba et al., 2022)	CA-Markov	GIS RS	Monitor ecosystem services and changes in LULC.	Indian Institute of Technology Arusha	India Tanzania

					Nelson Mandela African Institution of Science and Technology Water Institute University of Environment and Sustainable Development	Tanzania Tanzania Ghana
Togo	(Kombate et al., 2022)	RF	GEE EOD	Evaluating land cover changes and forest-cover dynamics.	Department of Foreign Affairs, Trade and Development Government of Canada Natural Sciences and Engineering Research Council University de Sherbrooke University de Lome	Canada Canada Canada Canada Togo
Tunisia	(Kadri et al., 2023)	RF	GEE	Evaluating LULC changes.	Agricultural Research Centre for International Development Climate Change Adaptation Program for Vulnerable Territories Institute of Arid Regions National Agronomic Institute National Research Institute for Rural Engineering, Water and Forestry	France Tunisia Tunisia Tunisia Tunisia
Uganda	(Osaliya et al., 2020)	MLPNN Markov	Not specified	Predicting LULC changes in semi-arid catchments.	University of Nairobi Makerere University Regional Universities Forum for Capacity Building in Agriculture Carnegie Corporation of New York	Kenya Uganda Uganda USA

West Coast Benin Cote d'Ivoire Gambia, the Ghana Guinea Guinea- Bissau Liberia Nigeria Senegal Sierra Leone	(Liu et al., 2020)	GBC ANN RF	GEE	Mapping coastal mangrove forests.	California Institute of Technology East Carolina University Harvard University University of Delaware University of Maryland US Forest Service NASA	USA USA USA USA USA USA USA
Zambia	(Chundu et al., 2024)	DTR KNN NB SVM	Not specified	Evaluating the growth of cropland and built-up areas.	African Union European Union University of Zambia	Ethiopia Belgium Zambia
Zimbabwe	(Sibanda & Ahmed, 2021)	CA- Markov RF	Not specified	Predicting LULC changes & their impacts on wetlands.	University of Witwatersrand Lupane State University	South Africa Zimbabwe

5.3 Hydrometeorological Hazard Reduction

AI has the potential to boost DRR and resilience to natural hazards (ITU, 2024). Although AI experiences challenges in DRR efforts, its development seems promising for various natural hazards (Kuglitsch *et al.*, 2023). For effective DRR, AI must not only be applied to prospective hydrometeorological risk but also to current and inevitable hydrometeorological hazards. This section explores AI projects used for combatting hydrometeorological hazards in Africa and focus on flooding, drought, landslides, wildfires, and tropical cyclones.

Each hazard section aims to include at least one model from each African country published between the year 2020 to 2024. These hazards are discussed according to their most prominent model functions. For instance, detecting, evaluating, assessing, monitoring, mapping, predicting and forecasting. It is important to note that these functions are inter-connected and often happen simultaneously. Due to the complexity of each hazard, AI models face various developmental challenges in each project. However, the focus in this section is on AI models and their implementation on various hydrometeorological related hazards.

Flooding is the most common and widespread hazard in the world (Dyvik, 2024). It is also the deadliest, claiming more than five thousand lives annually (WMO, 2020). Therefore, it seems fitting to start this section with examples from AI projects reducing flood risk in Africa.

5.3.1 Flooding

Considered one of the most dangerous phenomena, floods spread and recur in various countries all over the world (Mokhtari *et al.*, 2023). Tamiru and Dinka (2021) notes that the number of household displacement due to floods in Africa are increasing drastically. Although flooding is seen as a common environmental threat, its occurrence and intensity has dramatically increased due to climate change (Nti *et al.*, 2021). However, all is preserved, flooding can be managed and if properly controlled, facilitate fertility and nutrients of soil (Tan *et al.*, 2020).

In this section, African flood reduction is discussed in terms of various AI model functions. These include susceptibility mapping, monitoring and assessment, and prediction. Susceptibility mapping projects are discussed first in this section. Countries that use AI for susceptibility mapping includes Algeria, Burkina Faso, Egypt, Ghana, Morocco, Mozambique, and Tunisia. All these countries require susceptibility maps because they have a high vulnerability to floods (Ziadi & Keraghel, 2024; Sougue *et al.*, 2024; Abdrabo *et al.*, 2023; Forson *et al.*, 2022; Echogdali *et al.*, 2022; Lundgren & Strandh, 2022; Dahri & Abida, 2020).

Also, floods in these countries significantly affect arid and semi-arid regions and require further assessment of vulnerable areas (Zekouda *et al.*, 2020; Coly *et al.*, 2024; Hassan, Yassine & Amin, 2022; Boafo *et al.*, 2020; Djamel, Houari & Fares, 2020; Lundgren, 2020; Aouissi, Nsiri & Ahmed, 2024). AI susceptibility maps have the potential to assist in these assessments (Das, 2020). Second, African countries using AI for assessing and monitoring floods are discussed. These AI projects include the examples of Ethiopia, Libya, Malawi, Mozambique, Niger, Tanzania, Tunisia, and Zambia.

These countries find AI flood monitoring and assessment valuable as they all are subjected to projected climate change induced flooding events (Bulti, Abebe & Biru, 2021; Noureddine, Eslamian & Katlane, 2021; Otto *et al.*, 2022; Adedeji *et al.*, 2021; Mzava, Valimba & Nobert, 2021; Gaaloul, 2024; Milupi, Wallace & Janes, 2022). Also, their informal settlements are prone to developing next to water sources which increases the risk of flooding (Bernhofen, Blenkin & Trigg, 2023; Bikis & Pandey, 2023; Kumwenda, 2024; Zehra *et al.*, 2019; Mahamane, Oumarou & Mantinan, 2023; John, 2020; Khemiri *et al.*, 2024; Mwamba, 2020).

African countries participating in AI flood prediction projects include African countries such as Algeria, Cameroon, Guinea, Ghana, Kenya, Mauritius, Nigeria, Rwanda, Sudan, Tanzania, and Zimbabwe. Prediction projects are relevant to these countries as all of them have experienced severe and unexpected flooding in the last two years (Metz, 2024; Feukeng, 2024; IFRC, 2023; Naadi, 2023; Avery, 2024; Mohabuth & Slow, 2024; Khalid & Maishman, 2022; Samba & Macaulay, 2023; Mandil, 2024; Lasteck & Chibelushi, 2023; Muronzi, 2024). Calling for an urgency in mitigation and prevention measures.

Additionally, in all these countries, floods are amongst their costliest hazards to recover from (WBG, 2023; Nsangou *et al.*, 2022; IFRC, 2023; Asamoah, 2023; Njeru, 2024; Sadien, Doorga & Rughooputh, 2024; Jonathan *et al.*, 2020; Mbiyozo, 2022; Elagib *et al.*, 2021; WB, 2021; Matsa & Mupepi, 2022). Therefore, AI flood prediction is a potential investment for these countries. Flood susceptibility mapping can be considered a type of prediction measure; and is designed to characterise and identify flood-prone areas (Vojtek & Vojtekova, 2019).

5.3.1.1 Susceptibility mapping

Flood susceptibility mapping provides a quantitative assessment of an environment's vulnerability to flood hazard (Askar *et al.*, 2022). It provides maps of areas where vulnerable environments are identified for their flood hazard level of probability. These maps can be used for hazard reduction efforts through implementing environmental sustainability measures for more flood resilient areas.

For example, flash flood susceptibility mapping is done in Northeastern Algeria using various AI models (Mansour, Mrad & Djebbar, 2024). The study identified twelve influential analysis factors namely LULC, slope, distance to river, accumulation of flow, rainfall, plan curvature, stream power, soil type, terrain roughness, drainage density, elevation, and topographic wetness. From the multiple models used for prediction, the model deemed the most accurate was LR which enabled flash flood susceptibility mapping accuracy of 88% using the Area Under Curve (AUC) technique. The project includes agents from the University Mohamed Cherif in Algeria (Mansour, Mrad & Djebbar, 2024).

Burkina Faso uses AI to assess flood susceptibility (Bonkougou, 2021). The project makes use of Frequency Ratio (FR) and LR models to produce flood susceptibility maps and predict problematic flooding areas. The study aims to identify areas vulnerable to flooding using the two AI models combined with remote sensing data and GIS techniques (Bonkougou, 2021). Autonomous agent involvement includes WASCAL in Ghana, the Pan African University in Algeria, the AU in Ethiopia, and the Association of African Universities (AAU) in Ghana.

In Egypt, AI is popular for susceptibility mapping and prediction of floods. For instance, AI is used for flood susceptibility mapping in Ras Gharib and the Red Sea (Youssef *et al.*, 2022). The comparative study found that CNN is 17% more accurate than SVM models. The project involves autonomous agents such as the Geological Hazards Centre in Saudi Arabia, the University Kebangsaan in Malaysia, the University of Technology Sydney in Australia, and the South Vally University in Egypt (Youssef *et al.*, 2022).

Another Egyptian project uses AI to determine flash flood hazard susceptibility prediction in South Ras El-Zait on the Gulf of Suez Coast (Abu El-Magd, 2022). The project uses RF and Naïve Bayes (NB) approaches to generate flash flood models. These models showed to be accurate according to the AUC rating (Abu El-Magd, 2022). Autonomous agents involved are from the Suez University in Egypt that use R and QGIS (open platforms) to code the data retrieved from the study (Abu El-Magd, 2022).

Furthermore, Ghana utilises AI for mapping flood prone and hazardous areas in rural landscapes (Ghansah *et al.*, 2021). The project uses Landsat image data and RF classification models to map flood and hazard susceptibility in the Nasi watershed. The results from the project can be used for national flood disaster management, flood mitigation, local administration and land use planning (Ghansah *et al.*, 2021). The autonomous agent involvement includes the University of Miami in USA, Koforidua Technical University in Ghana, and the King Abdulaziz University in Saudi Arabia (Ghansah *et al.*, 2021).

Morocco uses AI to map vulnerability and variability of urban flooding in Tangier City (Bouramtane *et al.*, 2021). The ML algorithms of RT and SVM models are used in predicting urban flood vulnerability. Mapping of flood vulnerability has become crucial to flood risk assessment and urban management and planning (Bouramtane *et al.*, 2021). The project involves the Mohammed V University in Rabat Morocco, the University Sidi Mohammed Ben Abdellah in Morocco, the Seattle University in the USA, Avignon University in France, University Abdelmalek Essaadi in Morocco, the University of Ouagadougou in Burkina Faso, and the University of Toulouse in France.

In the Beira Area, Mozambique, AI is used for flood susceptibility mapping (Ramayanti *et al.*, 2022). The serious impact of floods on the Beira Area calls for urgent provision of appropriate flood susceptibility mapping AI models. The models used in the project include the Group Method of Data Handling (GMDH) and CNN (Ramayanti *et al.*, 2022). The project can be used to mitigate flood disaster risk and reduce it in the future. Autonomous agents involved are Kangwon National University in the Republic of Korea and the Korea Institute of Geoscience and Mineral Resources. Furthermore, the project is funded by the Ministry of Oceans and Fisheries in Korea.

Northeast Tunisia use AI for flood mapping and assessment efforts (Souissi *et al.*, 2022). With the region's susceptibility to floods, AI creates susceptibility maps based on various flood related factors. These include slope, distance from stream, rainfall, drainage density, LULC, and soil type (Souissi *et al.*, 2022). The project uses a Fuzzy Analytical Hierarchy Process (Fuzzy-AHP) model. Autonomous agents involved are the University of Tunis El Manar in Tunisia, the University of Carthage in Tunisia, the Tunisian Ministry of Agriculture, Water Resources and Fisheries, the Polytechnic Institute UniLaSalle Beauvais in France, and the Municipality of Takelsa in Tunisia (Souissi *et al.*, 2022).

Additionally, the Gabes catchment in Tunisia use AI to map flash flood susceptibility (Dahri *et al.*, 2022). The catchment is regularly devastated by floods owing to rapid population growth, indiscriminate land use, unregulated municipal systems, and urban sprawl. The project uses Artificial Network Process (ANP), and ANN models integrated with GIS techniques. Autonomous agent involvement includes the University of Sfax in Tunisia, the University of Kasdi Merbah-Ouargla in Algeria, the Thu Dau Mot University in Vietnam, and the National Polytechnic School in Algeria (Dahri *et al.*, 2022).

Susceptibility mapping is extensively important for reducing flood hazard. It indicates vulnerable areas and facilitates priority focused intervention efforts. AI enables accurate and timely susceptibility maps facilitating a more extensive understanding of vulnerable flood areas.

Monitoring and assessment are essential to flood hazard reduction and play a key role in tracking and understanding various floods.

5.3.1.2 Assessing and monitoring

Assessing and monitoring flooding in different African countries are extensively important for AI model functioning. Efficient model application facilitates efficient DRR, and a better understanding of the complexity associated with AI for reducing hydrometeorological hazards in Africa. AI Assessment and monitoring efforts are popular in various African countries.

For example, Ethiopia uses AI models in the geospatial analysis of flood vulnerability assessment (Tamiru & Dinka, 2021a). The flooding is due to sudden flashes of rainfall, causing the riverbanks to overflow. The project uses GIS and ANN techniques, which shows to be accurate methods for assessing flood vulnerability (Tamiru & Dinka, 2021a). Autonomous agent involvement includes the Wollega University in Ethiopia and the University of Johannesburg in South Africa (Tamiru & Dinka, 2021a). The project results can be used for practical flood management efforts.

In Libya's Derna region, AI is utilised for post-flood disaster change detection and assessment by comparing Sentinel-2 images from before and after the flood (Bouchelkia, Tahraoui & Kheddam, 2024). The AI model used for this project is DNN and facilitates precise and automated detection of disaster change. The study includes autonomous agents from the University of Science and Technology Houari Boumediene (USTHB) in Algeria (Bouchelkia, Tahraoui & Kheddam, 2024). Results for this study contributes to emergency assessment and management efforts in Libya (Bouchelkia, Tahraoui & Kheddam, 2024).

Malawi uses AI to improve flood damage assessments in areas with limited data (Wouters *et al.*, 2021). The project aims to extract individual building information and determine damage based on building vulnerability. The AI algorithm used for this study is SVM which classifies delineated buildings (Wouters *et al.*, 2021). Autonomous agent involvement includes the University of Amsterdam in the Netherlands, and the Netherlands Red Cross (Wouters *et al.*, 2021). Furthermore, the study acquired financial research support from the Dutch Research Council in the Netherlands.

Moreover, the Karonga District and Lilongwe city in Malawi is utilising AI for flood vulnerability assessment in rural and urban informal settlements (Mwalwimba, Manda & Ngongondo, 2024). Flood vulnerability assessments inform the DRR and preparedness process in urban and rural areas (Mwalwimba, Manda & Ngongondo, 2024). The project makes use of ANN to identify and determine vulnerabilities. The study concludes that household flood vulnerability is due to place

settlements, inadequate risk knowledge, limited access to communication, lack of early warning systems and access to income of households.

The project involves autonomous agents from the Catholic University of Malawi, Mzuzu University in Malawi, and the University of Malawi (Mwalwimba, Manda & Ngongondo, 2024). Furthermore, the project received financial support from the Norwegian Programme for Capacity Building in Higher Education and Research for Development (NORHED) Project in Norway and the Centre for Resilient Agri-Food Systems (CRAFS) under the African Centres of Excellence programme from the University of Malawi (Mwalwimba, Manda & Ngongondo, 2024).

In Mozambique, AI is utilised for flood mapping and damage assessment efforts (Nhangumbe *et al.*, 2023). The project makes use of the RF based GEE platform to determine post flood damages. The data used for the assessment is composed from Sentinel 1 images and aid in training tools that produce efficient mitigation and preparedness measures. Autonomous agent involvement includes the KTH Royal Institute of Technology in Sweden and the Eduardo Mandlane University in Mozambique (Nhangumbe *et al.*, 2023).

Nigeria uses AI for flood vulnerability assessment along the lower Niger river (Olusola *et al.*, 2022). As the river basin plays a crucial role in achieving agricultural targets, its assessment becomes vital. The project derives data from Sentinel 1 imagery, derived from the RF based GEE platform. Autonomous agents involved in the project includes the University of the Free State in South Africa, Texas Tech University in the USA, the University of Ibadan in Nigeria, the Federal University of Technology in Nigeria, and the University of Warsaw in Poland (Olusola *et al.*, 2022).

The Kikuletwa River in Tanzania use AI for flood monitoring (Mdegela *et al.*, 2023). The study found that the best suited models for time-series data are AutoRegressive (AR), Autoregressive Integrated Moving Average (ARIMA), and Recurrent Neural Networks (RNN). Additionally, it found that wind is not necessarily the best indicator of floods, however, river level is crucial in flood prediction. Autonomous agent involvement includes the University of Antwerp-imec in Belgium, the Nelson Mandela African Institution of Science and Technology (NMAFST) in Tanzania, the i2CAT Foundation in Spain, and the Carnegie Mellon University Africa in Rwanda. The project received funding from the Flemish Interuniversity Council for University Development Cooperation (FICUDC) in Belgium (Mdegela *et al.*, 2023).

In Zambia, AI is used for flood monitoring and damage assessment (Shilengwe *et al.*, 2023). The project uses synthetic aperture radar and optical sensor techniques with the RF based GEE cloud platform to assess and monitor flood damage. Sentinel-2 images were used to produce LULC maps for August 2020 which underwent pre and post GEE processing. The agents involved in

the project are the National Remote Sensing Centre from Zambia, the University of Zambia, the Zambian National Institute of Public Administration, and the Istanbul Technical University in Turkey (Shilengwe *et al.*, 2023).

In this section, AI Flood monitoring and assessment in Africa has shown to be diverse and integrated into various countries. Frequently used AI models include RF from the GEE cloud platform and variations of NN algorithms. Damage and vulnerability assessments and monitoring functions are mentioned often in these projects and indicate pre- and post-event interventions.

5.3.1.3 Prediction

Prediction forms a vital part of AI models reducing African floods. It is an extensively popular function in African flood reduction efforts and prospective risk management (Cirri, 2023). Prediction can assist in hazard prevention and minimization of damage; therefore, it can assist in the reduction of African flood hazard.

For instance, Google developed a flood monitoring and prediction system that involves more than 80 countries globally, of which include 23 African countries (Ndebele, 2023). They are Angola, Burkina Faso, Cameroon, Chad, the Democratic Republic of the Congo, Ghana, Guinea, Ivory Coast, Liberia, Malawi, Namibia, Nigeria, Sierra Leone, South Sudan, South Africa, Burundi, Eswatini, Guinea Bissau, Lesotho, Madagascar, Rwanda, Senegal, and Zimbabwe. Flood forecasting information is produced using two AI models namely the Hydrological Model (HM) and the Inundation Model (IM) (Google Research, n.d.). The platform is said to predict floods seven days in advance and shows to be an effective tool for data and prediction models.

In Algeria, ML and GIS is used to simulate urban flooding in the Wadis of Tebessa city (Talbi, Gherzouli & Fezzai, 2023). The study focus is on the relationship between water-level and different parameters of precipitation (Talbi, Gherzouli & Fezzai, 2023). By using various ML models, Extreme Gradient Boosting (XGBoost) showed to be the most effective and accurate in simulating urban flooding. The project involves autonomous agents such as the Algerian University of Guelma and the University Echahid Chikh Larbi Tbessi also in Algeria (Talbi, Gherzouli & Fezzai, 2023).

Cameroon uses AI algorithms ML and DL for flood forecasting in the Far-Northern region (Dtissibe *et al.*, 2024). Out of various ML and DL models, Long Short-Term Memory (LSTM) shows to be the best for short- and long-term flood forecasting (Dtissibe *et al.*, 2024). The results from the project can be used for the implementation of flood early warning systems and for defining efficient flood risk management policies. Autonomous agent involvement includes the University of

Maroua in Cameroon, The University of Versailles Saint-Quentin-en-Yvelines in France, the University of Garoua in Cameroon, the University of Ngaoundere in Cameroon, and Gaston Berger University in Senegal (Dtissibe *et al.*, 2024).

In the Gulf of Guinea, AI is used to detect sea level variability and draw predictions from the data (Shola, Yu & Wu, 2023). With the rise in sea levels due to climate change, AI can assist in predicting sea level changes and possible flood risk. After comparing various ML and ANN models, the study revealed RF and GBC as the most accurate AI models (Shola, Yu & Wu, 2023). Autonomous agent involvement extends to the Ocean University in China and the Nigerian Institute for Oceanography and Marine Research (Shola, Yu & Wu, 2023).

Ghana uses AI models to enhance flood prediction accuracy (Nti *et al.*, 2021). The project makes use of four ML algorithms namely LSTM, XGBoost, RF, and Random Tree (RT) (Nti *et al.*, 2021). The results show the potential of developing ML models for efficient and effective flood prediction. The project involves agents from the University of Energy and Natural Resources in Ghana (Nti *et al.*, 2021). The merit of the study is that it is the first to use a combination of environmental factors (in Ghana) and ML algorithms to develop intelligent flood models which help stakeholders make informed decisions (Nti *et al.*, 2021).

Kenya uses AI for river flow modelling and flood prediction in the ungauged Perkerra catchment in Baringo Country (Chebii, Mukolwe & Ong'or, 2022). Due to ANN's success in modelling hydrological predictions, the project makes use of this algorithm to determine daily rainfall and discharge levels (Chebii, Mukolwe & Ong'or, 2022). Abnormal levels of rainfall have caused devastating effects to the Perkerra catchment and have produced flood event associated with socioeconomic losses (Chebii, Mukolwe & Ong'or, 2022). The projects involve the Masinde Muliro University of Science and Technology in Kenya.

Mauritius uses AI for flood prediction efforts (Dhunney *et al.*, 2020). Trained by 20 000 climatic data records, ANN models are used for prediction. The records collected over a period of two years included climate input features such as minimum and maximum temperature, humidity, and rainfall (Dhunney *et al.*, 2020). The output is then concluded in terms of 'flood' or 'no flood'. The project includes autonomous agents such as Cyberange Global Holdings from Singapore, the University of Mauritius, Curtin University in Australia, and Cairo University in Egypt (Dhunney *et al.*, 2020).

In Northern Madagascar AI is utilised for modelling the onset and end dates of monsoon circulation (Rabeniaina, Rakotovoao & Ratiarison, 2023). Monsoon season has a tremendous effect on the development of flash floods. The study proposes the use of an ANFIS model to

improve forecasting accuracy. The study found that the monsoon circulation duration is 73 days, occurring from 29th of December to the 5th of March. Agent involvement extends to the University of Antananarivo in Madagascar (Rabenaiaina, Rakotovao & Ratiarison, 2023).

In Nigeria, AI is used for predicting flood prone areas (Ighile, Shirakawa & Tanikawa, 2022). The project predicts flood susceptible areas based on historical records from 1985-2020. The GIS incorporated AI algorithms of ANN and LR are trained and tested to produce accurate maps predicting flood prone areas. Both models are considered viable for predicting flood prone areas however ANN showed to be more accurate (Ighile, Shirakawa & Tanikawa, 2022). The project includes autonomous agents from the Nagoya University in Japan.

Additionally, in Nigeria's Kebbi State, ML is used for flood prediction (Lawal, Yassin & Zakari, 2021). ML popularity in prediction models is due to their low computational requirements and observational data reliance (Lawal, Yassin & Zakari, 2021). The project uses various ML models, however, finds that LR is the most accurate model. Autonomous agent involvement includes the Federal University of Dutse in Nigeria, the University of Brunei Darussalam in Brunei, and the University of Electronic Science and Technology of China.

Rwanda uses AI in flood and streamflow predictions (Macharia *et al.*, 2023). For collecting data from ungauged rivers, an AI streamflow model was developed by using ML and process-based models. The most accurate ML model showed to be GBC which ranked the highest skill with the Kling-Gupta Efficiency score (Macharia *et al.*, 2023). Autonomous agents involved in the project includes the University of Colorado Boulder in the USA, the Regional Centre for Mapping of Resources for Development in Kenya, and Bridges to Prosperity in the USA (Macharia *et al.*, 2023).

In Sudan, AI is used for flood classification and prediction efforts (El-Sayed El-Mahdy *et al.*, 2024). The study aims to use AI techniques as a modelling tool to establish the risk of the Nile flooding in southern cities. Comparing various AI models, the projects found that FFNN was the most accurate in determining classification and establishing predictions. The study also found that increasing the hidden NN layers showed to influence the level of model accuracy. The project includes agents such as the Cairo University and the Beni Suef University, both located in Egypt (El-Sayed El-Mahdy *et al.*, 2024).

Furthermore, Tanzania predicted spatiotemporal patterns in floods with Sentinel-1 radar images in major rice growing river basins (Micheal *et al.*, 2023). Rice growing is rainfed and lies in lowland river basins where extreme floods are frequent. The AI model used for the project is the RF based GEE platform that was utilised for classification efforts, change detection and threshold

methodology. Agent involvement includes the Sokoine University of Agriculture in Morogoro Tanzania, the University of Copenhagen in Denmark, and the Tanzania Agricultural Research Institute in Dodoma Tanzania (Micheal *et al.*, 2023). The project was financed by the Danish International Development Agency.

In Zimbabwe, AI is used to model flood hazards and determine significant factors that explain the probability of flood events in the Beitbridge district (Chikwiramakomo *et al.*, 2021). Dry climate flooding are under-researched domains and hinder understanding complex factors influencing susceptibility levels. The project makes use of the AI model, LR to predict spatial variations in flood hazards. Autonomous agents involved in the project includes the University of Zimbabwe, and the International Rescue Committee in Zimbabwe (Chikwiramakomo *et al.*, 2021). The project was funded by the International Rescue Committee in Zimbabwe, under the DRR project of the Beitbridge district.

Many African AI models involved in prediction efforts show a need for reducing and preventing causalities and infrastructural damage. Prediction models for African flooding show valuable for various policy makers and stakeholders. Determining the susceptibility of flood is almost synonymous to predicting flood. However, where prediction involves likelihood estimation of future hazards, susceptibility mapping involves identification of hazard prone areas (Mersha & Meten, 2020). Both source data from various domains, prediction uses historical data whereas susceptibility mapping uses data from different casual factors such as slope, rainfall etc. (Mersha & Meten, 2020).

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Table 5.3.1: Summary of AI flood hazard reduction project examples in Africa.

African Country	Project Reference	AI Model	Assisting Technology	Project Purpose	Autonomous Agents	Agent Country
Angola Burkina Faso Burundi Cameroon Chad Congo Eswatini Ghana Guinea Guinea-Bissau Ivory Coast Lesotho Liberia Madagascar Malawi Namibia Nigeria Rwanda Senegal Sierra Leone South Africa Sudan Zimbabwe	(Google Research, n.d.)	HM IM	Not specified	Monitoring and predicting floods.	Google	USA
Algeria	(Mansour, Mrad & Djebbar, 2024)	LR	Not specified	Mapping and predicting flash flood susceptibility.	University Mohamed Cherif	Algeria
Algeria	(Talbi, Gherzouli &	XGBoost	GIS	Predicting floods	University Echahid Chikh	Algeria

	Fezzai, 2023)			through simulation.	Larbi Tbessi University of Guelma	Algeria
Bukina Faso	(Bonkougou, 2021)	FR LR	GIS RS	Mapping flood susceptibility and predicting problematic areas.	Pan African University African Union Association of African Universities WASCAL	Algeria Ethiopia Ghana Ghana
Cameroon	(Dtissibe et al., 2024)	LSTM	Not specified	Forecasting floods.	University of Garoua University of Maroua University of Ngaondere University of Versailles Saint-Quentin-en-Yvelines Gaston Berger University	Cameroon Cameroon Cameroon France Senegal
Egypt	(Abu El-Magd, 2022)	NB RF	R QGIS	Susceptibility prediction of flash floods.	Suez University	Egypt
Egypt	(Youssef et al., 2022)	CNN	Not specified	Susceptibility mapping and predicting floods.	University of Technology Sydney South Vally University University Kebangsaan Geological Hazards Centre	Australia Egypt Malaysia Saudi Arabia
Ethiopia	(Tamiru & Dinka, 2021a)	ANN	GIS	Assessing flood vulnerability.	Wollega University University of Johannesburg	Ethiopia South Africa
Ghana	(Ghansah et al., 2021)	RF	Landsat	Mapping flood and hazard susceptibility.	Koforidua Technical University King Abdulaziz University University of Miami	Ghana Saudi Arabia USA
Ghana	(Nti et al., 2021)	LSTM RF RT XGBoost	Not specified	Enhance flood predicting accuracy.	University of Energy and Natural Resources	Ghana
Guinea	(Shola, Yu & Wu, 2023)	GBC	Not specified	Predicting sea level variability.	Ocean University Institute for Oceanography	China Nigeria

		RF			and Marine Research	
Kenya	(Chebii, Mukolwe & Ong'or, 2022)	ANN	Not specified	Predicting flood and modelling flow.	Masinde Muliro University of Science and Technology	Kenya
Liberia	(Bouchelkia, Tahraoui & Kheddami, 2024)	DNN	Sentinel-2	Assessing and detecting flood damage.	University of Science and Technology (USTHB)	Algeria
Madagascar	(Rabeniana, Rakotovo & Ratiarison, 2023)	ANFIS	Not specified	Predicting monsoon occurrence dates.	University of Antananarivo	Madagascar
Malawi	(Mwalwimba, Manda & Ngongondo, 2024)	ANN	Not specified	Assessing flood vulnerability in rural and urban settlements.	Catholic University of Malawi Mzuzu University University of Malawi NORHED	Malawi Malawi Malawi Norway
Malawi	(Wouters et al., 2021)	SVM	Not specified	Assessing flood damage based on building vulnerability.	Dutch Research Council Netherlands Red Cross University of Amsterdam	Netherlands Netherlands Netherlands
Mauritius	(Dhunni et al., 2020)	ANN	Not specified	Predicting floods.	Curtin University Cairo University University of Mauritius Cyberange Global Holdings	Australia Egypt Mauritius Singapore
Morocco	(Bouramtane et al., 2021)	RT SVM	Not specified	Mapping vulnerability and variability of urban flooding.	University of Ouagadougou Avignon University University of Toulouse Mohammed V University University Abdelmalek Essaadi University Sidi Mohammed Ben Abdellah Seattle University	Burkina Faso France France Morocco Morocco Morocco USA
Mozambique	(Nhangumbe et al., 2023)	RF	GEE	Assessing and mapping flood damage.	Eduardo Mandlane University KTH Royal Institute of Technology	Mozambique Sweden

Mozambique	(Ramayanti et al., 2022)	CNN GMDH	Not specified	Mappiing flood susceptibility.	Institute of Geoscience and Mineral Resources Kangwon National University Ministry of Oceans and Fisheries	Korea Korea Korea
Nigeria	(Ighile, Shirakawa & Tanikawa, 2022)	ANN	Not specified	Predicting flood prone areas.	Nagoya University	Japan
Nigeria	(Lawal, Yassin & Zakari, 2021)	LR	EOD	Predicting floods.	University of Brunei Darussalam University of Electronic Science and Technology Federal University of Dutse	Brunei China Nigeria
Nigeria	(Olusola et al., 2022)	RF	GEE Sentinel 1	Assessing river-basin flood vulnerability.	Federal University of Technology University of Ibadan University of Warsaw University of the Free State Texas Tech University	Nigeria Nigeria Poland South Africa USA
Rwanda	(Macharia et al., 2023)	GBC	Not specified	Predicting floods and streamflow.	Regional Centre for Mapping of Resources for Development Bridges to Prosperity University of Colorado Boulder	Kenya USA USA
Sudan	(El-Sayed El-Mahdy et al., 2024)	FFNN	Not specified	Predicting and classifying floods.	Beni Suef University Cairo University	Egypt Egypt
Tanzania	(Mdegela et al., 2023)	AR ARIMA RNN	Not specified	Monitoring river floods.	FICUDC University of Antwerp-imec Carnegie Mellon University Africa i2CAT Foundation NMAIST	Belgium Belgium Rwanda Spain Tanzania

Tanzania	(Micheal et al., 2023)	RF	GEE Sentinel 1	Predicting spatiotemporal flood patterns.	University of Copenhagen Agricultural Research Institute Sokoine University of Agriculture	Denmark Tanzania Tanzania
Tunisia	(Dahri et al., 2022)	ANN ANP	GIS	Mapping flash flood susceptibility.	National Polytechnic School University of Kasdi Merbah-Ouargla University of Sfax Thu Dau Mot University	Algeria Algeria Tunisia Vietnam
Tunisia	(Souissi et al., 2022)	Fuzzy-AHP	Not specified	Mapping and assessing flood.	Polytechnic Institute UniLaSalle Beauvais Ministry of Agriculture, Water Resources and Fisheries Municipality of Takelsa University of Carthage University of Tunis El Manar	France Tunisia Tunisia Tunisia Tunisia
Zambia	(Shilengwe et al., 2023)	RF	GEE Sentinel 2	Monitoring and assessing flood damage.	Istanbul Technical University National Institute of Public Administration National Remote Sensing Centre University of Zambia	Turkey Zambia Zambia Zambia
Zimbabwe	(Chikwiramakomo et al., 2021)	LR	Not specified	Predicting dry climate flood hazard.	International Rescue Committee University of Zimbabwe	Zimbabwe Zimbabwe

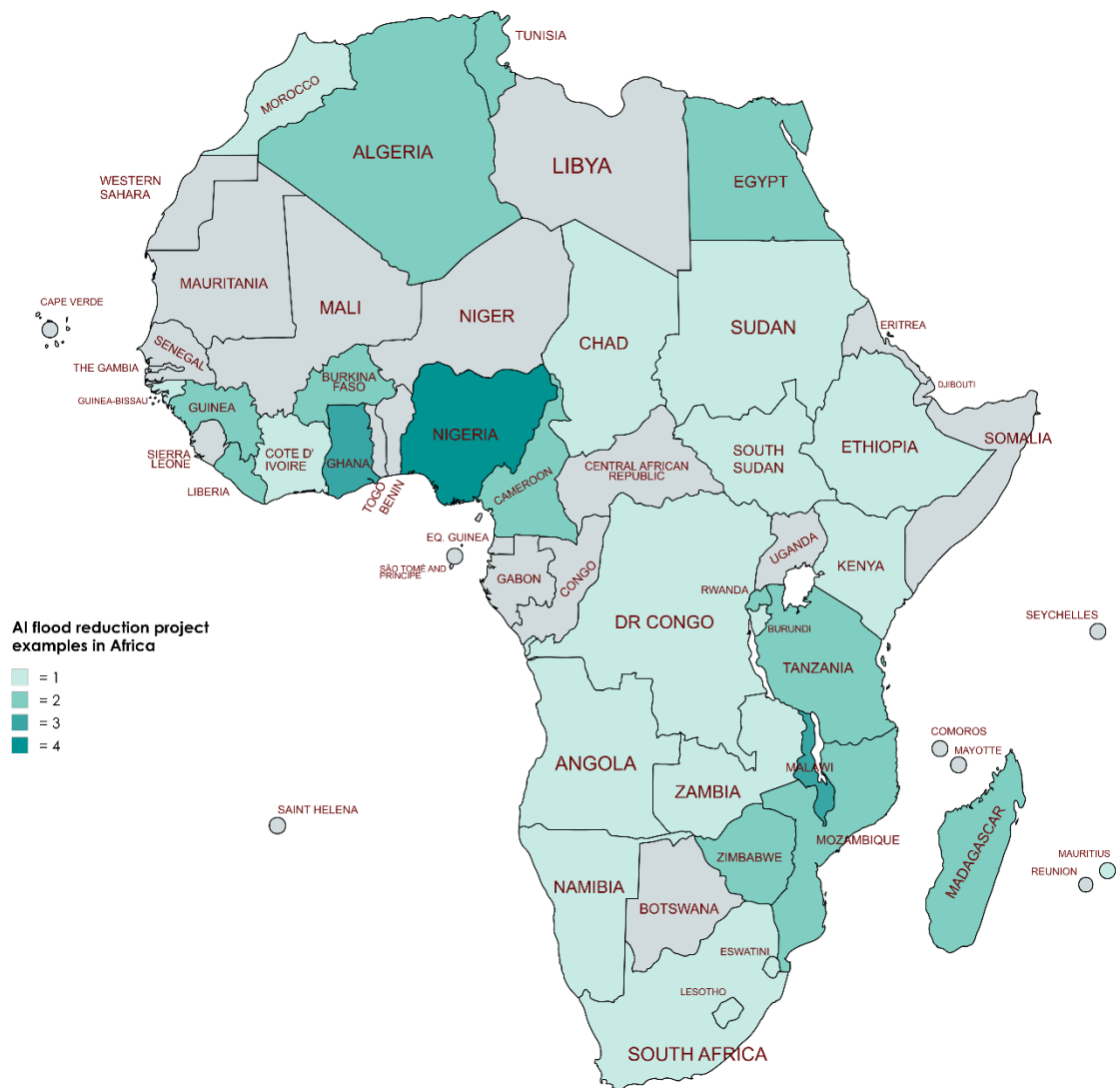


Figure 5.3.1: Map of AI for flood reduction project examples in Africa.

Flooding is extensively common in Africa, however, so is drought. The lack of water usually results in serious dehydration and can cause irreversible damage to humans, crops and livestock (Mishra, 2023). As most of Africa's economy and workforce depends on agriculture (Yeboah & Jayne, 2019), it is imperative to incorporate the use of AI projects in forecasting, monitoring and predicting drought. In the following section AI models reducing drought in Africa is explored.

5.3.2 Drought

Many have attempted to define drought; however, the nature of its complexity has prohibited the formation of a universally recognised definition (Kikon & Deka, 2021). Nevertheless, drought is generally known as being the product of a precipitation deficit over a long period (Nandgude, *et al.*, 2023). It is caused by various complex hydrometeorological anomalies which result in the

overall complication of reduction efforts (Nandgude, *et al.*, 2023). AI techniques are widely used to assess, monitor and forecast drought (Kikon & Deka, 2021).

Africa's heavy reliance on its agricultural sector creates a dire need for drought prediction and reduction efforts (Adamaagashi *et al.*, 2023). In this section, AI used for drought reduction is discussed according to its functions in monitoring, predicting and forecasting activities. Different African countries have shown interest in drought monitoring through the integration of AI. Botswana, Kenya, Ethiopia, Malawi, Sahel, and Nigeria are used in this section as examples of AI for drought monitoring in Africa.

These countries are relevant to AI drought monitoring projects as they all have a drought prone agricultural sector (Motsumi, Ziervogel & New, 2023; Wens *et al.*, 2020; Maru, Hailelassie & Zeleke, 2023; Sato *et al.*, 2020; Elagib, Ali & Musa, 2024; Aladelokun, 2023). Monitoring vulnerable areas are great for early warning systems and early intervention efforts. Additionally, all these countries could benefit from monitoring projects as they all experience recurring drought hazards (Mugari, Manundire & Bolaane, 2020; Kirui *et al.*, 2022; Tofu, Haile & Tolossa, 2023; Mtilatila *et al.*, 2020; Abdourahamane *et al.*, 2022; Abaje, 2023).

Various African countries use AI for drought prediction projects. Some examples include Kenya, Mozambique, South Africa, Egypt, Ghana, Madagascar, Niger, Morocco, Rwanda, Tanzania, Tunisia, and Sierra Leone. These countries benefit from drought prediction models because they all experience climate change related land surface temperature (LST) changes (Ochieng, Nyandega & Wambua, 2022; Emeteri & Fayomi, 2020; Bhaga *et al.*, 2020; Abou Samra, 2021; Sarfo *et al.*, 2023; Rigden *et al.*, 2024; Badamassi, El-Aboudi & Gbetkom, 2019; El Garouani *et al.*, 2021; Uwimbabazi *et al.*, 2022; Machiwa *et al.*, 2021; Mohamed *et al.*, 2023; Mustafa, El-Hamid & Tarawally, 2021).

Also, many people in these countries lose their livelihoods due to the devastation of droughts (Imana & Zenda, 2023; Baez, Caruso & Niu, 2019; Bahta & Nyaki, 2024; Ahmed & Sallam, 2020; Yiridomoh, Sullo & Bonye, 2020; Fayad, 2023; Ado, Savadogo & Abdoul-Azize, 2019; Woodmansee *et al.*, 2024; Nzeyimana *et al.*, 2024; Mdemu, 2021; Jendoubi *et al.*, 2020; Abiona & Ajefu, 2022).

African AI drought forecasting is explored with regards to project examples of Algeria, Benin, Kenya, Egypt, Ethiopia, Nigeria, Somalia, Zambia, Senegal, Chad, and Sudan. These countries can benefit from AI drought forecasting as they are all susceptible to drought driven land desertification (Alliouche & Kouba, 2023; Assogbadjo *et al.*, 2022; Hitimana *et al.*, 2021; Fadl *et*

al., 2022; Reda & Gidey, 2021; Akanwa *et al.*, 2024; Omar, Hassan & Mohamed, 2022; Sambo, 2021; Gangneron *et al.*, 2022; Takoutsing *et al.*, 2022; Magboul, Salih & Eltayeb, 2020).

Additionally, they all aim to systematically adapt to drought for more sustainable agricultural sectors (Hafida & Djihad, 2024; Moutouama *et al.*, 2022; Simtowe *et al.*, 2020; Awaad, 2022; Ramadan *et al.*, 2024; Eze *et al.*, 2020; Warsame & Abdi, 2022; Hamazakaza *et al.*, 2022; Kone, 2024; Absakine, 2024; Ahmed, 2020). The complexity associated with drought and its reduction increases the challenging nature of modelling their non-linear and dynamic systems (Wang & Razmjooy, 2024). AI used for monitoring drought has gained explosive interest and has helped in understanding, forecasting and predicting droughts (Balti *et al.*, 2020).

5.3.2.1 Monitoring

Drought monitoring is traditionally done by statistical models such as drought indicators and remote sensing methods. Unfortunately, both methods have systemic limitations (Zhang *et al.*, 2023a). However, AI has become integrated with these methods and show immense promise for extending functionality and accuracy (Zhang *et al.*, 2023a).

For example, Botswana uses AI for drought monitoring in arid and semi-arid environments (Byakatonda *et al.*, 2023). The project aims to study the increasing temperatures of arid and semi-arid locations in Botswana using an ANN model. The model is integrated with nonlinear AR and exogenous inputs. Autonomous agent involvement includes the Gulu University in Uganda, the Botswana International University of Science and Technology, the Botswana University of Agriculture and Natural Resources, and the University of Botswana (Byakatonda *et al.*, 2023).

Additionally, Botswana uses AI for the development of drought early warning systems based on the monitoring of agricultural productivity (Kemper, 2022). A data science approach towards statistical and ML methods was used for retrieving relevant information on drought risk. ML algorithms such as NB classification and RF regression was included in the project, integrated with indexes such as the SPI and the Southern Oscillation Index (SOI). The project aims to examine the impact data science can have on understanding the complexities of drought risk. Agent involvement extends to the University of Bonn in Germany and the United Nations World Food Programme (Kemper, 2022).

In Kenya the assimilation of satellite data and sensors are done through a variety of ML algorithms for monitoring. This aids toward drought early warning estimation of ground water use and demand (Frankhauser *et al.*, 2022). The ML models include XGBoost, LR, NB, KNN, and RF. The project includes an array of autonomous agents for example the University of Colorado Boulder

in the USA, Regional centre for mapping of resources for development in Kenya, NASA in the USA, SweetSense Inc. in the USA, Science Applications International Corporation in the USA, US Agency for international development in the USA, and the University of Maryland in the USA (Frankhauser *et al.*, 2022).

The upper Tekeze Basin in Ethiopia uses AI for monitoring spatio-temporal drought dynamics (Fentaw, Yimer & Zeleke, 2023). The aim of the project is to derive a comprehensive understanding of drought dynamics for endorsing sustainable drought risk management efforts. GEE (the RF based platform) was used to obtain data, process trends, and calculate drought indices (Fentaw, Yimer & Zeleke, 2023). Agents involved extend to the Ethiopian universities of Addis Ababa University, Woldia University, and Debre Berhan University (Fentaw, Yimer & Zeleke, 2023).

North Malawi uses AI for monitoring and assessing groundwater storage depletion using Nasa's Gravity Recovery and Climate Experiment (GRACE) data and land surface models (Sichone, 2024). The project made use of ANN to better the spatial resolution of GRACE maps. These maps show that the depletion of freshwater resources is increasing and urge officials and public to enhance conservation efforts in Malawi. Autonomous agent involvement extends only to the Catholic University of Malawi (Sichone, 2024).

In the Sahel region of Africa, AI is utilised to develop a new multivariate agricultural drought composite index for monitoring agricultural drought (Houmma *et al.*, 2022). Sahel region consists of Burkina Faso, The Gambia, Niger, Guinea, Cameroon, Mali, Nigeria, Chad, Mauritania, and Senegal. The new drought composite index is based on RF and RS data. Autonomous agent involvement includes the Hassan II Institute of Agronomy and Veterinary in Morocco, the EU in Belgium, University de Toulouse in France, Abdou Moumouni University in Niger, and the National Institute of Agricultural Research in Morocco (Houmma *et al.*, 2022).

Nigeria uses AI to help determine the performance of drought indices and evaluate the impact of those indices on maize output (Adepoju, Ogundunmade & Adenuga, 2024). Drought indices are used for the detection, classification and control of drought conditions. In this project ANN was used to evaluate the impact of these indices on the northern states of Nigeria. The model was evaluated using several activation functions and found that the lowest mean square errors were generated by a rectified linear unit. Also, as training percentage increases so does the mean square errors. Agents involved extends to the University of Ibadan in Nigeria (Adepoju, Ogundunmade & Adenuga, 2024).

Drought monitoring projects in this section are mainly concerned with its use in agricultural drought and early-warning systems. These efforts are important for reducing African drought disaster risk. AI prediction efforts may also have the potential to aid in African drought reduction activities.

5.3.2.2 Prediction

The prediction of drought is important for various systems such as reservoir levels, agricultural production and climate change adaptation (Katipoglu, 2023). AI use for hydrological and meteorological drought has become extensively popular in recent years (Katipoglu, 2023). With its extensive success and accuracy, predicting drought is becoming more efficient than ever (Sundararajan *et al.*, 2021).

For example, the Unit for Research on Informatics for Droughts in Africa (URIDA) developed tools for predicting African drought (ITIKI, 2022). The Information Technology and Indigenous Knowledge with Intelligence (ITIKI) drought prediction tool (launched in 2019), aids small holding farmers (in Kenya, Mozambique and South Africa) in using ML algorithm ANN (ITIKI, 2022). Autonomous agents active in this project are USAID from the USA, South African weather service, Central University of technology of the Free State in South Africa, and University of KwaZulu Natal in South Africa (ITIKI, 2022).

Egypt uses AI to predict high-resolution references for evapotranspiration in arid areas suffering from water scarcity and scarcity of precipitation (Sobh, Nashwan & Amer, 2022). Various ML models were used for prediction, however, the RF model showed to be the most accurate. RF predictors include minimum and maximum temperatures, relative humidity and wind speed. Autonomous agent involvement extends only to the Arab Academy for Science, Technology and Maritime Transport in Egypt (Sobh, Nashwan & Amer, 2022).

AI is used for a mango orchard in Tamale Ghana to conduct drought monitoring and prediction methods (Hobart *et al.*, 2024). The project utilises earth observational data (EOD), climate scenarios and data driven methods to investigate the relationship between various drought predictors. The AI model used for the study is a Wavelet-ANFIS algorithm popular in robust predictions. Autonomous agents involved in the project are the Leibniz Institute for Agricultural Engineering and Bioeconomy in Germany, the University for Developmental Studies in Ghana, and the Federal Agency for Technical Relief in Germany. It was funded by the EU Horizon 2020 Research and Innovation Programme (Hobart *et al.*, 2024).

Madagascar uses AI for predicting climate change, and dew and rain evolution in drought prone, semiarid southwestern areas (Rasoafaniry, Muselli & Beysens, 2024). Within the context of global warming and scarce freshwater resources, it becomes important to evaluate non-rainfall water contribution and evolution. Through utilising ANN, the project finds that dew is responsible for 30% of the total water balance during drought season. The project involved autonomous agents from the University of Corsica Pascal Paoli in Paris, France (Rasoafaniry, Muselli & Beysens, 2024).

In Niger, AI is utilised for both drought and flood prediction through monitoring the Niger river basin (Ogunjo, Olusola & Olusegun, 2024). Due to the integral role of this basin in West Africa, it is critical to ensure its ecosystemic health. The project found that LSTM is the most accurate ML model for investigating variations in annual river flow recorded from sensors at eight different stations. Autonomous agent involvement includes the Federal University of Technology in Nigeria, York University in Canada, and the University of Warsaw in Poland (Ogunjo, Olusola & Olusegun, 2024).

Morocco uses AI for predicting and modelling drought related yield losses (Hakam, Baali & Ali, 2022). Rainfed agricultural vulnerability is intensifying with relation to agro-meteorological factors such as humidity, temperature, radiation, sunshine, and hydrometry. The project developed methods for modelling and early prediction of crop yields in the Garab plain. Various ML models were used however RF showed to be the most accurate one. Agents involved in the project includes the Sidi Mohamed Ben Abdellah University in Morocco and a geospatial technologies expert at Barthauer Software GmbH in Germany (Hakam, Baali & Ali, 2022).

Rwanda uses AI to monitor and predict groundwater quantity in drought prone areas (Kombo, 2022). The project aims to provide a low-cost and low-power IoT and ML model for monitoring and predicting groundwater quantity. The AI model used for the project is the hybrid model based on Ensemble Empirical Mode Decomposition (EEMD)-Support Vector Regression (SVR)-RF. The hybrid model showed to be much more effective than its components on their own. The agent involvement extends only to the University of Rwanda (Kombo, 2022).

South Africa uses AI to assess, characterise and predict drought in the Luvuvhu river catchment (Mathivha, 2020). The Limpopo River basin in South Africa has experienced an increased drought frequency in recent years. By using data obtained from the South African Weather Service (satellite data, the Department of Water and Sanitation, and NASA's earth data Giovanni repository; ML based techniques were used for drought prediction. The project found that the most efficient was the model of LSTM. Autonomous agent involvement extends only to the University of Venda in South Africa (Mathivha, 2020).

Furthermore, South Africa uses AI to predict evapotranspiration for optimum water usage in the agricultural irrigation scheme of Keiskammahoek in the Eastern Cape (Phesa, Woyessa & Mbatha, 2023). The project makes use of three models namely ANN, Auto-regressive Integrated Moving Average (ARIMA) and the hybrid between the two ARIMA-ANN. The hybrid model showed to be much more accurate than its components alone. Autonomous agent involvement includes the three South African universities namely Walter Sisulu University, the Central University of Technology, and the University of Zululand. Funding was obtained through the Department of Higher Education and Training in South Africa (Phesa, Woyessa & Mbatha, 2023).

Tanzania uses ML algorithms for the prediction of drought conditions in the Wami River sub-catchment (Lalika *et al.*, 2024). Five algorithms were compared in their ability to predict the most widely used drought index. LSTM was found to be the most accurate and efficient model. Results will aid planners and decision makers develop drought monitoring and early warning systems. The project involves autonomous agents from the Sokoine University of Agriculture in Tanzania, the Swiss Federal Institute of Technology in Switzerland, Amref health Africa in Tanzania, and the Tanzania Meteorological Agency (Lalika *et al.*, 2024).

Northern Tunisia uses AI to predict groundwater potentiality in the drought prone area of the Medjerda Basin (Trabelsi, Ali & Lee, 2022). The severity of water scarcity in Tunisia calls for efficient and accurate prediction models that aid in water management ventures. The project uses single methods ANN, RF and SVR, and develops a novel hybrid model called NB-RF-SVR. NB-RF-SVR outperforms the other models significantly in predicting groundwater levels.

Autonomous agents involved are the University of Jendouba in Tunisia, the Korea Institute of Geoscience and Mineral Resources, and the University of Science and Technology in Korea. The project was supported by two projects funded by USAID (Trabelsi, Ali & Lee, 2022). Freetown City in Sierra Leone uses AI for predicting and modelling land surface temperature (LST) based on land-cover changes and drought (Kaloop *et al.*, 2022). Land use and cover indices share a relationship with LST and require assessment for determining the impact.

ANN and an evolutionary algorithm called Gene Expression Programming (GEP) was used in the project and found that urban factors are the most influential on LST. Agents involved in this project are the Mansura University in Egypt, the University of Engineering and Technology Peshawar in Pakistan, the Coastal Research Institute in Egypt, the Southwest Jiaotong University in China, and the Incheon National University in Korea (Kaloop *et al.*, 2022). Also, the project was funded by the Korea Agency for Infrastructure Technology Advancement.

In this section, the various AI projects for African drought prediction showcases an active participation in African AI ecosystemic development. Although the concepts of forecasting and prediction are used simultaneously in this research, the overwhelming number of African projects focusing on drought forecasting require their own sub-section. Prediction and forecasting only differs by the type of data and the extent of its output. Forecasting is understood as analysing historical data and prediction is understood as relying more on current data (Seraydarian, Mosinyan & Kotolyan, 2023).

5.3.2.3 Forecasting

Drought forecasting is vital to adequate water resource management and planning (Fung *et al.*, 2020). Critical to drought reduction is developing robust forecasting models that help understand how different variables effect systemic outcomes (Dikshit & Pradhan, 2021). For example, in Algeria, AI is used for hydrological drought modelling (Achite *et al.*, 2022). Forecasting drought in this project requires standardized metrics of rainfall and runoff data that aids in long-term planning and management of water resources.

The study uses various ML techniques to predict drought in the Wadi Ouahrane Basin, however, found that SVM outperforms all the other models. Autonomous agents include the Hassiba Benbouali University of Chlef in Algeria, the National Higher School of Agronomy in Algeria, the Hanyang University in Korea, and the Housing and Building National Research Centre in Egypt. The study is supported by the Lower-Level and ore Disaster Safety Technology Development Program funded by the Algerian Ministry of Interior and Safety Grant (Achite *et al.*, 2022).

Additionally, the Wadi Mina Basin in Algeria uses AI for meteorological drought forecasting (Achite *et al.*, 2023). The project used five ML models and found that SVM was the most accurate AI model. Autonomous agents involved in the research includes Hassiba Benbouali University of Chlef in Algeria, the University of Oran in Algeria, the Construction and Project Management Research Institute in Egypt, the Hanyang University in Korea, the University of Agriculture and Technology in India, the Thu Dau Mot University in Vietnam, the Van Lang University in Vietnam, the Hong Kong Polytechnic University in China, the Cairo University in Egypt, and the Mansoura University in Egypt (Achite *et al.*, 2023).

Benin also uses AI for drought forecasting in the Alibori Department (Vodounon, Soude & Mamadou, 2022). Like other West African countries, Benin has suffered from the effects of climate change. The country has recorded more than half a dozen droughts since the 1960ies which harshly effect the agricultural sector. The SPI is utilised with ML approaches to accurately model drought. The ML approaches include RF and XGBoost algorithms. Autonomous agent

involvement extends to various departments in the Benin Institute of Mathematics and Physics (Vodounon, Soude & Mamadou, 2022).

Furthermore, South Benin uses AI for time series data forecasting in Abomey-Calavi (Agossou, Kim & Yang, 2021). In Benin groundwater resources are used as a primary source of water for industrial, domestic and agricultural activities. The project aims to predict future probable groundwater drought using a RNN model. Agents involved are the Korean Water Resources Association and the Kookmin University in Korea (Agossou, Kim & Yang, 2021). The study showed that groundwater drought is not mainly caused by rainfall scarcity but rather an overexploitation of water resources (Agossou, Kim & Yang, 2021).

Kenya's pastoral communities use AI for forecasting vegetation conditions and determining drought early warning systems (Barrett *et al.*, 2020). The aim of the project is to forecast future environmental and socioeconomic indicators of drought. Data was derived from Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS) databases. AI models applied are AR and Gaussian process modelling methods. Autonomous agents involved include the University of Sussex in the UK, and the National Drought Management Authority in Kenya. The funders of this project are the Science and Technology Facilities Council in the UK (Barrett *et al.*, 2020).

Egypt uses AI for forecasting drought phenomena based on limited inputs (Elbeltagi *et al.*, 2024). The project uses advanced stacked integration methods for forecasting long-term drought severity whilst utilising CNN-LSTM models. CNN-LSTM models show to outperform all the other applied models and is the most suitable for advanced future investigations.

Autonomous agents include the Mansoura University in Egypt, the Indian Institute of Technology, Bahria University in Pakistan, Bennett University in India, Zhejiang Ecological Civilization Academy in China, the Maharana Pratap University of Agriculture and Technology in India, Ohio State University in the USA, the Ministry of Water Resources and Irrigation in Egypt, and the Zhejiang University in China. Furthermore, the project was funded by the National Science and Technology Support Projects in the USA (Elbeltagi *et al.*, 2024).

Tareke and Awoke (2023) developed a hydrological drought forecasting and monitoring system in Ethiopia, using the ML algorithm ANN. With no outside funding or special grants, the research found that the heavy influence of climate change on streamflow can be predicted using AI (Tareke & Awoke, 2023). ANN is efficient in determining hydrological drought in areas with good relationships between precipitation and streamflow. However, in arid areas ANN shows to be more accurate in determining meteorological drought. This project involved the two Ethiopian

universities known as Wollo University, and Addis Ababa Institute of Technology (Tareke & Awoke, 2023).

Nigeria uses AI for accurate prediction of drought characteristics and forecasting the standardised precipitation and evapotranspiration index (Ogunrinde *et al.*, 2020). Prediction of drought requires efficient and robust techniques that can deduce the stochastic relationship between the past and the future. Using ANN models, the project found that modelling data-driven forecasts can produce outputs monthly and drive the development of an early warning system. Agent involvement extends only to the Federal University of Technology in Nigeria (Ogunrinde *et al.*, 2020).

Somalia uses AI for drought forecasting in the Hiran region (Abdullahi *et al.*, 2023). The project aims to improve drought forecasting through the use and comparison of various ML algorithms. From three different models, SVR was the most accurate in predicting the standardised precipitation index (SPI). Autonomous agents involved are exclusively from Somalia and include the Simad University, the Institute for Water and Environmental Sustainability, the Somalia National University, the Abrar University, and the Somalia Netrich Technologies Center (Abdullahi *et al.*, 2023).

Zambia uses AI for the development of drought indicators through monitoring and forecasting systems (Sleimi, Ghosh & Amarnath, 2022). The project uses convolutional LSTM and PCA models to achieve effective monitoring and accurate prediction. Drought factors such as vegetation, precipitation, temperature, evapotranspiration and soil moisture were integrated using the PCA model and produced a novel cloud based multi-source drought index. Agent involvement includes the International Water Management Institute in Sri Lanka and funding from the Consultative Group for International Agricultural Research (CGIAR) trust fund in the USA (Sleimi, Ghosh & Amarnath, 2022).

Senegal uses AI for sub-seasonal prediction of summer temperatures (Kenne *et al.*, 2024). Although numerical weather prediction models are accurate in capturing predictors for changing temperature, they neglect exploiting sub-seasonal temperature forecasts. Out of six ML models, Gated Recurrent Units (GRU) showed to be the most accurate model. Autonomous agent involvement includes the African Institute for Mathematical Sciences in Senegal, the University Cheikh Anta Diop in Senegal, the Centre Universitaire de Formation et de Recherche in France, and the University of Yaounde in Cameroon (Kenne *et al.*, 2024).

Lake Chad Basin, situated between Chad, Niger, and Nigeria uses AI for temperature and precipitation forecasting (Manfouo *et al.*, 2023). Lake Chad is a data scarce environment frequently impacted by severe drought due to climate change and agricultural expansion. The

project aim is to conduct a comparison between statistical downscaling models and LSTM. The LSTM AI model showed to be most accurate in predicting temperature and precipitation. Autonomous agent involvement in the project includes research and funding from the University of Stellenbosch in South Africa (Manfouo *et al.*, 2023).

Sudan uses AI to enhance sorghum forecasting models in rainfed sectors (Alnayer *et al.*, 2023). With sparse and unpredictable rainfall in the El-Gadarif State, ML algorithms are utilised to aid in prediction efforts. A comparison was done between MLP and XGBoost regressor models and found that XGBoost notably outperforms MLP. Autonomous agent involvement includes the University of Khartoum in Sudan, the Wad Medani Ahlian University in Sudan, and the Technological University of Dublin in Ireland (Alnayer *et al.*, 2023).

In this section, the variety of forecasting AI projects in Africa show promising prospects for AI development in DRR. The projects mentioned have versatile reasons for development such as agricultural drought forecasting, climate change induced drought forecasting, and evapotranspiration and precipitation forecasting (to name a few). African countries using AI drought monitoring systems can potentially help build capacity for drought DRR. AI drought forecasting and prediction also contributes to African drought reduction efforts and establish vast networks of interdisciplinary and cooperative agents.

Table 5.3.2: Summary of AI drought hazard reduction project examples in Africa.

African Country	Project Reference	AI Model	Assissting Technology	Project Purpose	Autonomous Agents	Agent Country
Algeria	(Achite et al., 2022)	SVM	Not specified	Forecasting drought in water basin.	Hassiba Benbouali University of Chlef Ministry of Interior and Safety Grant National Higher School of Agronomy Housing and Building National Research Centre Hanyang University	Algeria Algeria Algeria Egypt Korea
Algeria	(Achite et al., 2023)	SVM	Not specified	Forecasting meteorological drought.	Hassiba Benbouali University of Chlef University of Oran Hong Kong Polytechnic University Cairo University Construction and Project Management Research Institute Mansoura University University of Agriculture and Technology Hanyang University Thu Dau Mot University Van Lang University	Algeria Algeria China Egypt Egypt Egypt India Korea Vietnam Vietnam
Benin	(Agossou, Kim & Yang, 2021)	RNN	Not specified	Forecasting groundwater quantity.	Kookmin University Water Resources Association	Korea Korea
Benin	(Vodounon, Soude	RF	Not specified	Forecasting drought in	Benin Institute of Mathematics	Benin

	& Mamadou, 2022)	XGBoost		agriculture.	and Physics	
Botswana	(Byakatonda et al., 2023)	ANN AR	Not specified	Monitoring drought in arid- and semi-arid areas.	International University of Science and Technology University of Agriculture and Natural Resources University of Botswana Gulu University	Botswana Botswana Botswana Uganda
Botswana	(Kemper, 2022)	NB RF	Not specified	Monitoring for drought early-warning systems.	University of Bonn United Nations World Food Programme	Germany USA
Burkina Faso Cameroon Chad Gambia Guinea Mali Mauritania Niger Nigeria Senegal	(Houmma et al., 2022)	RF	RS	Monitoring agricultural drought.	European Union University de Toulouse Hassan II Institute of Agronomy and Veterinary National Institute of Agricultural Research Abdou Moumouni University	Belgium France Morocco Morocco Niger
Chad Niger Nigeria	(Manfouo et al., 2023)	LSTM	Not specified	Forecasting temperature and precipitation.	University of Stellenbosch	South Africa
Egypt	(Elbeltagi et al., 2024)	CNN- LSTM	Not specified	Forecasting drought phenomena.	Zhejiang Ecological Civilization Academy Zhejiang University Mansoura University Ministry of Water Resources and	China China Egypt Egypt

					Irrigation Institute of Technology Maharana Pratrap University of Agriculture and Technology National Science and Technology Support Projects Ohio State University	India India USA USA
Egypt	(Sobh, Nashwan & Amer, 2022)	RF	Not specified	Predicting evapotranspiration.	Arab Academy for Science, Technology and Maritime Transport	Egypt
Ethiopia	(Fentaw, Yimer & Zelege, 2023)	RF	GEE	Monitoring spatio- temporal drought dynamics.	Addis Ababa University Debre Berhan University Woldia University	Ethiopia Ethiopia Ethiopia
Ethiopia	(Tareke & Awoke, 2023)	ANN	Not specified	Forecasting hydrological drought.	Addis Ababa Institute of Technology Wollo University	Ethiopia Ethiopia
Ghana	(Hobart et al., 2024)	Wavelet- ANFIS	EOD	Predicting and monitoring drought in agriculture.	EU Horizon 2020 Research and Innovation Programme Federal Agency for Technical Relief Leibniz Institute for Agricultural Engineering and Bioeconomy University for Developmental Studies	Belgium Germany Germany Ghana
Kenya	(Barrett et al., 2020)	AR Gaussian	Landsat MODIS	Forecasting future indicators of drought.	National Drought Management Authority Science and Technology Facilities Council University of Sussex	Kenya UK UK
Kenya	(Frankhauser et al., 2022)	KNN LR	Satellite data RS	Monitoring for drought early-warning system.	Regional centre for mapping of resources for development	Kenya

		NB RF XGBoost			Agency for international development NASA Science Applications International Corporation University of Colorado Boulder University of Maryland	USA USA USA USA USA
Kenya Mozambique South Africa	(ITIKI, 2022)	ANN	Not specified	Predicting drought.	Central University of technology South African weather service University of KwaZulu Natal USAID	South Africa South Africa South Africa USA
Madagascar	(Rasoafaniry, Muselli & Beysens, 2024)	ANN	Not specified	Predicting evolution of drought prone areas.	University of Corsica Pascal Paoli	France
Malawi	(Sichone, 2024)	ANN	GRACE	Monitoring and assessing groundwater depletion.	Catholic University	Malawi
Morocco	(Hakam, Baali & Ali, 2022)	RF	Not specified	Predicting drought related yield losses.	Barthauer Software GmbH Sidi Mohamed Ben Abdellah University	Germany Morocco
Niger	(Ogunjo, Olusola & Olusegun, 2024)	LSTM	RS	Predicting drought and flood.	York University Federal University of Technology University of Warsaw	Canada Nigeria Poland
Nigeria	(Adepoju, Ogundunmade & Adenuga, 2024)	ANN	Not specified	Monitoring drought impact on maize.	University of Ibadan	Nigeria
Nigeria	(Ogunrinde et al., 2020)	ANN	Not specified	Forecasting of precipitation and evapotranspiration.	Federal University of Technology	Nigeria
Rwanda	(Kombo, 2022)	EEMD-	Not specified	Predicting water quantity	University of Rwanda	Rwanda

		SVR-RF		in drought prone area.		
Senegal	(Kenne et al., 2024)	GRU	Not specified	Forecasting sub-seasonal temperatures.	University of Yaounde Centre Universitaire de Formation et de Recherche African Institute for Mathematical Sciences University Cheikh Anta Diop	Cameroon France Senegal Senegal
Sierra Leone	(Kaloop et al., 2022)	ANN GEP	Not specified	Predicting and modelling LST.	Southwest Jiaotong University Coastal Research Institute Mansura University Agency for Infrastructure Technology Advancement Incheon National University University of Engineering and Technology Peshawar	China Egypt Egypt Korea Korea Pakistan
Somalia	(Abdullahi et al., 2023)	SVR	Not specified	Forecasting drought.	Abrar University Institute for Water and Environmental Sustainability National University Netrich Technologies Center	Somalia Somalia Somalia Somalia
South Africa	(Mathivha, 2020)	LSTM	Giovanni	Predicting drought in river catchment.	University of Venda	South Africa
South Africa	(Phesa, Woyessa & Mbatha, 2023)	ARIMA-ANN	Not specified	Predicting evapotranspiration for agriculture.	Central University of Technology Department of Higher Education and Training University of Zululand Walter Sisulu University	South Africa South Africa South Africa South Africa
Sudan	(Alnayer et al., 2023)	XGBoost	Not specified	Forecasting rainfall in drought prone areas.	Technological University of Dublin Wad Medani Ahlian University	Ireland Sudan

					University of Khartoum	Sudan
Tanzania	(Lalika et al., 2024)	LSTM	Not specified	Predicting river drought conditions.	Swiss Federal Institute of Technology Amref health Africa Meteorological Agency Sokoine University of Agriculture	Switzerland Tanzania Tanzania Tanzania
Tunisia	(Trabelsi, Ali & Lee, 2022)	NB-RF-SVR	Not specified	Predicting ground potentiality in drought prone area.	Institute of Geoscience and Mineral Resources University of Science and Technology University of Jendouba USAID	Korea Korea Tunisia USA
Zambia	(Sleimi, Ghosh & Amarnath, 2022)	LSTM PCA	Not specified	Forecasting and monitoring drought.	International Water Management Institute CGIAR trust fund	Sri Lanka USA

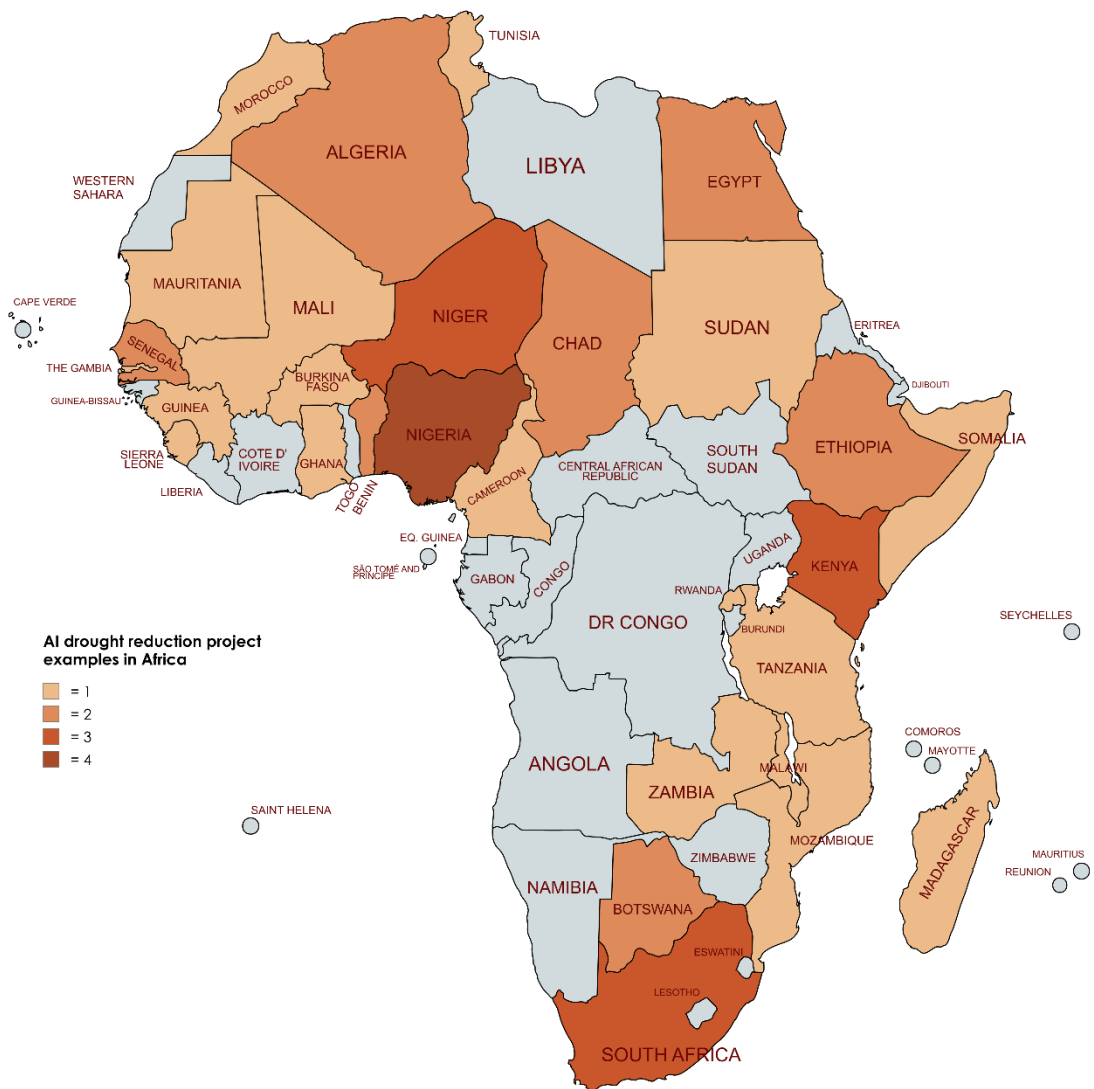


Figure 5.3.2: Map of AI for drought reduction project examples in Africa.

The complexity associated with drought has made efforts to reduce it in Africa extremely challenging. Africa not only faces frequent floods and droughts, but also an increased number of landslides. Landslides are devastating geohazards responsible for the loss of countless lives. With the rapid expansion of urbanisation, landslides are becoming increasingly problematic (Sim, Lee & Wong, 2022). The following section explores uses for AI in landslide risk and impact reduction projects.

5.3.3 Landslides

Much of Africa is prone to landslide hazards and in a changing climate the region remains increasingly at risk of devastating effects (Nahayo *et al.*, 2023). As climate and landslides only

overlap partially in terms of spatial-temporal scales, determining their impact on one another is extensively difficult (Gariano & Guzzetti, 2016). Landslides are described as a mass wasting process, acting on engineered and natural slopes (Gariano & Guzzetti, 2016). Simply, it is the mass movement of rock, debris or various states of earth, down a gravity driven slope. Although Africa experiences a multitude of landslides, AI projects in this section is lacking in comparison to the projects reducing flood and drought DR.

Nevertheless, some African countries are participating in AI landslide reduction efforts. African countries using AI for evaluating and assessing landslide DR are explored through the examples of Algeria, Ethiopia and Morocco. These countries can benefit from AI landslide evaluations and assessments as they all experience complex and unexpected landslides (Nassim *et al.*, 2022; Hearn, 2018; Elmoulat & Brahin, 2022). Also, in these countries, land use changes tend to happen on vulnerable landslide areas (Bourenane & Bouhadad, 2021; Woldesenbet, Telila & Feyessa, 2023; Obda *et al.*, 2022).

Examples of African countries using AI for susceptibility mapping of landslides include Algeria, Cameroon, Egypt, Morocco, Nigeria, Rwanda, and Zimbabwe. These countries are relevant to landslide susceptibility mapping as they all experience extreme and devastating landslides (Hallal *et al.*, 2024; Wantim *et al.*, 2023; Gamal, Abdelfattah & Maher, 2024; Habiballah, Witam & Iboussina, 2023; Ajake *et al.*, 2022; Mind'je *et al.*, 2019; Muchaka *et al.*, 2022). Additionally, these countries have areas of high vulnerability to landslides (Naima & Hynda, 2022; Djukem *et al.*, 2024; AbdelAziz & Al-Saeed, 2023; Sbihi *et al.*, 2024; Akintan *et al.*, 2023; Mugisha *et al.*, 2020; Chikodzi & Khumalo, 2021).

African countries predicting and modelling landslides through AI projects include the examples of Ethiopia, Kenya, Nigeria and Rwanda. These countries can benefit from modelling and predicting models as all of them have landslide prone areas threatening food security (Tadesse, Uncha & Toma, 2024; Obwocha *et al.*, 2022; Jumiyati *et al.*, 2021; Aloys & Vincent, 2024). Also, they all experience an array of trigger inducing landslides (Mebrahtu *et al.*, 2021; Njiraini, Okaka & Omondi, 2022; Gbadebo *et al.*, 2021; Uwihirwe, Hrachowitz & Bogaard, 2020).

Landslides can be characterised as hazards with high impact, wide distribution and devastating damages (He *et al.*, 2024). Therefore, it is essential to assess landslide susceptibility for developing regional DRM measures (Wang *et al.*, 2021). Various African countries can benefit from landslide assessment and evaluation models (Depicker *et al.*, 2020). AI assessment and evaluation projects used for African landslides are explored first.

5.3.3.1 Assessment & evaluation

Landslide susceptibility assessments are crucial to regional risk mitigation (Wang *et al.*, 2021). The evaluation of landslide inventories is the foundation for studying distribution, formation, susceptibility, risk assessment and landscape evolution (Qi *et al.*, 2021). AI can assist various countries in assessing and evaluating landslides (He *et al.*, 2024).

For example, in the Djebahia region of Algeria, AI is used for landslide susceptibility assessments (Matougui, Djerbal & Bahar, 2024). The project aims to compare the performance of ensembles with accordance to their inherent variation. Many models were assessed and found that the highest performing algorithm was Adaptive Boosting (AdaBoost). However, finer results were shown by the heterogeneous Stacking (ST) model and the Dynamic Ensemble Selection (DES) model which had the most accurate land density distribution output. The autonomous agent involvement extends to the University of Sciences and Technology Houari Boumediene in Algeria (Matougui, Djerbal & Bahar, 2024).

Furthermore, AI is used in the upper Blue Nile in Ethiopia for landslide susceptibility evaluations (Desalegn, Mulu, & Damtew, 2022). The study aims to identify landslide hotspots by generating maps and utilising GIS, AHP, and MCDM models. The results showed that AHP methods are good quality estimators of landslide susceptibility and inveterate test consistency in generated maps. Autonomous agent involvement only extends to the Debre Markos University in Ethiopia (Desalegn, Mulu, & Damtew, 2022).

The north-east of Morocco uses AI for producing landslide susceptibility assessments along the Taza-El Hoceima (Cherifi *et al.*, 2022). Due to the recurrent challenges landslides constitute in Morocco, its anticipative action has become crucial. Using five ML algorithms and twelve environmental parameters, the results allow for anticipatory mapping of landslides for over 98 km. The model found by the study to be most accurate was RF. Autonomous agent involvement includes the Moroccan universities namely Sidi Mohamed Ben Abdellah University and Han (Cherifi *et al.*, 2022).

Assessment and evaluation efforts are extensively important to understanding landslides and their DR. In this section, different AI projects assessed and evaluated landslide susceptibility. Landslide susceptibility is basically the measurement of landslide hazard occurrence likelihood in a specific area (Reichenbach *et al.*, 2018). Susceptibility mapping is crucial to understanding landslides and their potential (Lokesh *et al.*, 2024). AI susceptibility maps are utilised for DRR efforts in various countries (Pradhan *et al.*, 2023).

5.3.3.2 Susceptibility mapping

Landslide susceptibility maps provide a detailed geographical image of a vulnerable area (Mersha & Meten, 2020). Susceptibility mapping cannot predict time nor frequency, but it can predict location of occurrence (Huang *et al.*, 2024). The production of landslide susceptibility maps is crucial to developing land use plans in vulnerable regions (Sujatha & Sudharsan, 2024).

For example, Western Algeria uses AI for landslide susceptibility mapping efforts in the Mostaganem coast district (Senouci *et al.*, 2021). The study combined AHP & GIS and found outputs with excellent reliability and accuracy. It made use of GIS tools; the Raster calculator and the Weighted Overlay Method to combine aspect, lithology, slope, rainfall, distance to stream, and curvature plain. Autonomous agent involvement includes the University of Mostaganem in Algeria, the University of Porto in Portugal, and the University of Mohamed Ben Ahmed Oran in Algeria. Funding was provided in part by the University of Mostaganem and the University of Porto (Senouci *et al.*, 2021).

Cameroon uses AI to map rainfall triggered landslides in the Western highlands (Mfondoum *et al.*, 2021). The project adopts the Sudden Landslide Identification Product (SLIP), and the Detecting Real-Time Increased Precipitation (DRIP) algorithms developed by NASA. The method uses Landsat 8 satellite images and daily rainfall data for mapping landslides in real-time. Autonomous agent involvement includes the University of Yaounde I in Cameroon, the Institute of Mining and Geological Research in Cameroon, the University of Toulouse in France, Mohammed V University in Morocco, University of Texas in USA, and the University of Aix Marseille in France. The project was funded by the private consulting firm of StatsN'Maps in the USA (Mfondoum *et al.*, 2021).

Furthermore, Cameroon uses AI for landslide susceptibility mapping in Bafoussam and the surrounding areas (Segue *et al.*, 2024). The study uses a combination of statistical methods, ML algorithms, and multi-criteria decision making (MCDM) models. The most accurate susceptibility mapping ML models showed to be LR and NB. The study stresses the importance of integrating multiple methodologies for comprehensive risk management and assessment. The agents involved in the study are the University of Yaounde I in Cameroon and the Cameroonian Institute of Mining and Geological Research (Segue *et al.*, 2024).

Egypt is utilising AI for producing landslide susceptibility maps in the Wadi Feiran region (Youssef *et al.*, 2023). Hundreds of landslides occur annually after rainfall, which has increased the need for effective landslide hazard assessments. The project consists of comparing three ML models and found that ANN outperformed both the LR and an ensemble model. Autonomous agent

involvement includes the Sohag University in Egypt, the University of Patras in Greece, and Shiraz University in Iran (Youssef *et al.*, 2023).

In Morocco, AI is used for landslide hazard assessment and susceptibility mapping (Hamidi *et al.*, 2023). Landslides are considered one of the most significant natural hazards in the setting of the Rif region. Four ML models were used for the study namely SVM, LR, Classification and Regression Trees (CART), and Multivariate Discriminant Analysis (MDA). All four models were found to have similar accuracy levels. Agents involved in the study includes the University of Mohammed V de Rabat in Morocco, the Seattle University in the USA, the Geosciences Environnement Toulouse in France, the Avignon University in France, and the Mediterranean Environment and Modelling of Agro-hydrosystems in France (Hamidi *et al.*, 2023).

In the Orumba North erosion-prone region of Nigeria, AI is utilised for landslide susceptibility mapping (Nwazelibe, Unigwe & Egbueri, 2023). The study uses GIS and LR to produce accurate landslide prediction maps. It finds that the southern part of the region is most prone to landslides whereas, the northern region is the least likely. Autonomous agents involved are Albert Ludwig University of Freiburg in Germany, Alex Ekwueme Federal University in Nigeria, and the Chukwuemeka Odumegwu Ojukwu University in Nigeria (Nwazelibe, Unigwe & Egbueri, 2023).

Furthermore, western Rwanda uses AI and GIS for landslide susceptibility mapping (Nwazelibe *et al.*, 2023). The study made use of three landslide susceptibility mapping methods namely ANN, Shannon Entropy (SE) and Frequency Ratio (FR). AUC values provided reliable accuracy measures for the three models and found ANN to be the most accurate. Autonomous agents involved in the study are the Albert Ludwig University of Freiburg in Germany, the Chukwuemeka Odumegwu Ojukwu University in Nigeria, Oklahoma State University in the USA, Texas Christian University in the USA, and the King Fahd University of Petroleum and Minerals in Saudi Arabia (Nwazelibe *et al.*, 2023).

In Zimbabwe, AI is used for landslide detection and mapping across satellite sensors (Das & Wegmann, 2022). Due to the 2019 Cyclone Idai, thousands of landslides and floods have been triggered across southeastern Africa. The study utilised three ML algorithms namely ANN, RF, and SVM and found that RF was the most reliable and accurate model. The RF model used the PlanetScope satellite data and attained 97.88% prediction accuracy. Autonomous agents involved are the Center for Geospatial Analytics, and the Department of Marine, Earth and Atmospheric Sciences in North Carolina State University, USA (Das & Wegmann, 2022).

In this section, AI projects used for susceptibility mapping are utilised by various African countries. They fundamentally involve maps of vulnerable African areas prone to heavy rainfall and erosion.

AI landslide prediction and modelling projects are also inclined to applications in high-risk environments (Jiang *et al.*, 2022). Various examples of AI projects are explored in the following section on landslide prediction and modelling. AI landslide prediction projects use extensive geographical data to identify patterns in DR (Lokesh *et al.*, 2024). Whereas landslide susceptibility modelling is built upon the outputs of prediction and forecasting models (Chen & Li, 2020; Amato, 2021).

5.3.3.3 Prediction and modelling

Landslides are disreputably difficult to predict because of varying temporal and spatial factors that contribute to slope stability (Youssef *et al.*, 2023a). AI landslide prediction and modelling efforts can be beneficial for countries that are vulnerable to landslides. AI prediction and modelling projects are relevant to DRR, as both contribute to reducing the impact of prospective DR (see Chapter 3.2).

For example, Kenya utilises AI for seismic detection to monitor and predict susceptibility of landslides and earthquakes (Githu, Kagereki & Munyua, 2021). The study uses data obtained from the Worldwide Standardised Seismograph Station in Kilimambogo, Kenya. ANN is used to identify landslide and earthquake prone areas and showed to be accurate in its prediction efforts. Autonomous agent involvement includes Kenya's St. Pauls University in Nairobi, Jomo Kenyatta University of Agriculture and Technology in Nairobi, and the Karatina University in Nyeri, Kenya (Githu, Kagereki & Munyua, 2021).

Nigeria uses AI to map and predict the spatial likelihood of narrow landslides (Nnanwuba *et al.*, 2022). In Awgu, southeast Nigeria, landslides have become devastating hazards with limited research. The study uses three ML models namely XGBoost, NB, and RF to predict the likelihood of landslides. Autonomous agents include the Jilin University in China and the University of Nigeria. The work was funded by the National Natural Science Foundation of China and the Jilin Provincial University Science and Technology Department in China (Nnanwuba *et al.*, 2022).

In northwestern Ethiopia AI is used for modelling landslide susceptibility in the Abay Basin (Wubalem, 2020). Developing landslide susceptibility mapping is important for predicting landslide occurrences. The project applied various models for mapping efforts and found LR to be the most effective AI technique paired with GIS certainty factor. The model is used for landslide hazard mitigation, regional land use planning, and prevention efforts. The autonomous agent involvement only extends to the University of Gondar in Ethiopia (Wubalem, 2020).

Rwanda's upper Nyabarongo catchment uses AI for predicting landslide susceptibility and risks (Nsengiyumva & Valentino, 2020). The study compared RF, Logistic Model Tree (LMT), and Naïve Bayes Trees (NBT) with each other and integrated GIS techniques for prediction efforts. It finds that the hybrid model of NBT was the most effective and accurate prediction model. The study aims to inform further research on landslide risk reduction measures. Autonomous agents involved are the Institute of Policy Analysis and Research in Rwanda and the University of Parma in Italy (Nsengiyumva & Valentino, 2020).

In this section, prediction and modelling projects primarily concern the susceptibility of landslides in various vulnerable areas. Although AI projects related to the reduction of landslide hazards in Africa are few in this Chapter; AI project examples remain promising and indicate active participation and growth of an African HHR AI ecosystem.

Table 5.3.3: Summary of AI landslide hazard reduction project examples in Africa.

African Country	Project Reference	AI Model	Assisting Technology	Project Purpose	Autonomous Agents	Agent Country
Algeria	(Matougui, Djerbal & Bahar, 2024)	AdaBoost DES ST	Not specified	Assessing landslide susceptibility.	University of Sciences and Technology Houari Boumediene	Algeria
Algeria	(Senouci et al., 2021)	AHP	GIS	Mapping susceptibility of coastal district.	University of Mohamed Ben Ahmed Oran University of Mostaganem University of Porto	Algeria Algeria Portugal
Cameroon	(Mfondoum et al., 2021)	DRIP SLIP	Landsat 8	Mapping rainfall triggered landslides.	Institute of Mining and Geological Research University of Yaounde I University of Aix Marseille University of Toulouse Muhammed V University NASA StatsN'Maps University of Texas	Cameroon Cameroon France France Morocco USA USA USA
Cameroon	(Segue et al., 2024)	LR NB	MCDM	Mapping landslide susceptibility.	Institute of Mining and Geological Research University of Yaounde I	Cameroon Cameroon
Egypt	(Youssef et al., 2023)	ANN	Not specified	Mapping rainfall induced landslide susceptibility.	Sohag University University of Patras Shiraz University	Egypt Greece Iran
Ethiopia	(Desalegn, Mulu & Damtew, 2022)	AHP	GIS MCDM	Evaluating landslide susceptibility.	Debre Markos University	Ethiopia
Ethiopia	(Wubalem, 2020)	LR	GIS	Modelling landslide susceptibility.	University of Gondar	Ethiopia

Kenya	(Githu, Kagereki & Munyua, 2021)	ANN	Not specified	Modelling susceptibility of landslides and earthquakes.	Jomo Kenyatta University Karatina University St. Pauls University	Kenya Kenya Kenya
Morocco	(Cherifi et al., 2022)	RF	Not specified	Assessing landslide susceptibility.	Sidi Mohamed Ben Abdellah University Sultan Moulay Slimane University	Morocco Morocco
Morocco	(Hamidi et al., 2023)	CART LR MDA SVM	Not specified	Assessing and mapping landslide susceptibility.	Avignon University Geosciences Environment Toulouse Mediterranean Environment and Modelling of Agro-hydrosystems University of Mohammed V de Rabat Seattle University	France France France Morocco USA
Nigeria	(Nnanwuba et al., 2022)	NB RF XGBoost	Not specified	Mapping and predicting landslide likelihood.	Jilin University National Natural Science Foundation University of Nigeria	China China Nigeria
Nigeria	(Nwazelibe, Unigwe & Egbueri, 2023)	LR	GIS	Mapping landslide susceptibility.	Albert Ludwig University of Freiburg Alex Ekwueme Federal University Chukwuemeka Odumegwu Ojukwu University	Germany Nigeria Nigeria
Rwanda	(Nsengiyumva & Valentino, 2020)	NBT	GIS	Predicting landslide susceptibility and risk.	University of Parma Institute of Policy Analysis and Research	Italy Rwanda
Rwanda	(Nwazelibe et al., 2023)	ANN	GIS	Mapping landslide susceptibility.	Albert Ludwig University of Freiburg	Germany

					Chukwuemeka Odumegwu Ojukwu University	Nigeria
					King Fahd University of Petroleum and Minerals	Saudi Arabia
					Oklahoma State University	USA
					Texas Christian University	USA
Zimbabwe	(Das & Wegmann, 2022)	RF	Satellites	Detecting and mapping landslides.	North Carolina State University	USA



Figure 5.3.3: Map of AI used for landslide reduction project examples in Africa.

Many system changes and drivers can cause landslides to occur. Wildfires are amongst those drivers increasing landslide vulnerability. Due to the decrease in vegetation and the loss of root stability, landslide hazard potential increases (Rengers *et al.*, 2020).

Wildfire susceptibility, just as landslide susceptibility, are intensified by the growth of unregulated urban environments and changes in LULC (Shepherd, 2018). Wildfires have far-reaching effects on natural and man-made environments (Tymstra *et al.*, 2020). These effects can be categorized as long- and short-term, and may cause irreversible damage to the environment, animals and humans (Boroujeni *et al.*, 2024). In the next section, AI projects used for African wildfires are explored.

5.3.4 Wildfires

Wildfires are considered a major economic, environmental and social threat (Kouassi, Wandan & Mbow, 2020). It is one of the largest sources of deforestation and destruction around the world (Samee & Mohamed, 2021). The negative effects of wildfires outweigh the benefits of natural forest fires with decreasing air quality, landslides, erosion, and cardiovascular diseases (Edwards *et al.*, 2022). The continuous rise in wildfire frequency and severity has increased the attention to wildfire management and reduction efforts (Ramadan *et al.*, 2024a).

In this section, AI projects reducing the effects and risk of African wildfires are explored. These project examples include detection, mapping and prediction efforts. Research on AI wildfire detection in African countries is limited. Examples of African AI wildfire detection projects include Angola, and Egypt. Both these countries may benefit from AI wildfire detection projects as they experience a high frequency of these hazards in certain areas (Nieman, 2022; ThinkHazard, 2020). Additionally, wildfires have caused changes to natural vegetation in these countries (Catarino *et al.*, 2020; El Atfy, Uhl & Jasper, 2023).

AI wildfire mapping is important for DRR and include the examples of Algeria, Morocco, South Africa, Tunisia, and Kenya. All these countries can benefit from AI wildfire mapping projects as they experience extensively damaging forest fires (Bentekhici, Bellal & Zegrar, 2020; Castro *et al.*, 2022; Constant & Taylor, 2020; Saidi, Younes & Anselme, 2021; Karani, Sichangi & Gachiari, 2021). Also, they all have areas with high vulnerability to wildfires (Djabri *et al.*, 2023; El Mazi *et al.*, 2024; Heyns *et al.*, 2020; Rezgui *et al.*, 2024; Kigomo & Kuria, 2024).

Wildfire prediction projects are explained using the examples of Algeria, Botswana, Cote d'Ivoire, Ghana, Kenya, Madagascar, Morocco, Tunisia, and South Africa. Wildfire prediction can be useful to these countries as all of them experience a high frequency of wildfire risk (Benbakkar *et al.*, 2024; Maabong & Mphale, 2021; Kouassi, Wandan & Mbow, 2022; Dadzie & Mary, 2022; Kigomo & Kuria, 2024; Champin, Taibi & Ballouche, 2022; Boubekraoui *et al.*, 2023; Belhadji-Khedher, El-Malki & Mouillot, 2020; Moyo *et al.*, 2020).

Additionally, all these countries experience wildfires that are exemplified by climate change (Zerouali *et al.*, 2023; Singo *et al.*, 2023; Diabate & Dibi-Anoh, 2024; Kantanka *et al.*, 2023; Ndalila, Lala & Makindi, 2024; Wan & Roy, 2022; Boubekraoui *et al.*, 2024; Touhami *et al.*, 2023; Liu *et al.*, 2023). Therefore, AI wildfire prediction models can aid in reducing the unpredictability of climate change in these countries. Wildfires are not always preventable, however if detected early enough, their effects can be reduced (Mohapatra & Trinh, 2022).

5.3.4.1 Detection

Often wildfires occur in remote locations, making early detection difficult (Rashkovetsky *et al.*, 2021). Early wildfire detection can improve response time and damage control (Mohapatra & Trinh, 2022). Therefore, wildfire early warning systems are convenient for reducing DR in vulnerable areas. Conventional fire detection methods have shown latency and low reliability in the past, whereas AI systems show improvements in detection accuracy and time (Ramadan *et al.*, 2024a).

For example, Angola uses AI for detecting fire disturbances in forests (Santi *et al.*, 2022). The project aimed at utilising the Global Navigation Satellite System Reflectometry (GNSS-R) for the detection forest fire disturbances. Data was collected using the NASA Cyclone GNSS constellation. Classifiers based on SVM, and RF were used to distinguish burned from not-burned areas; and regressors based ANN, RF, and SVR were used for estimating the fraction of burned areas. Autonomous agents involved are the National Research Council in Italy, Deimos Space in UK, La Sapienza University of Rome in Italy, and Tor Vergata University in Italy (Santi *et al.*, 2022).

In Egypt, AI is used for fire detection and suppression efforts (Samee & Mohamed, 2021). The control and detainment of wildfires are challenging and complex ventures. Due to the flow of spatially spreading processes, many parameters must be considered in modelling fire dynamics, spread rates, and directional biases. The study uses a DL technique known as the Ant Colony Algorithm (ACA). It found that ACA can be run continuously and adapt to changes in real-time. Autonomous agents only extend to the University of Alexandria in Egypt (Samee & Mohamed, 2021).

Even though there is a lack in documented research on AI wildfire detection projects in Africa, it does not eliminate potential existing undocumented projects. This is true for all the mentioned HHR AI projects in this research. African wildfires are significantly devastating hazards which induce chaos and destruction (Uitto, 2021). Mapping projects are essential to detection efforts, as detection cannot happen without precise location (Wang *et al.*, 2021a). AI wildfire susceptibility mapping has proven to be beneficial for fire-prevention plans (Bjanes, De La Fuente & Mena, 2021).

5.3.4.2 Mapping

AI mapping shows great promise for reducing various hazards (Pourghasemi *et al.*, 2020). It provides detailed data and efficiency to assessment efforts (Gholamnia *et al.*, 2020). The motion

filled nature of wildfires demand accurate mapping of vulnerable and exposed areas (Iban & Sekertekin, 2022). AI wildfire maps are discussed in this section according to fire severity mapping, fire susceptibility mapping, fire damage mapping, and fire tracking maps. Various African countries use AI wildfire mapping projects.

For example, northern Algeria uses AI for accurate fire severity mapping (Zikiou *et al.*, 2024). The devastation caused by forest fires in Algeria requires effective mitigation and management efforts. Understanding the severity of wildfire impact is crucial to these ventures. The study uses satellite imagery analysis, GIS and ML techniques to assess the severity levels of the forest fires. ML algorithms in this project includes SVM and CNN. Autonomous agents are Yale University in the USA, the University of Granada in Spain, and the Mouloud Maameri Tizi Ouzou University in Algeria (Zikiou *et al.*, 2024).

In northern Morocco AI is coupled with remote sensing to determine forest fire susceptibility maps (Seddouki *et al.*, 2023). Three GIS based ML algorithms are utilised in the study and include XGBoost, RF, and SVM models. The most accurate model is identified as the XGBoost algorithm and showed the most accurate forecasting outputs. The result of this study provides crucial support to management of the Mediterranean forest ecosystem and enhance efficient planning of forest resource protection ventures. Autonomous agents involved are the Hassan II University of Morocco (Seddouki *et al.*, 2023).

South Africa is utilising AI for producing burned area maps of the southern Cape forestry region (Xulu, Mbatha & Peerbhay, 2021). Planted forests have suffered from damaging fires for the past decade and account for over 80% of the country's timber losses. Accurate mapping and detection are critical to South African fire management efforts. The project uses the RF based GEE cloud platform to categorise burn severity areas and carbon monoxide plumes using Sentinel 2 and 5. Autonomous agents include the South African universities of the Free State, Zululand, and KwaZulu-Natal (Xulu, Mbatha & Peerbhay, 2021).

Tunisia uses AI for wildland forest fire mapping and tracking (Mouelhi *et al.*, 2022). Real-time video tracking of smoke and fire proves useful to regional measures and evaluating damages. The study uses ANN and NB models to map and track wildfires. The experimental results proved accurate and robust in establishing preliminary fire localisation. The models were effective when tested on various wildfire-smoke scenarios. Autonomous agents are the University of Tunis in Tunisia, and the University of Toulon in France (Mouelhi *et al.*, 2022).

Kenya uses AI for modelling and mapping wildfire risk in the Aberdare Afromontane Forest ranges (Kigomo & Kuria, 2024). Establishing wildfire risk maps is vital to creating and sensitizing

awareness of the mobilisation of resources and fire prevention strategies. The project uses an AHP model integrated with GIS techniques. The results indicate that land cover is the most important factor in developing wildfire risk maps. Autonomous agents extend to the Kenya Forestry Research Institute (Kigomo & Kuria, 2024).

Mapping wildfires are essential to obtaining data and determining hazard severity (Iban & Sekertekin, 2022). Wildfires are notoriously complex and unpredictable (Turney, 2024). Mapping can be utilised for predictive purposes, which mostly involve location detection and the establishment of vulnerable environments (Yousefi *et al.*, 2020). Wildfire prediction is crucial to the reduction of its risks and effects in Africa (Kouassi, Wandan & Mbow, 2020). Accurate prediction efforts prove vital to early detection and the management of prospective wildfire DR.

5.3.4.3 Prediction

The extensive complexity inherent to wildfires makes their prediction challenging (Sayad, Mousannif & Moatassime, 2019). AI for predicting wildfires has shown promising results and may be ideal for optimising existing statistical models (Wood, 2021). Access to a multitude of data sources can enable more accessible training data for AI prediction models (Baynes, 2024). In this section, these models predict wildfires in various African environments.

For example, Algeria uses AI for the prediction of wildfires in forests (Zaidi, 2023). As one of the most affected in the Maghreb countries, Algeria faces the consequences of wildfires years after their occurrence. Due to the lack in datasets, prediction of wildfires in Algeria is limited to mapping various risk areas with high vulnerability levels. The study compared five ML models namely LR, KNN, SVM, ANN, and RF; and found ANN to be the most accurate and efficient prediction model. The autonomous agents involved are the Qassim University of Saudi Arabia, which both researched and funded the study (Zaidi, 2023).

In Botswana, AI is used for predicting and monitoring wildfires in the rangeland areas of the Kgalagadi district (Kaduyu, 2023). The increased frequency of wildfire occurrences in Botswana poses significant danger to rangeland ecosystemic well-being. Therefore, the study aims to predict and monitor wildfires using RF and LR models. The RF model used observed fire occurrence points and select environmental variables for prediction. The LR model was used to develop a wildfire probability map that was applied to best performing variables. Agent involvement includes the Botswana University of Agriculture and Natural Resources (Kaduyu, 2023).

Cote d'Ivoire uses AI for predictive modelling of wildfire occurrence and damage to the tropical savanna ecosystem in West Africa (Kouassi, Wandan & Mbow, 2020). Cote d'Ivoire is amongst the African countries with the most forestry and environmental problems during the dry season. The study used satellite historical data to appropriate a wildfire forecasting model. The model used was the ARIMA technique and showed promising results. Autonomous agent involvement includes the Institut National Polytechnique Félix Houphouët-Boigny in Cote d'Ivoire and the University of Pretoria in South Africa (Kouassi, Wandan & Mbow, 2020).

Ghana uses AI for establishing future potential impact of environmental and climate changes on wildfire spread (Dahan *et al.*, 2024). The study explores how climate change affects the spreading of wildfire in the forest-savannah mosaic and the Guinean savannah. By using RF regression, the results predicted a decrease in rainfall and an increase in drought. Increasing the environments exposure and vulnerability to wildfire risk. Autonomous agents involved are the University for Developmental Studies in Ghana, the Université Gaston Berger de Saint Louis in Senegal, and the University of Nairobi in Kenya (Dahan *et al.*, 2024).

In Kenya, AI is used for predicting monthly vegetation on fire frequency (Orero, Omondi & Omolo, 2024). The study gives a comprehensive analysis of historical data on fire and climate for establishing prediction outputs. The AI algorithm NB and Bayesian Negative Binomial (BNB) is used in conjunction with MODIS data from 2000-2018. The results showed that BNB outperformed the NB model in forecasting accuracy. Autonomous agents involved in the study include the University of Nairobi in Kenya, the Strathmore University in Kenya, and the University of Witwatersrand in South Africa (Orero, Omondi & Omolo, 2024).

Madagascar utilises AI for predicting forest fires (Edwards *et al.*, 2022). The island of Madagascar has struggled for decades to manage and control its forest fires. Lacking research, the study aimed at producing a cost effective and flexible AI model for predicting forest fires. The RF based GEE cloud platform is used to train an ANN model and predict forest fires a month in advance. The final model gave accurate results and an efficient performance. Autonomous agents involved in the study are the USA Harvard University in Cambridge and in Boston (Edwards *et al.*, 2022).

Northern Morocco uses AI for predicting seasonal forest fires (Mharzi-Alaoui *et al.*, 2022). The prediction of forest fire risk is a vital component to combating strategies and territorial risk management. MODIS and Landsat satellite imagery data is used. It represented variables such as rainfall, Normalised Difference Vegetation Index (NDVI), wind, water balance, and evapotranspiration. RF is used to find the most fitting link between predictors and variables of seasonal forest fire risk. Autonomous agents are the Mohammed VI Polytechnic University in Morocco, University of North Carolina in the USA, Hassan II Institute of Agronomy and Veterinary

Medicine in Morocco, the Moroccan National Center for Climatic and Forest Risk Management, and the Department of Forest and Water in Morocco (Mharzi-Alaoui *et al.*, 2022).

Tunisia uses AI for forest fire risk prediction (Salhi *et al.*, 2023). The focus of the study is to develop an intelligent approach to preventing and predicting wildfires caused by various predictors. The study uses ML and evolutionary DL techniques to create an ANN model that can respond in real-time through interacting with the IoT. Using the program Python, fire risk prediction was established for the year 2025 across the Jandouba delegations. Autonomous agents involved are the National Engineering School of Tunis in Tunisia, the Northern Border University in Saudi Arabia, and the University of Tunis in Tunisia (Salhi *et al.*, 2023).

South Africa uses AI for developing an integrated grassland fire danger assessment system in the Golden Gate Highlands National Park (Mofokeng, Adelabu & Jackson, 2024). The assessment of fire risk should establish possible predictors of the hazard and become key to sustainable management efforts. The study uses LR, DT, RF, and SVM in combination with the GEE platform. It found that DT has the highest precision for success rate and model fit, compared to the other models. The autonomous agents extend to the University of the Free State in South Africa (Mofokeng, Adelabu & Jackson, 2024).

Table 5.3.4: Summary of AI wildfire hazard reduction project examples in Africa.

African country	Project Reference	AI Model	Assisting Technology	Project Purpose	Autonomous Agents	Agent Country
Algeria	(Zaidi, 2023)	ANN	Not specified	Predicting forest wildfires.	Qassim University	Saudi Arabia
Algeria	(Zikiou et al., 2024)	CNN SVM	GIS Satellite-images	Mapping forest fire severity.	Mouloud Maameri Tizi Ouzou University University of Granada Yale University	Algeria Spain USA
Angola	(Santi et al., 2022)	ANN RF SVM SVR	GNSS-R NASA GNSS	Detecting wildfire disturbances in forest.	La Sapienza University of Rome National Research Council Tor Vergata University	Italy Italy Italy
Botswana	(Kaduyu, 2023)	LR RF	Not specified	Predicting and monitoring wildfires.	University of Agriculture and Natural Resources	Botswana
Cote d'Ivoire	(Kouassi, Wandan & Mbow, 2020)	ARIMA	Satellite data	Predictive modelling of wildfire.	Institut National Polytechnique Félix Houphouët-Boigny University of Pretoria	Cote d'Ivoire South Africa
Egypt	(Samee & Mohamed, 2021)	ACA	Not specified	Detecting and suppressing wildfire.	University of Alexandria	Egypt
Ghana	(Dahan et al., 2024)	RF	Not specified	Predicting climate change impact on wildfire.	University for Developmental Studies University of Nairobi Université Gaston Berger de Saint Louis	Ghana Kenya Senegal
Kenya	(Kigomo & Kuria, 2024)	AHP	GIS	Mapping and modelling wildfire risk.	Forestry Research Institute	Kenya

Kenya	(Orero, Omondi & Omolo, 2024)	BNB	MODIS	Predicting monthly vegetation on fire frequency.	Strathmore University University of Nairobi University of Witwatersrand	Kenya Kenya South Africa
Madagascar	(Edwards et al., 2022)	ANNRF	GEE	Predicting forest fires.	Harvard University in Boston Harvard University in Cambridge	USA USA
Morocco	(Mharzi-Alaoui et al., 2022)	RF	Landsat MODIS	Predicting seasonal forest fires.	Department of Forest and Water Hassan II Institute of Agronomy and Veterinary Medicine Mohammed VI Polytechnic University National Center for Climatic & Forest Risk Management University of North Carolina	Morocco Morocco Morocco Morocco USA
Morocco	(Seddouki et al., 2023)	XGBoost	GIS	Mapping forest fire susceptibility.	Hassan II University	Morocco
South Africa	(Mofokeng, Adelabu & Jackson, 2024)	DT	GEE	Predicting grassland fire danger.	University of the Free State	South Africa
South Africa	(Xulu, Mbatha & Peerbhay, 2021)	RF	GEE Sentinel 2 Sentinel 5	Mapping burned areas.	University of the Free State University of KwaZulu-Natal University of Zululand	South African South Africa South Africa
Tunisia	(Mouelhi et al., 2022)	ANN NB	Not specified	Mapping and tracking forest fire.	University of Toulon University of Tunis	France Tunisia
Tunisia	(Salhi et al., 2023)	ANN	Python	Predicting wildfires caused by various predictors.	Northern Border University National Engineering School of Tunis University of Tunis	Saudi Arabia Tunisia Tunisia



Figure 5.3.4: Map of AI for wildfire reduction project examples in Africa.

Although this section is lacking in literature, it is important to recognise existing efforts in African AI wildfire reduction. A section truly lacking in published work is AI for tropical cyclone reduction in Africa. These projects are rare because of the challenges associated with data and the complexity of fluid thermodynamics (McGraw & Beucler, 2023).

5.3.5 Tropical Cyclones

Tropical cyclones occur in various countries and have shown rising levels of frequency and intensity (Dube & Nhamo, 2021). Many have found AI to be a promising means of understanding and predicting tropical cyclones (Chen, Zhang & Wang, 2020). In this section, very few documented AI projects could be located on African reduction efforts.

To broaden the search parameters, the researcher included AI projects that concern the reduction of tropical cyclones from the Atlantic and the Indian Ocean. The Atlantic Ocean meets the shores of Algeria, Libya, Egypt, Morocco, Mauritania, Senegal, The Gambia, Guinea-Bissau, Guinea, Sierra Leone, Liberia, Cote d'Ivoire, Ghana, Togo, Benin, Nigeria, Cameroon, Equatorial Guinea, Gabon, Republic of Congo, Angola, Namibia and South Africa. Whereas the Indian Ocean meets the shores of South-Africa, Mozambique, Madagascar, Tanzania, Kenya, Somalia, Djibouti, Eritrea, Sudan and Egypt.

AI for tropical cyclone detection is discussed using the examples of the Atlantic and Indian Ocean. The African countries in contact with the Atlantic and Indian ocean can benefit from AI automatic detection projects because both oceans are warming and influencing atmospheric circulation (Bronseleer & Zanna, 2020; Dhame *et al.*, 2020). Additionally, both have high levels of tropical cyclone DR as they are prone to atmospheric instability (Heukamp *et al.*, 2022; Lenka *et al.*, 2022).

Furthermore, AI for predicting tropical cyclones is explored in this section through considering the Atlantic and Indian Ocean. African countries in contact with these oceans can benefit from AI predicting tropical cyclones as both oceans experience increased frequency of these hazards (Lima *et al.*, 2021; Swapna *et al.*, 2022). Also, both are exposed and impacted by the effects of climate change (Franco *et al.*, 2020; Douglass & Cooper, 2020).

Examples of African countries that use AI for predicting tropical cyclones are Egypt and Mozambique. Both these countries can benefit from AI tropical cyclone prediction projects as they are vulnerable to sea-level rise and storm surges (Torresan *et al.*, 2020; Mucova *et al.*, 2021). Additionally, both countries are planning smart-city development and sustainable infrastructure (Abdelfattah *et al.*, 2022; Calzada, 2023).

Detection of tropical cyclones can help protect current livelihoods in vulnerable countries (Dube & Nhamo, 2021a). Existing algorithmic performance in tropical cyclone detection has been infrequent (Wu & Duan, 2023). However, AI models have shown promise in producing automatic and timely tropical cyclone detection (Nair *et al.*, 2021).

5.3.5.1 Detection

Tropical cyclone detection is essential to mitigating natural hazards and damages to infrastructure, livelihoods and the economy (Fang, Sheng & Wang, 2022). Additionally, it is crucial for executing advanced warning to affected regions (Nair *et al.*, 2021). In this section, AI is used for automating tropical cyclone detection.

For example, in the Atlantic coastal area, AI is used to detect tropical cyclones (Malothu, Prasad & Krishna, 2022). The automatic detection of tropical cyclone cyclical patterns is challenging due to cloud obstructions. The study presents an automatic tropical cyclone detection algorithm. It uses satellite imagery and computer vision task Optical Flow Estimator (OFE) with the AI algorithm of Residual Networks (RN). Autonomous agents include Indian institutions of the Jawaharlal Nehru Technological University Kakinada and the Gudlavalleru engineering college (Malothu, Prasad & Krishna, 2022).

Similarly, AI is used in the Indian Ocean to automate detection and tracking tropical cyclones (Nair *et al.*, 2021). The study uses DL algorithms with satellite images and remote sensing technology. DL algorithms include the mask region-convolutional neural network (MR-CNN) for detection, CNN for classification, and NB for optimization. The project includes the autonomous agents from the Indian Institute of Technology, Delhi in India (Nair *et al.*, 2021).

In this section, AI cyclone detection is used for automatically identifying the formation of this hazard. Making it possible to evacuate and prepare for its impact. Similarly, timely tropical cyclone prediction is crucial to the reduction and management of its risk and impact (Kuleshov *et al.*, 2020). Prediction of cyclone behaviour is extensively difficult as many complex interactions and aspects play a vital role in its emergence (Wang *et al.*, 2022a).

5.3.5.2 Prediction

Tropical cyclones have posed significant challenges to infrastructure, communities and human lives (Jayaraman *et al.*, 2023). AI weather models struggle with predicting out-of-distribution gray swan hazards (possible but unlikely hazards) because of their rarity and lack of training datasets (Sun *et al.*, 2024). Due to computational restraints, uncertainties in the meteorological forces and relevant oceanic physics are partially accounted for (Nederhoff *et al.*, 2024). Therefore, AI used for mitigation of these adverse effects is crucial for improving preparedness efforts (Jayaraman *et al.*, 2023).

For example, AI is used for predicting Indian Ocean cyclone parameters and track (Chand *et al.*, 2022). Precise prediction of a cyclone track entails considering pressure, time of crossing, landfall point and windspeed. ANN uses the data from the International Best Track Archive for Climate Stewardship (IBTrACS) and the National Oceanic and Atmospheric Administration (NOAA) to determine cyclone parameters. Autonomous agents are the Andhra Pradesh State Disaster Management Authority in India and the Florida State University in the USA (Chand *et al.*, 2022).

In the North Atlantic and eastern North Pacific Ocean, AI is utilised for predicting tropical cyclone rapid intensification (Griffin, Wimmers & Velden, 2022). CNN is used for this project as it learns from spatial fields and physical features. It uses satellite imagery of two-dimensional structures and their changes to indicate rapid intensification. The study found that CNN is more effective at predicting rapid intensification than the existing scalar assessment of satellite brightness temperature. Autonomous agents include the University of Wisconsin in the USA (Griffin, Wimmers & Velden, 2022).

AI is used for tropical cyclone intensity estimation over the Indian Ocean (Biswas, Kumar & Pandey, 2021). Tropical cyclones can cause heavy rain resulting in floods and strong winds resulting in extensive damage. Various AI models are used in the study to estimate cyclone grade and maximum sustained surface wind speed. XGBoost outperformed all other AI algorithms and provided the most accurate results. Autonomous agents are the Department of Computer Science in Indraprastha Institute of Information Technology in India and the University of Delhi in India (Biswas, Kumar & Pandey, 2021).

In the Atlantic Ocean, AI is used to forecast probabilistic tropical cyclone intensity (Meng *et al.*, 2023). The study proposes a hybrid AI model between LightGBM (Light Gradient Boosting Machine) and NGBoost (Natural Gradient Boosting) to create the TCP-NGBoost (Tropical Cyclone Probabilistic Natural Gradient Boost) algorithm. The AI model uses satellite data from a statistical dynamical model named SHIPS (Statistical Hurricane Intensity Prediction Scheme). Autonomous agents are the Chinese Beijing Normal University, China University of Petroleum, Chinese Academy of Sciences, Southern Marine Science and Engineering Guangdong Laboratory in China, and the Polytechnical University of Madrid in Spain (Meng *et al.*, 2023).

Developing efficient smart cities in Egypt requires various DRR ventures, one being accurate cyclone intensity predictions (Jayaraman *et al.*, 2023). The novel technique called Linear Support Vector Regressive Gradient Descent Jaccardized Deep Multilayer Perceptive Classifier (LEGEMP) is used to assist in reducing the complexity of severity prediction. The study found that the LEGEMP model produced reliable and precise predictions. Autonomous agents are the Deemed University in India, the Delta University for Science and Technology in Egypt, the Princess Nourah bint Abdulrahman University in Saudi Arabia, and the King Salman International University in Egypt (Jayaraman *et al.*, 2023).

Mozambique applies AI for predicting compound flooding due to the impact of tropical cyclones (Nederhoff *et al.*, 2024). Tropical cyclones come with a certain degree of uncertainty, which this study aimed to include in calculating flood risk. The forecasting model includes uncertainties such as forward speed, track, intensity, and wind speed. Gaussian Error Distribution (GED) and AR

techniques are utilised for considering inherent uncertainties linked to tropical cyclones. Agent involvement includes Delta USA, Naval Research Lab in USA, UNESCO-IHE Institute for Water Education in the Netherlands, and the Marine and Coastal Management in Netherland (Nederhoff *et al.*, 2024).

The limited projects in tropical cyclone prediction are due to the extensive complexity associated with the hazard and the lack in training datasets (Sun *et al.*, 2024). Attempts in developing African AI tropical cyclone reduction models are present but still in its infancy. Although there are not many documented projects, ML can improve understanding and predicting tropical cyclones (McGraw & Beucler, 2023).

Table 5.3.5: Summary of AI tropical cyclone hazard reduction project examples in Africa.

African Country	Project Reference	AI Model	Assisting Technology	Project Purpose	Autonomous Agents	Agent Country
Atlantic Coast	(Malothu, Prasad & Krishna, 2022)	RN	OFE Satellite-images	Detecting tropical cyclones.	Gudlavalleru engineering college Jawaharlal Nehru Technological University Kakinada	India India
Atlantic Coast	(Griffin, Wimmers & Velden, 2022)	CNN	Satellite-images	Predicting cyclone rapid intensification.	University of Wisconsin	USA
Atlantic Coast	(Meng et al., 2023)	TCP-NGBoost	Not specified	Forecasting probabilistic tropical cyclone intensity.	Beijing Normal University Guangdong Laboratory University of Petroleum Polytechnical University of Madrid	China China China Spain
Egypt	(Jayaraman et al., 2023)	LEGEMP	Not specified	Predicting cyclone intensity.	Delta University for Science and Technology King Salman International University Deemed University Princess Nourah bint Abdulrahman University	Egypt Egypt India Saudi Arabia
Indian Ocean	(Biswas, Kumar & Pandey, 2021)	XGBoost	Not specified	Estimating cyclone intensity.	Indraprastha Institute of Information Technology University of Delhi	India India
Indian Ocean	(Chand et al., 2022)	ANN	IBTrACS NOAA	Predicting cyclone parameters and track.	Andhra Pradesh State Disaster Management Authority Florida State University	India USA

Indian Ocean	(Nair et al., 2021)	CNN MRCNN	RS Satellite- Images	Detecting and tracking tropical cyclones.	Indian Institute of Technology	India
Mozambique	(Nederhoff et al., 2024)	AR GED	Not specified	Predicting cyclone induced flooding.	Marine and Coastal Management UNESCO-IHE Institute for Water Education Delta Naval Research Lab	Netherlands Netherlands USA USA

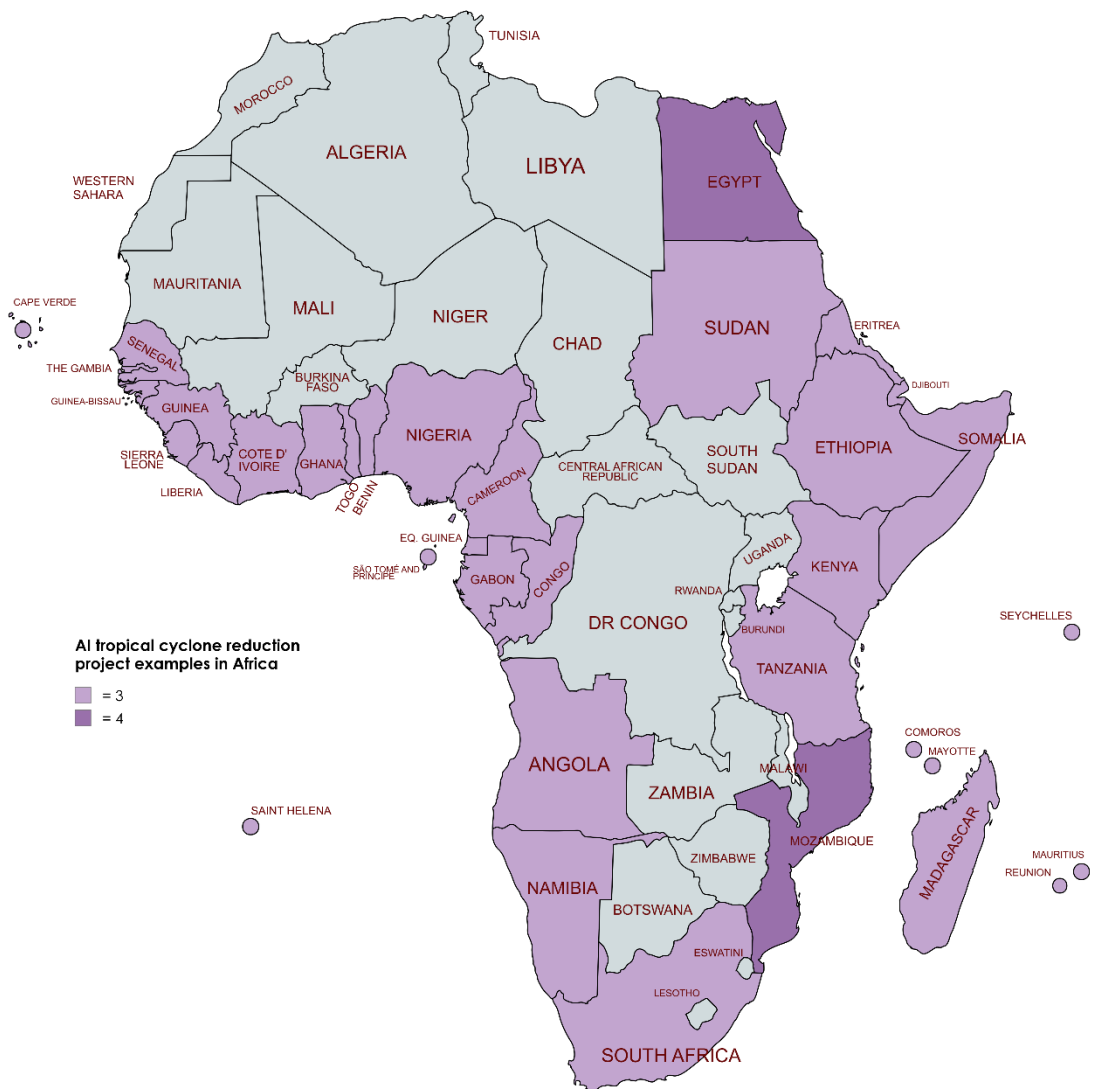


Figure 5.3.5: Map of AI for tropical cyclone reduction project examples in Africa.

The examples mentioned in this section are limited, however, contain AI models and assisting technologies unheard of in the other project sections. This can be due to the complexity associated with tropical cyclone models and the attempt to match this complexity with AI models. Perhaps, in the future there will be more AI tropical cyclone projects to explore in Africa.

5.5 Conclusion

In this Chapter, many AI project examples were explored and summarised. This chapter indicates that there are multiple projects being developed in Africa for HHR. The extensivity of these project examples show high interest in AI for DRR in Africa. Water management and LULC efforts are among the most popular projects and were located the easiest of all the mentioned categories. Whereas wildfire and tropical cyclone reduction are among the least popular project examples in

Africa and were extensively challenging to locate. This Chapter explored the fourth objective in the research which is to investigate different AI projects specifically involved in reducing African hydrometeorological hazards and identify autonomous agent involvement.

This was achieved by first exploring prospective hydrometeorological hazard reduction with relation to CCA. This section considered water management projects and land use and land cover (LULC) efforts. Water management was discussed in terms of water-quantity and -quality projects. Water quality and quantity consisted of projects focused on AI evaluating, monitoring and predicting efforts. LULC projects were explored through urbanisation & rural development, and environmental conservation. Both sub-categories were discussed with relation to AI evaluating, mapping, monitoring, and predicting efforts.

Secondly, corrective and residual hydrometeorological DRR projects were explored through flooding, drought, landslides, wildfires and tropical cyclones. Flood reduction projects in Africa were discussed according to AI prediction, susceptibility mapping, monitoring and assessment. Drought reduction projects were identified and discussed with relation to forecasting, predicting, and monitoring efforts. Furthermore, landslide reduction projects were explored through considering AI assessment and evaluation, susceptibility mapping, and prediction and modelling. Wildfire reduction projects were discussed in terms of AI mapping, prediction, and detection ventures. Also, tropical cyclone reduction was explored by considering AI detection and prediction projects.

Lastly, each section concludes with a summary of the AI project examples included in the research using a Table. Tables were compiled for each sub-section to structure and visually simplify the data collected on the project examples. Furthermore, a geographical map was included to visually represent the African countries involved in each section and their amount of involvement.

Ultimately, this Chapter aimed at identifying and exploring AI projects used for CCA & HHR in Africa. In the following Chapter, all the AI project examples are discussed in connection to one another. The themes identified in this Chapter is explored further and coded to create various network graphs. The network graphs are then discussed and assessed for similarities and/or patterns. This is an attempt to portray the high level of complexity involved in AI used for hydrometeorological DRR in Africa.

CHAPTER 6 FINDINGS

6.1 Introduction

AI used for combatting hydrometeorological hazards in Africa has shown to be a versatile and vibrant ecosystem. The collection and exploration of AI project examples for African HHR between 2020 and 2024, indicates a range of R&D activities. The project examples mentioned in Chapter 5 forms part of the African DRR AI ecosystem, expanding by imploring interdisciplinary agents and stakeholders. The collaboration of various agents and entities are crucial to the development of sustainable and resilient AI models for HHR in Africa (Eke, Chintu & Wakunuma, 2023).

This section illustrates and explains the key details and insights to the study. The purpose of this Chapter is to describe, analyse and discuss the AI project examples mentioned in the literature of Chapter 5, which is coded into quotations² and establish nodes to help visually represent the project examples into various network graphs. As mentioned in Chapter 2, CAS network theory is more concerned with understanding the connections between nodes than the nodes themselves (Polishchuk, 2018).

Firstly, the dominant nodes identified in the various project examples are tabulated to indicate key role-players presented by the data. This helps identify the most weighted nodes in the various networks. Secondly, each sub-section of Chapter 5 is discussed according to the most prominent network connections. These connections established by considering each connection weight in the graph. They are discussed and analysed according to the various project example dynamics such as AI model use (single or hybrid), assisting technology included, project functions, and autonomous agent relationships. These connections are visually represented in a co-occurring network graph (for each section) to indicate the elaborate formation of a DRR AI ecosystem in Africa.

The most prominent connection discussed in water management is between ANN and predicting water quantity. In LULC, RF and GEE have the most prominent connection in the network. Flood reduction's most prominent network connections include ANN and RF predicting floods, predicting floods and Nigeria, and assessing and mapping floods using RF. Prominent network connections in drought reduction consists of RF and monitoring drought. Landslide reduction network

² Quotations consist of the various AI HHR project examples in Africa. The number of quotations equals the node weight. In other words, the number of quotations a node has attributes to the scale and prominence of a node.

connections are between LR and landslide susceptibility, and GIS and landslide susceptibility. Wildfire reduction's prominent connections include RF and wildfire prediction, and GIS and wildfire mapping. Lastly the most prominent connections in tropical cyclone reduction examples include Egypt/Mozambique and tropical cyclone prediction, and CNN and satellite images.

Lastly, all the mentioned projects are compiled into a geographic map of Africa, indicating the most active countries focused on reducing hydrometeorological hazards and using AI to advance DRR. The most weighted nodes in the various project examples are discussed first. This is done to indicate prominent involvement from various AI models, assisting technologies, project functions, and local/national and international autonomous agents.

6.2 Prominent nodes

The prominent nodes identified in Table 6.2 shows the involvement of key entities in reducing African hydrometeorological hazards using AI. Combined, the African countries with the most project examples in the literature equates to Egypt (10) and Nigeria (10). These countries have various motivations for imploring these project examples. For instance, Egypt's evapotranspiration processes are projected to drastically change due to climate change (Mokhtar et al., 2024; Ads, Pingale & Khare, 2023).

Furthermore, Egypt struggles with rapid and unregulated urban expansion trends (urban sprawl) (Salem, 2024; Saber et al., 2020; Youssef, Sewilam & Khadr, 2020), and increased hazards due to environmental degradation (AbdelRahman, Afifi & Scopa, 2022; The World Bank, 2019; Ibrahim, 2020). Nigeria undergoes extreme exposure to climate change induced floods (Echendu, 2023; Ani, Anyika & Mutambara, 2022) and suffers multiple economic and environmental losses from unexpected hazards (Amaechina et al., 2022). Additionally, Nigeria experiences extensive erosion prone landscapes (Nwazelib, Unigwe & Egbueri, 2023) and drought driven crises (Shiru et al., 2020).

The most used AI model is identified as RF (35), and the most frequently utilised assisting technology is RS (15). RF is a popular model because of its ability to constantly expand analysis into branch-like shapes and easily integrate data with other statistical and AI models (Ramos & Sappa, 2024). This model is also efficient at analysing multiple data sources and complex relationships for establishing various risk factors (Mobley et al., 2021; Canadas et al., 2023). RF can effectively consider the interplay between risk factors and is regarded as one of the most efficient ML models for hazard reduction (Collins et al., 2018).

Table 6.2: Prominent nodes in using AI for HHR in Africa project examples.

Category	African country	AI models	Assisting Tech	Project Function	Local/national AA	International AA
Water management	Egypt (3) South Africa (3) Ghana (3)	ANN (15)	RS (3)	Quantity prediction (12)	Egypt (8)	China (7)
LULC	Egypt (3) Ghana (3)	RF (22)	RS (9)	Conservation mapping (9) Conservation prediction (9)	Ghana (10)	USA (18)
Flood	Nigeria (4)	RF (8)	GEE (3) GIS (3)	Prediction (14)	Algeria (7)	USA (7)
Drought	Nigeria (4)	ANN (8)	RS (3)	Forecasting (13)	South Africa (9)	USA (10)
Landslide	Algeria (2) Cameroon (2) Ethiopia (2) Morocco (2) Nigeria (2) Rwanda (2)	LR (4)	GIS (6)	Susceptibility mapping (8)	Morocco (4)	USA (7)
Wildfire	Algeria (2) Kenya (2) Morocco (2) South Africa (2) Tunisia (2)	RF (5)	GEE (3) GIS (3)	Prediction (9)	Morocco (5) South Africa (5)	USA (4)
Tropical cyclone	Egypt (4) Mozambique (4)	AR (2)	Satellite-images (3)	Prediction (8)	Egypt (3)	India (7)

RF is also integrated with other AI models as well as assisting technologies for more effective and applicable projects. RS technological advancements increase efficiency in hazard analysis and resource management efforts (Duan *et al.*, 2021). RS is a useful tool for evaluating and monitoring changes in environments without requiring physical presents (El Mahrad *et al.*, 2020). RS and AI integration facilitates a variety of hazard reduction applications (see Chapter 5) and facilitate more efficient projects in African HHR efforts.

The most prominent project function in these examples is prediction (52). Prediction efforts are the most used project function as AI is extraordinarily efficient for its execution (see Chapter 3). It is crucial in DRR for enhancing accuracy in identifying patterns and complex interactions (Sharmin *et al.*, 2023), rapidly processing data for producing real-time updates (Scragg, 2024), improving predictions of rapid intensification processes (Heo, 2024), and aiding in CCA (Hao *et al.*, 2024). Although prediction is a popular use for AI, the high-risk nature of such models must comply with extensive reliability requirements (Maubner *et al.*, 2024). These requirements are facilitated by policy and agent involvement.

The most weighted local/national autonomous agent in these examples is South Africa (14) and the most weighted international autonomous agent is the USA (46). Due to South Africa's extensive AI policy framework, AI developmental collaborations between its country and various other countries are encouraged (DCDT, 2024). South Africa has extensive academic involvement in AI and various institutional prioritisation of R&D efforts (University of Cambridge, 2025). Furthermore, the country has extensive governmental involvement in AI for DRR ventures (Mashishi, 2023).

The USA has long standing humanitarian links to Africa and aim to help increase the regions developmental growth (USAID, 2024). The USA shares bilateral ties with most African countries and are utilised to help African DRR efforts. The country is extensively prominent in Africa as elaborate organisations such as Google and NASA stem from it (see Chapter 5). Additionally, mutual interest in democratic governance and equality facilitates deeper ties between the USA and Africa (see Chapter 4). Ties and relationships are important for understanding the nodes involved in the project examples. In the following section, the various nodes involved in these projects are discussed according to network graphs and their most prominent connections.

6.3 Climate Change Adaptation Networks

AI used for CCA project examples in Africa are discussed in this section through network graphs referencing the examples mentioned in Chapter 5's water management and LULC. Water management is used for increasing CCA and improve resilience when facing water challenges

(UNEP, 2024b). Whereas LULC projects are used for increasing CCA and improving the sustainability of land when changes occur (Assede *et al.*, 2023). Water management projects are discussed first.

6.3.1 Water management network connections

Water management enables countries to avoid and reduce the risks associated with drought and flood hazard (Ward *et al.*, 2020). In this section data from Chapter 5 is discussed and illustrated according to prominent network connections. It is crucial to consider the weight of the connection between nodes in the network graph rather than the weight of the nodes alone. The connection described in this section is between ANN and predicting water quantity. It is the most significant and prominent connection in the network as illustrated by Figure 6.3.1.

6.3.1.1 ANN and predicting water quantity

The connection between ANN and water quantity prediction consists of 5 AI projects from the countries of Egypt, Libya, Madagascar, Ghana, and Benin (see section 5.2.1.3). All these countries have use for water quantity prediction as they are susceptible to flash floods, require sustainable water systems and attempt to minimise water waste (see section 5.2.1). The connection primarily relates to sustainable water systems, groundwater level predictions, CCA, and rainfall forecasting.

African countries using ANN in water quantity prediction projects benefit from this model because it can efficiently discover non-linear relationships in data and find patterns to establish prediction models (Kurani *et al.*, 2021). Also, it can rapidly solve and adapt to complex systemic issues (Hoang *et al.*, 2021). In the connecting projects, ANN is used as a single and hybrid model. As a single model, ANN is efficient for water quantity prediction (Velasco *et al.*, 2024). Although ANN has many alluring qualities, any AI model utilised in isolation is limited to its own restricted abilities.

Therefore, single models are usually outperformed by hybrid ones. In the connecting projects ANN is frequently used in combination with MLP, DL and LSTM. These hybrid models are more accurate and efficient than single ANN models (Kumar, Choudhary & Thomas, 2024; Kowsher *et al.*, 2021). Autonomous agents in the connecting projects mainly involve institutions from the country of application; or institutions from other local/national countries. The lack of international project management could be an avoidance of the complex dynamics associated with barriers such as language and time zones (Parth, 2008).

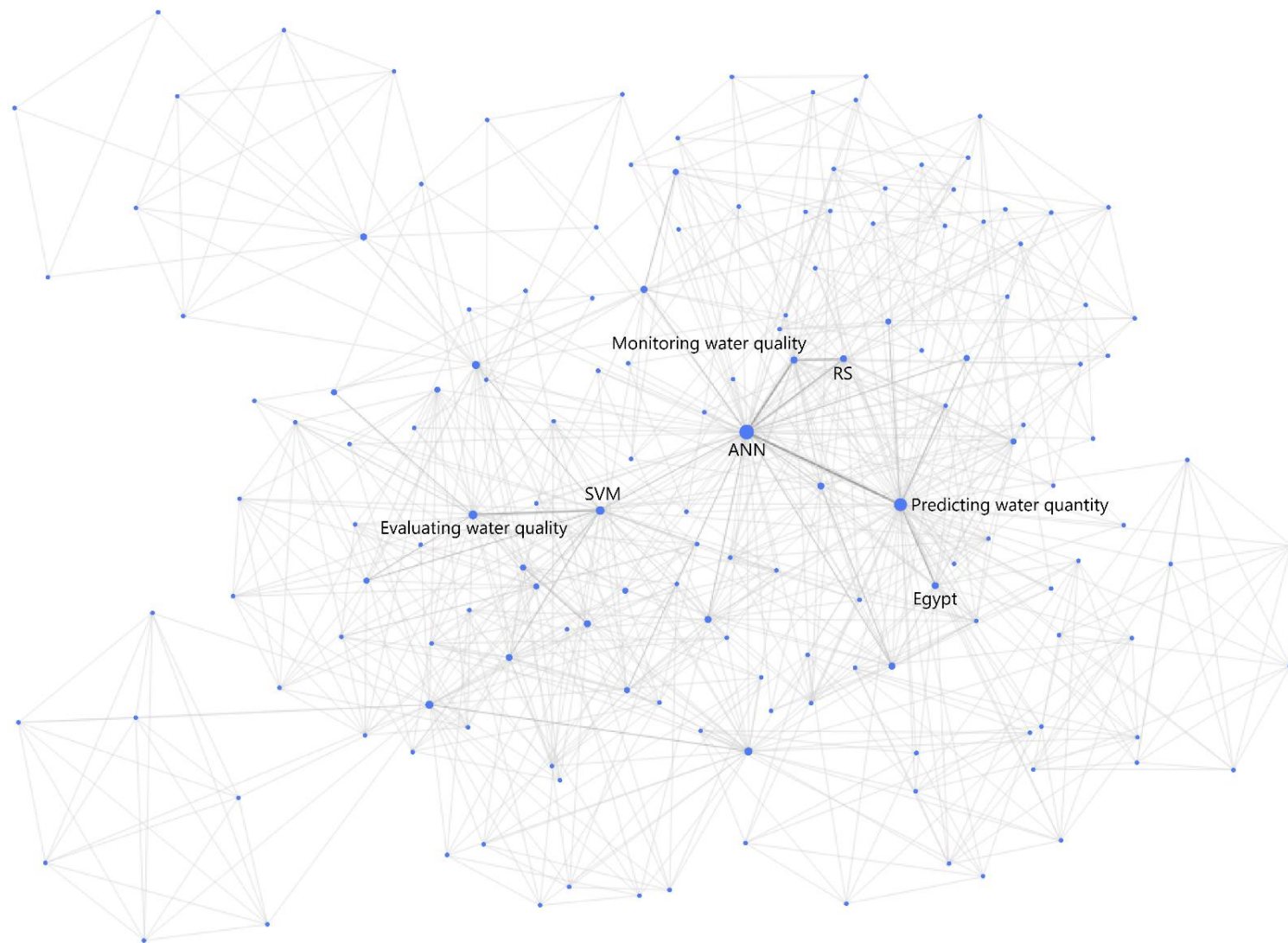


Figure 6.3.1: Co-occurrence network graph of AI for African water management.

Exclusively local involvement can limit the potential insights gained from international autonomous agent collaboration. On the other hand, exclusively international autonomous agents in African water management projects create the risk of overlooking essential information engrained in local knowledge. Consequently, the most resilient and sustainable projects include both local and international autonomous agents (Parnell & Gangwish, 2023).

Only one project example connecting ANN and water quantity prediction involved both local and international agents (Aizansi, Ogunjobi & Ogou, 2024). Communication and comprehension challenges can be partially overcome when agents are familiar with one another (Yousef, 2024). It is important to note that any ecosystem uses diversity to fuel its evolution (Gliessman, 2022) (see Chapter 2). On the other hand, excessive diversity of autonomous agents and no local involvement also poses risks such as discoordination, misdirection and a lack in practical project implementation (see section 2.2.4).

The autonomous agents from the connecting project examples include various universities and institutions such as WASCAL, the Competence Centre of Burkina Faso and the National Agency of Meteorology (Benin). Out of 5 connecting projects, 2 involve Chinese autonomous agents. China is a key role-player in the African water sector. Chinese banks and companies are actively financing and developing water related projects across the continent (Tukic & Burgess, 2019; Godfrey & Ross, 2016).

Since the 1999's 'go out' policy launched in China, it has positioned itself as Africa's largest supplier and investor (Tukic & Burgess, 2019). The excessive investment in water sectors raise concerns about the extent of China's control over African resources (Dok & Thayer, 2019). Furthermore, WASCAL is also a prominent actor in African water management, facilitating West African research and education related to climate change and water management, DRM, LULC and marine sciences (WASCAL, 2020).

The extensivity of the nodes and connections in AI used for African water management efforts indicate the growth of a dynamic and constantly changing ecosystem. In addition to water management, land use and cover (LULC) is essential to HHR. In the following section, CCA efforts utilise LULC AI projects for determining various measures related to conservation and urbanisation in Africa.

6.3.2 Land use and land cover network connections

Land use and land cover (LULC) hazards can be driven by climate change which benefit greatly from CCA efforts (Barati *et al.*, 2023). AI models show promise in reducing the risks associated

with rapid urbanisation, unplanned development, and environmental degradation. In this section that LULC data collected in Chapter 5 is illustrated in the network graph of Figure 6.3.2 and discussed according to the prominent network connections between RF and GEE. The force-directed network graph (Figure 6.3.2) indicates a compilation of interacting complex systems forming an AI LULC African ecosystem.

The network graph in this section is much denser and contains more nodes than the graph on AI used for African water management. This is because there were more African projects available for exploration. However, it is interesting to note that in the African LULC conservation activities, water and its management is a primary focus. Showing once more how sections and boundaries between AI hydrometeorological reduction efforts are fluid and overlapping.

6.3.2.1 RF and GEE

The co-occurrence connections between RF and GEE are extensive as seen in Figure 6.3.2 and consists of 8 projects. These include mapping LULC changes in Benin, evaluating LULC effects on vegetation in Cote d'Ivoire, evaluating and monitoring mangrove dynamics in the Gambia, mapping land use changes in Mozambique, monitoring urban expansion in Somalia, evaluating forest cover dynamics in Togo, evaluating LULC changes in Tunisia, and mapping mangrove forests on the West African Coast (see Table 5.2.2).

The RF model and the GEE tool is mostly utilised alone and rarely accompanying other AI models or assisting technologies. Evaluating GEE data with RF algorithms creates detailed and extensive geographical maps (Feizizadeh *et al.*, 2021). These maps aid in more accurate estimations of LULC characteristics, facilitating a cost and time efficient process (Magidi *et al.*, 2021). Time and cost efficiency are important variables in utilising AI models for African DRR projects as Africa has limited amounts of both.

Autonomous agent involvement primarily consists of both local/national and international entities. This indicates the diversity of interest in African LULC AI projects and creates evolutionary opportunities (see Chapter 2). These agents include universities from and governmental involvement. Ghana, the USA and Canada are the most prevalent autonomous agents in these projects. Ghana collaborates on project examples involving Benin and Cote d'Ivoire. Both countries have diverse ties to Ghana through history (Obaseki-Osemwegie, 2014; Saffu, 1970), trade (OEC, 2022; African Development Bank, 2024b), and free roaming mobile services (Sehloho, 2024).

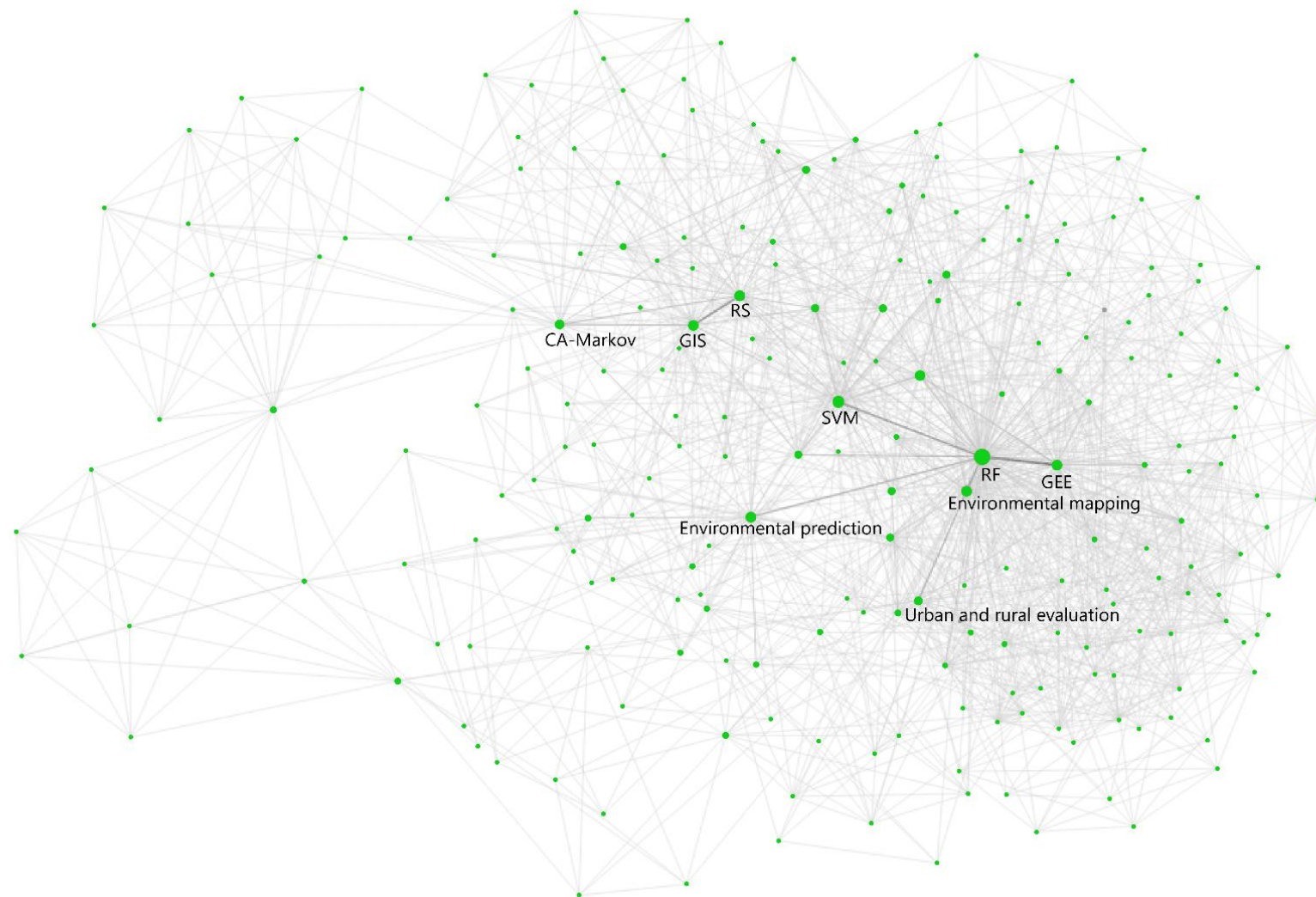


Figure 6.3.2: Co-occurrence network graph of AI for LULC project examples in Africa.

These connections may be partially due to their close proximity to one another. The involvement of these countries in the projects are relevant as they share similar biomes and climatic impacts (Schmidt & Muggah, 2021). The USA is involved in Mozambique and the West Coast of Africa. USA development agencies are embracing AI transformation for reducing the most pressing issues in Africa (Day, 2024). The USA has enforced and self-appointed responsibility to African welfare (Archibong *et al.*, 2022).

Additionally, various Canadian autonomous agents contribute to Togo. Canada and Togo have various connections related to their bilateral relations (Government of Canada, 2024). However, its most important connections stem from developmental growth and African collaborations (Global Affairs Canada, 2024). Canada is extensively involved in African CCA and assist in data collection and processing initiatives (Dossavi, 2022). Considering the sheer number of publications, rapid urbanisation and environmental degradation are clearly amongst the most concerning issues in Africa.

Water management and LULC are important factors to consider when trying to reduce and avoid the development of hydrometeorological hazards. However, CCA efforts are not always effective due to the complexity associated with most hydrometeorological hazards. Therefore, AI model applications are challenging and require robust and reliable techniques for enhancing accuracy. In the following section, various hydrometeorological hazards are discussed and illustrated according to different network graphs. Furthermore, their most prominent node connections are identified and discussed.

6.4 Hydrometeorological Hazard Reduction

Hydrometeorological hazards have an immense effect on the planet and require more research in terms of information and communication technology ventures (Kaur & Sood, 2020). In this section, HHR AI project examples in Africa are discussed with reference to floods, droughts, landslides, wildfires and tropical cyclones. AI Flood reduction projects are discussed first referencing complex network formation and dominant network connections.

6.4.1 Flood network connections

African floods are frequent and severe events that impact many populations (Douglas, 2017). AI flood reduction projects are utilised for HHR and improving resilience and preparedness efforts (Saravi *et al.*, 2019). AI flood reduction presents ample opportunities for African development and its pursuit in reaching the SDGs (Okosi, 2024). This section discusses the various AI flood reducing project examples according to various prominent network connections. Using a co-

occurrence table, these nodes and their connections are coded into a network graph (Figure 6.4.1).

The most prominent connections in Figure 6.4.1 are between numerous nodes. These connections include ANN and predicting floods (3), RF and predicting floods (3), Nigeria and predicting floods (3), and RF and assessing and monitoring floods (3). In this section, all four dominant connections have identical weights. The distribution of many weak yet prominent connections indicate the dilution on a complex system (see Chapter 2). ANN used in predicting floods are discussed first.

6.4.1.1 ANN and predicting floods

The connection between the AI model ANN and the project function of flood prediction consists of 3 quotations. These projects include predicting floods in Kenya, Mauritius and Nigeria. All these countries can benefit from flood prediction as they face frequent and devastating floods that extensively impacts economic growth (see section 5.3.1). ANN is a popular algorithm used for flood prediction ventures in Africa (Fofana *et al.*, 2023). It is a well-studied algorithm in flood prediction projects; however, it has limited empirical evidence for generalising its use in smaller countries (Dhunni *et al.*, 2020).

ANN models are often used with other AI algorithms for optimising flood prediction (Tabbussum & Dar, 2021). However, in these project examples ANN models are used as a single method devoid of other AI models or specified assisting technologies. Autonomous agent involvement in these projects is either exclusively local, exclusively international or an amalgamation between the two. These agents include African universities and a corporation from Singapore. There are no dominant autonomous agents present in these projects, however, those involved contribute to the R&D of ANN for flood prediction.

None of the autonomous agents identified in these projects were dominant and may indicate that there is a lack in correspondence between connecting project examples. Another AI model that shares a prominent connection to predicting floods in Africa is RF. Similar to ANN, RF can extensively benefit flood prediction efforts (Albertini *et al.*, 2024).

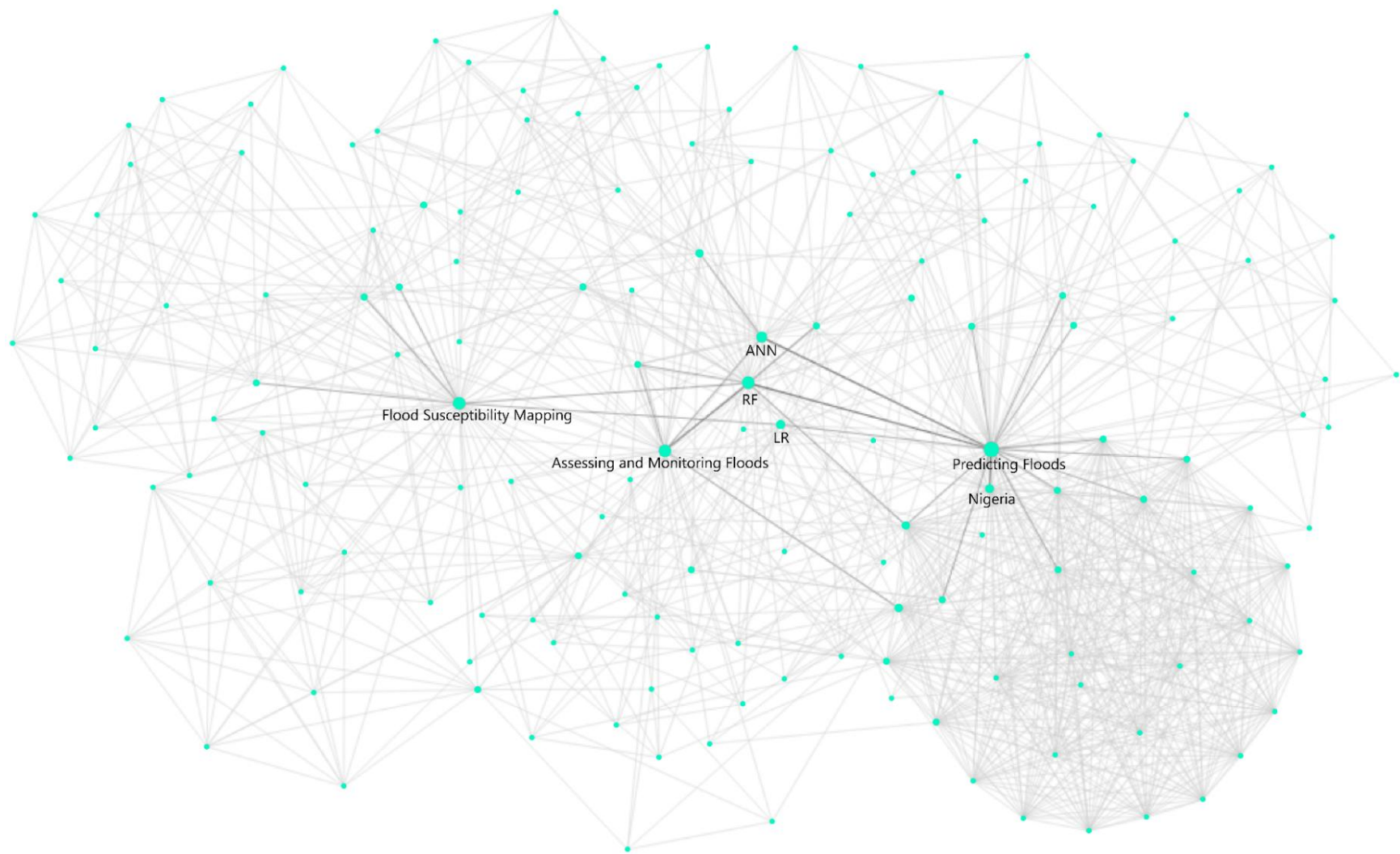


Figure 6.4.1: Co-occurrence network graph of AI for African flood reduction.

6.4.1.2 RF and predicting floods

The connection between the AI model RF and the project function of flood prediction consists of 3 quotations. These projects include predicting floods in Ghana, Guinea and Tanzania. All these countries can benefit from flood prediction as they endure multiple floods damaging livelihoods (see section 5.3.1). RF is frequently used for flood prediction ventures in Africa (Byaruhanga *et al.*, 2024). The model finds intricate patterns by employing numerous tree-based algorithms for generating repeated predictions (Wahba *et al.*, 2024).

Although the algorithm is used for many flood prediction projects, it only provides robust predictions for small to medium flood hazards (Schoppa, Disse & Bachmair, 2020). In these project examples RF is used with multiple AI models namely GBC, LSTM, RT and XGBoost. GBC and RF are essentially both classifiers. RF classifier combines multiple DTs with random sampling to improve accuracy of flood prediction (Albertini *et al.*, 2024). Whereas the ensemble method GBC sequentially builds DTs attempting to correct errors from previous trees (Ibrahim, 2024). Another boosting ensemble method used with RF is XGBoost (Tseng, 2018). RF uses the method of 'bagging' where multiple trees are trained independently (Altman & Krzywinski, 2017).

On the other hand, XGBoost uses boosting which sequentially train trees, with each new tree attempting to correct the errors from the previous one (Natras, Soja & Schmidt, 2022). The RT algorithm is essentially a single DT within a RF model (Zhou *et al.*, 2020). Therefore, DTs grouped together form a RF algorithm. Furthermore, RF and LSTM are used as a hybrid model for various prediction efforts (Tran *et al.*, 2023). The models integrate effectively to produce an accurate and efficient flood prediction technique (Lin *et al.*, 2024).

Autonomous agents involved in the connecting projects include numerous universities and research institutes. Tanzania contains the dominant autonomous agents in the connecting projects. Tanzania is significantly invested in flood reduction measures (Panman *et al.*, 2021). The country has various grants and funding for flood hazard reduction activities (Juntunen, 2024; GFDRR, 2022). Furthermore, Tanzania greatly encourages AI R&D in flood prediction (Mdegela *et al.*, 2023; Lamanna *et al.*, 2021). In Figure 6.4.1, the flood prediction function also shares a significant connection to Nigeria.

6.4.1.3 Nigeria and predicting floods

The connection between the project function of flood prediction and the African country of Nigeria consists of 3 quotations. Nigerian flood prediction project examples involve the AI models of HM, IM, ANN, and LR. Google AI systems named HM and IM are specifically designed for the use in

their flood-hub project. HM specialises in forecasting the amount of water flow and IM specialises in predicting the areas impacted by water flow (Matias, 2023). ANN and flood prediction (as mentioned in section 6.4.1.1) are an ideal connection for African flood reduction efforts.

LR is also an effective model used for flood prediction and are frequently used for determining the probability of a flood hazard (Rifath *et al.*, 2024). LR uses binary classification to indicate flood likelihood (Mosavi, Ozturk & Chau, 2018) and produce outputs that are easily interpreted (Defontaine *et al.*, 2023). Therefore, all these AI models are beneficial and practical for predicting floods in Nigeria. Furthermore, the connecting projects include limited assisting technologies, however, mentions the use of EOD with LR.

EOD refers to information gathered on the earths chemical, physical and biological systems (Willige, 2024). It is considerably used in flood prediction and monitoring activities (Schumann *et al.*, 2022). EOD is primarily accessed in Nigeria through satellite imagery derived from their own satellites (NigeriaSat-1 and NigeriaSat-2) (Foboade, 2023).

Autonomous agent involvement in the connecting projects exclusively consist of universities. There are no dominant autonomous agents involved in these projects. The following prominent connection discussed is between RF and assessing and monitoring floods.

6.4.1.4 RF and assessing and monitoring floods

The connection between the AI model of RF and the project function of assessing and monitoring floods have a weight of 3 quotations. Assessing and monitoring floods using RF models include the countries of Mozambique, Nigeria and Zambia. These countries benefit from assessing and monitoring flood hazard as they face climate change induced flooding and contain informal settlements situated next to waterbodies (see section 5.3.1). Additionally, these countries assess and monitor floods due to their social vulnerability and susceptibility to them (Lundgren & Strandh, 2022; Oyedele *et al.*, 2022; Umar *et al.*, 2022).

RF is useful for analysing and tracking flood activity, allowing for more accurate flood assessing and monitoring efforts in Africa (Wahba *et al.*, 2024). In all the connecting projects RF is used as a single model. RF models can be efficient when used alone, however, their effectivity increases when hybridised with other AI methods (Abbasi *et al.*, 2021). This is also true for RF and assisting technologies. The assisting technologies included are GEE, Sentinel 1 and Sentinel 2. The GEE platform is essentially used with sensors like Sentinel 1 and 2 for flood assessment and monitoring ventures (Sy *et al.*, 2023; Nghia *et al.*, 2022, Chen & Zhao, 2022).

Integration of these assisting technologies create accurate flood monitoring and assessment projects (Wang *et al.*, 2023a; Lam, Niculescu & Bengoufa, 2023; Albertini *et al.*, 2024a). Autonomous agents involved in these connecting projects are local/national and international universities and institutes. The most weighted autonomous agent is Zambia (3). Agents from this country widely involved in AI flood assessment and monitoring projects. Zambia and Turkey, for instance, are collaborating and share connections that stem from prominent bilateral ties (Kunda, 2023) and investment treaties (UNCTAD, 2020).

The widespread involvement of nodes in AI flood reduction project examples for Africa indicates that a vibrant and extensive AI ecosystem is developing. Although floods are the most common hazard the world over, drought is not far behind it. In the following section, African AI drought reduction project examples are discussed and described according to a network graph and dominant network connections.

6.4.2 Drought network connections

Drought is a severe hazard experienced by most of the African region (Ayugi *et al.*, 2022). Reducing this hazard aids African countries with elevated levels of food security and access to water resources. These measures may assist in reducing famine (Rubin, 2022), environmental degradation (Hermans & McLeman, 2021) and ecosystemic damage (Walz *et al.*, 2021). In this section, data collected in Chapter 5 is compiled into a co-occurrence network graph and discussed accordingly. The dominant node connection is identified as being between RF and monitoring drought (4), therefore it is the only connection discussed.

6.4.2.1 RF and monitoring drought

The connection between RF and monitoring drought consists of 4 AI project examples. The connection between these nodes primarily consists of monitoring drought for early-warning systems in Botswana and Kenya, agricultural drought in Burkina Faso, Cameroon, Chad, Gambia, Guinea, Mali, Mauritania, Niger, Nigeria and Senegal, and spatio-temporal drought dynamics in Ethiopia. All these countries can benefit from monitoring drought as they experience extensive drought occurrence and high risk of drought in agricultural sectors (see section 5.3.2).

These countries can benefit from RF in monitoring drought as the model is extensively efficient in processing complex relationships between various environmental variables such as precipitation, temperature, vegetation, and soil moisture (Wang *et al.*, 2022b). Furthermore, the model can determine which variables contribute most to drought prediction and provide insights into key drivers of drought (Dikshit, Pradhan & Almari, 2020). RF is used as a single method and

hybridised in some of the project examples. The models used with RF are NB, KNN, LR and XGBoost.

RF and NB are usually combined using an ensemble method where each models' predictions are joined to produce an output (Aridas, Kotsiantis & Vrahatis, 2017). RF and KNN is amalgamated by primarily using both models and comparing their weights to increase the accuracy of the results (Lin & Jeon, 2012). RF and LR fused by 'stacking', which entails predictions from RF as features of LR allowing for more accuracy in complex datasets (Ulanowicz *et al.*, 2023). RF and XGBoost models are combined by using the predictions of both as input to produce a new ensemble method, usually with increased accuracy (Brownlee, 2021).

The autonomous agents involved in the RF for monitoring drought project examples in Africa include various international and local/national entities. The monitoring project in Botswana only involves universities from Germany and the USA (Kemper, 2022). These countries support Botswana through developmental cooperation (GIZ, 2019; US Embassy Gaborone, n.d.). Monitoring agricultural drought in Burkina Faso, Cameroon, Chad, Gambia, Guinea, Mali, Mauritania, Niger, Nigeria and Senegal shows the involvement of autonomous agents from the EU in Belgium, universities from France and Niger, and two research institutions from Morocco (see Table 5.3.2).

The EU is extensively involved in West Africa and have interest in the access to raw materials (minerals and resources) (Martin, 2024), economic trade partnerships (European Commission, 2016), managing migration patterns (Mouthaan, 2022), facilitating regional stability and safety (EU, 2023), and encouraging sustainable development (Kitz, 2024). France is connected to West Africa via extensive historical and cultural ties (Ricart-Huguet, 2021). Furthermore, France has extensive interest in west African military development and growth (Zimmerman, 2020).

Niger faces challenges present in most of West Africa, such as extremist groups (European Commission, 2019), food insecurity (WBG, 2024a), developmental issues (African Development Bank Group, 2024a) and political instability (Kante, 2024) to name a few. The Ethiopian project example uses RF for monitoring spatio-temporal drought dynamics (Fentaw, Yimer & Zeleke, 2023). This project exclusively involves local autonomous agents from three universities. As mentioned in section 6.3.1, projects involving only local entities are easier to navigate however may lack international input and best practice initiatives.

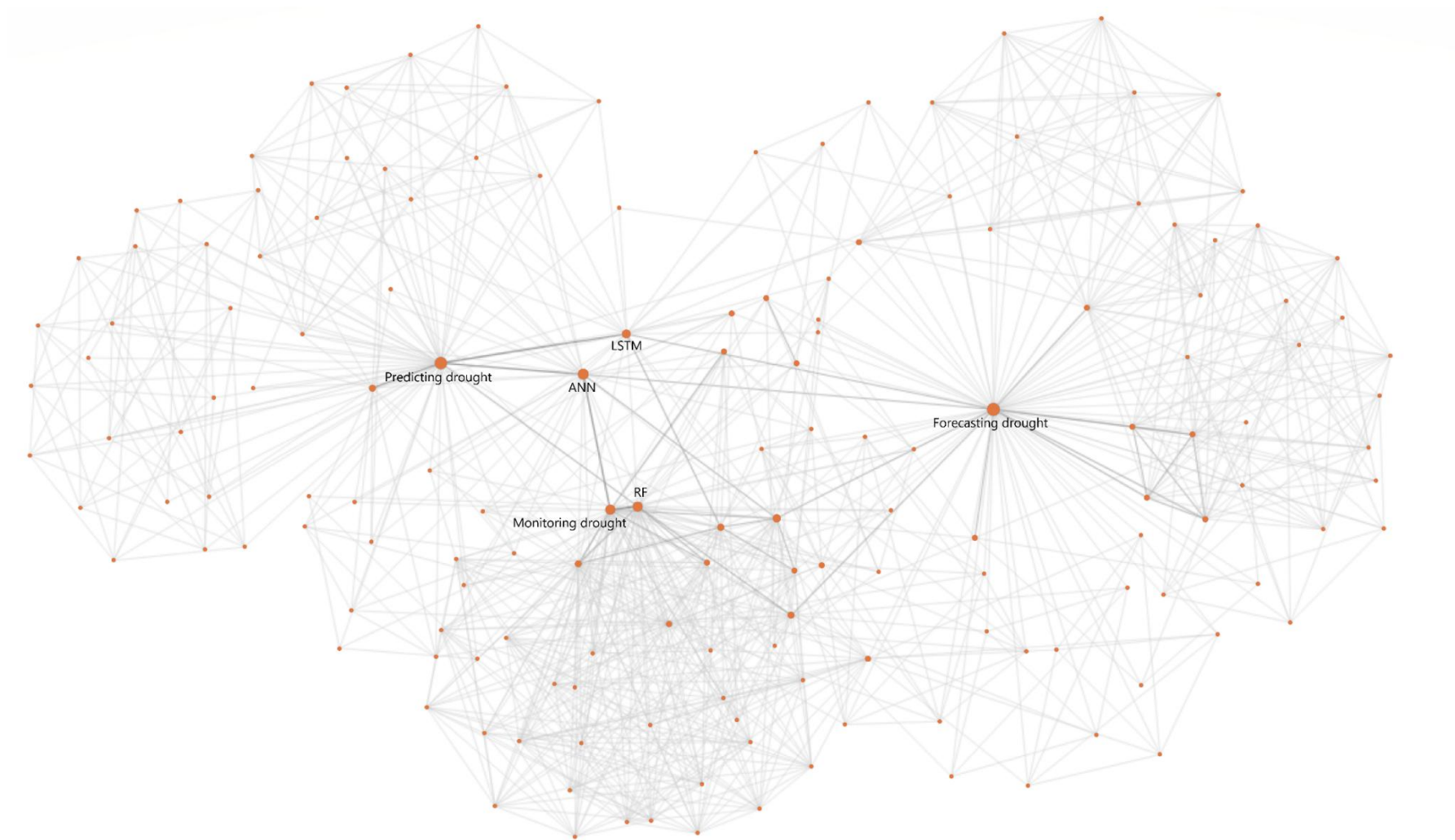


Figure 6.4.2: Co-occurrence network graph of AI for drought reduction project examples in Africa.

Kenya uses RF with other AI models to monitor drought for producing early warning systems. Autonomous agent involvement includes both local and international collaboration between the universities and governmental institutions. For instance, the autonomous agents from Kenya and the USA are connected by extensive trade relations (Hillman & Sacks, 2021), facilitating Kenyan digital development (International Trade Administration, 2024), and providing humanitarian assistance (USAID, 2024).

In these project examples, prominent role players include the USA, the EU and Germany. Due to the dominance of these countries, their relation to one another is essential. The USA and Germany have extensive trade connections and share bilateral relations (Rooks, 2024). Germany is one of the six founding members of the EU (Federal Foreign Office, 2024). On the other hand, the USA and the EU are strategic partners with elaborative trade and technological development relations (European Commission, 2024).

Drought reduction project examples in Africa indicate extensive co-operation and collaboration efforts between various local/national and international autonomous agents. This dense network shows elaborative efforts in African drought reduction. The loss of vegetation during drought creates further risk for hazards such as landslides. In the following section, landslide reduction project examples are discussed with relation to a network graph and prominent network connections.

6.4.3 Landslide network connections

Landslide reduction and management efforts are essential to the socio-economic development in Africa (Okolo & Wen, 2022). The project examples include various African countries, all of which are combined into a co-occurrence network graph (Figure 6.4.3). Figure 6.4.3 represents a CAS made up of multiple interacting systems within the context of AI for landslide reduction project examples in Africa. The most significant connections discussed in this section includes LR and landslide susceptibility mapping (3) and GIS and landslide susceptibility mapping (3). Discussed first is the former.

6.4.3.1 LR and landslide susceptibility mapping

The connection between landslide susceptibility mapping and LR consists of 3 AI project examples residing in Cameroon, Morocco and Nigeria. All these countries find landslide reduction useful as they experience extensive vulnerability and frequent occurrence of landslide hazards (see section 5.3.3). LR is a popular model for landslide susceptibility mapping because it provides

a robust way of identifying the relationship between multiple environmental factors and landslide hazard probability (Chowdhury *et al.*, 2024).

LR is functional in landslide susceptibility mapping as it uses binary classification algorithms (Ngo *et al.*, 2021), clear interpretability (Das & Lepcha, 2019), and widespread applicability to various landslide datasets (Ma, Shao & Xu, 2023). In the connecting project examples, LR is primarily used in a hybrid fashion including the AI models of NB, CART, MDA, and SVM. LR determines how continuous variables play a role in landslide susceptibility (Shang *et al.*, 2023), whereas NB is ideal for classifying landslide prone areas (Tsangaratos & Ilia, 2016).

LR and CART algorithms also complement one another in determining landslide susceptibility. Similar to LR and NB hybridisation, LR is used as a form of analysis that estimates the linear relationships between landslide variables; and CART is used as a classification model set on solving complex problems in large datasets (Pham, Prakash & Bui, 2018). MDA is used with LR because it can model and predict the relationships between landslide variables such as geo-environmental factors and erosion (Hosseinalizadeh *et al.*, 2019). Whereas SVM is used with LR to fulfil the lack of consideration for non-linear relationships between landslide variables (Lee, Hong & Jung, 2017).

LR is also used with assisting technologies in the connecting project examples and include GIS and MCDM tools. GIS and LR are compatible in landslide susceptibility mapping efforts as GIS provides substantial environmental data of which LR can derive relevant lithology and landslide variables (Ayalew & Yamagishi, 2005). LR and MCDM are also complimentary to one another in landslide susceptibility mapping. MCDM uses qualitative analysis (Jari *et al.*, 2023), hierarchical decision-making (Aslam *et al.*, 2022) and offers a holistic view of the data (Tesfa & Sewnet, 2024).

Whereas LR focuses on quantitative relationships (Mao *et al.*, 2024), uses predictive algorithms (Kavzoglu, Sahin & Colkesen, 2013) and statistical analysis (Barman *et al.*, 2024) to determine landslide susceptibility maps. Consequently, LR is used with these assisting technologies to provide more efficient and accurate models that help map landslide susceptibility in the connecting project examples. Autonomous agents in the connecting projects primarily involve local/national and international autonomous agents from universities and institutions from Cameroon, Morocco, Nigeria, Germany, France and the USA.

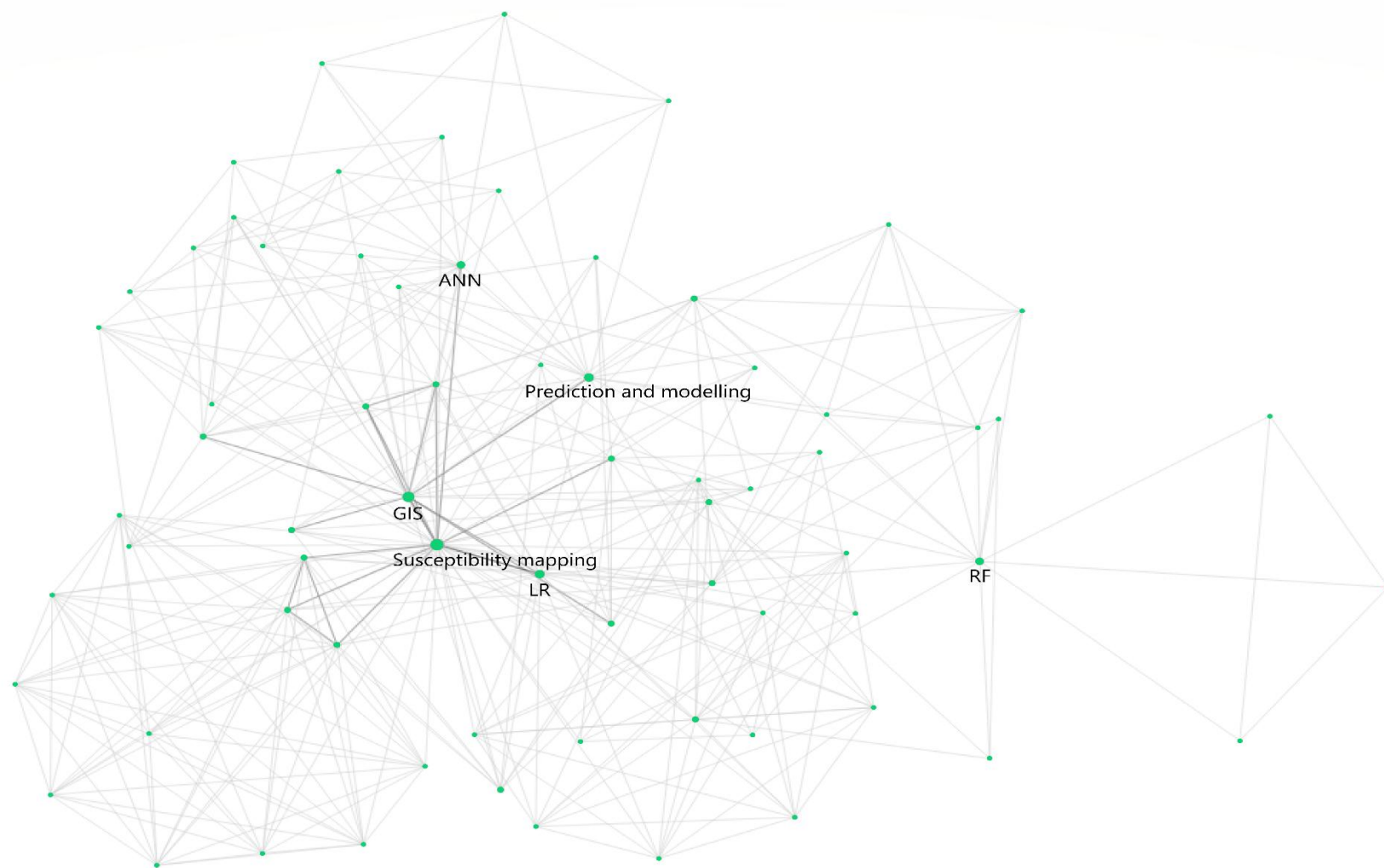


Figure 6.4.3: Co-occurrence network graph of AI for landslide reduction project examples in Africa.

Combining the efforts of local/national and international entities ensures collaborative diversity and best practice initiatives (see Chapter 2). It is interesting to note that most of the international countries involved in African landslide reduction project examples are former colonisers of those countries. The most prominent international autonomous agent in the connecting project examples is from France. French mapping in Africa is not a novel occurrence. In the name of development, the French national geographical institute was tasked with mapping all the French-speaking African countries in 1945 (UN Economic and Social Council, 1963). Reinforcing historical ties and interest in African mapping practices.

LR and landslide susceptibility mapping is connected by complex project examples. AI models play an integral role in these projects however so does assisting technologies. GIS and landslide susceptibility connecting project examples are discussed next.

6.4.3.2 GIS and landslide susceptibility mapping

The connection between GIS and landslide susceptibility mapping consists of 3 project examples from the countries of Algeria, Nigeria and Rwanda. As mentioned in section 5.3.3, these countries can benefit from landslide susceptibility mapping as they are extensively vulnerable and prone to landslide hazard occurrences. GIS is used in collaboration with AI models to produce accurate landslide susceptibility maps. These models include AHP, LR and ANN present in the connecting project examples.

GIS and AHP is used for multi-criteria evaluations and provide insightful information on present and future landslides (Jazouli, Barakat & Khellouk, 2019). LR and GIS is used for mapping landslide susceptibility through effective data integration (Chowdhury *et al.*, 2024) and mapping outputs (Shang *et al.*, 2023). GIS and ANN are efficient in landslide susceptibility mapping as they allow for complex analysis of environmental variables and data integration (Gameiro *et al.*, 2021). All these connecting project examples exclusively use single AI methods. Although these methods are still efficient in mapping landslide susceptibility, their effectivity is elevated by the GIS assisting tool.

Autonomous agents involved in these project examples consist of various local/national and international university collaborations. With the limited research on landslide reduction practices, university involvement is crucial to building R&D in AI efforts. The Algerian project includes 2 universities from Algeria and 1 from Portugal. Algeria and Portugal are connected by trade agreements (Algeria Press Service, 2023), energy advancements (Atalayar, 2024) and diplomatic relations (Diplomatic Portal, n.d.). Additionally, Portugal also faces extensive landslide risk (Araujo *et al.*, 2022) and could benefit from collaborations with Africa.

Nigeria and Germany also find academic advantage from their collaboration in developing AI for landslide susceptibility mapping. Germany does not experience landslides as much as they do mudslides (BBC, 2021), but nevertheless, the AI applications should be quite similar. Therefore, using Algeria as a testing ground for AI susceptibility mapping efforts should benefit Germany in developing mudslide susceptibility maps.

Furthermore, the connecting Rwandan project example consists of national and international autonomous agents from Germany, Nigeria, Saudi Arabia, and the USA. It is important to note that Rwanda does not have any autonomous agent involvement in this project. Rwanda has close diplomatic relations with Germany (Federal Foreign Office, 2024a), Nigeria (Ministry of Foreign Affairs Nigeria, 2019); Saudi Arabia (Saudi Press Agency, 2023) and the USA (US Department of State, 2022).

Although these project examples are few, they show great potential and prospective developmental ventures. The international involvement in mapping African countries should not be underestimated in terms of long-term effects. Unregulated collection of spatial data by foreign entities could threaten multiple socio-economic domains in Africa. Wildfires can increase the risk of landslides and cause environmental degradation. In the following section, wildfire reduction project examples are discussed and analysed according to CAS theory. It indicates the system in a network graph and identifies and discusses the most prominent network connections.

6.4.4 Wildfire network connections

Wildfires are becoming more frequent and more severe (MacCarthy, *et al.*, 2024). In comparison to the previously mentioned HHR project examples, wildfire reduction is quite scarce. Nevertheless, AI technology is increasing in African DRR efforts and should become more accessible in time. The connections identified as the most prominent and weighted are RF and wildfire prediction (3), and GIS and wildfire mapping (3). RF and wildfire prediction is discussed first.

6.4.4.1 RF and wildfire prediction

The connection between RF and wildfire prediction consists of 3 AI projects from the countries of Ghana, Botswana and Morocco. All these countries can benefit from wildfire prediction efforts as they experience extreme wildfire occurrence and are extensively vulnerable to the hazard due to environmental challenges (see section 5.3.4). The connection between RF and wildfire prediction involves ventures related to predicting and monitoring wildfires, predicting climate change impact on wildfire occurrence, and predicting seasonal forest fires.

The use of RF in the connecting project examples is beneficial for African countries as it uses bootstrap samples to enhance model robustness, critical in predictive accuracy (Shahzad *et al.*, 2024). RF provides significant insights into variables that contribute most to prediction efforts, aiding research focus on key prevention strategies (Gao, Lin & Hu, 2023). Furthermore, RF can handle datasets with missing values (Singh & Jeganathan, 2024), which is more likely as African data on wildfires are limited. The RF algorithm is used as a single method in 2 of the three project examples and as a hybrid model in 1. RF is an efficient model when used on its own, however benefits from hybridisation. LR is used with RF in the Botswanan project. LR and RF models fulfil one another's limitations. LR works with linear relationships between variables whereas RF works with complex relationships (Moghim & Mehrabi, 2024). When these models are compared, RF outperforms LR in most cases. However, when combined, they complement each other and produce increased accuracy in results.

Autonomous agent involvement in these connecting projects relate to agents from the local/national origins of Ghana, Botswana, Morocco, Kenya and Senegal, and international agents from the USA. Assisting technologies included in these projects are mainly unspecified, however, the Moroccan project includes the assisting tools of MODIS and Landsat. MODIS and Landsat are fused in this project, which is a technique that combines the images of both satellites to create high-resolution synthetic images (Filgueiras *et al.*, 2020). This aids in creating more accurate data for models to predict wildfires.

The connection between RF and wildfire prediction is one of the most prominent ones in the wildfire reduction project examples. The connection with the same weight is GIS and wildfire mapping. This connection is discussed and analysed next.

6.4.4.2 GIS and wildfire mapping

The connection between GIS and wildfire mapping consists of 3 project examples located in Algeria, Kenya and Morocco. All these countries can benefit from wildfire mapping as they experience severe and frequent forest fires (see section 5.3.4). Interestingly diplomatic tensions have been linked to the starting of wildfires in Algeria, blaming Zionists and Morocco for terror attacks in the country (Aljazeera, 2021). Additionally, Kenya experiences drought driven wildfires that strain response systems (International Association of Wildland Fire, 2025), and Morocco experiences seasonal wildfires that caused the loss of 652 hectares of land (Salas, 2024).

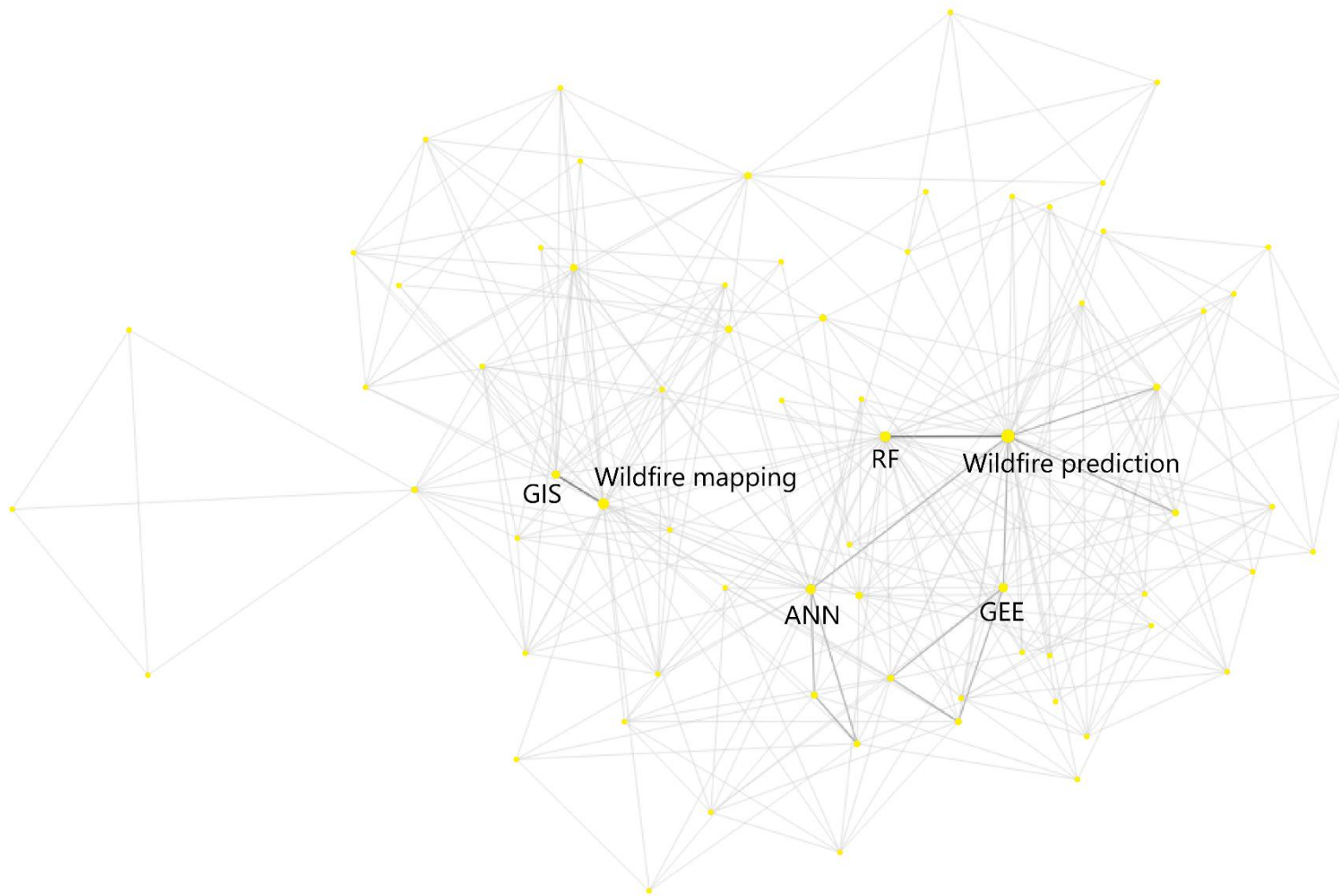


Figure 6.4.4: Co-occurrence network graph of AI for wildfire reduction project examples in Africa.

The connection between GIS and wildfire mapping consists of projects related to mapping and modelling wildfire risk, mapping forest fire susceptibility, and mapping forest fire severity. The use of GIS for mapping wildfires in Africa are beneficial as GIS allows for precise analysis of various spatial data related to potential fire risks (Gai, Weng & Yuan, 2011). Additionally, GIS can integrate diverse data from various satellite sources (Zagalikis, 2023) and aid in visualising risk patterns (Kallimani *et al.*, 2014). It can also help monitor wildfires in real-time and model fire behaviours (Zagalikis, 2023).

In the Algerian project example, GIS is used with the assisting tools of satellite imagery. GIS and satellite images are used together in wildfire mapping to aid in large-scale monitoring (Bahadori *et al.*, 2023) and to combine different wildfire causing variables for demarcating risk zone maps (Jaiswal *et al.*, 2002). The connecting projects use various AI models for mapping wildfires whilst using GIS. These models include CNN, SVM, AHP, and XGBoost. CNN and GIS are compatible in mapping wildfires as GIS is used to store and analyse geographical data whereas CNN is used to automatically extract features from this data for wildfire monitoring (Ramayanti *et al.*, 2024).

GIS and SVM is efficient for wildfire mapping as SVM are often employed with GIS to predict wildfire susceptibility based on risk factors, enabling the creation of detailed maps (Mishra *et al.*, 2024). GIS and AHP also work well together as GIS can be used to spatially analyse various environmental factors and AHP is used to identify and weigh the importance of those factors (Sivikaya & Kucuk, 2022). GIS and XGBoost is used for mapping wildfires because GIS data can be fed into the XGBoost algorithm to identify complex relationships between wildfire risk variables and aid in not only mapping but predicting them (Tran *et al.*, 2024).

Autonomous agents involved in the project examples consist of 2 projects exclusively using local entities (Morocco & Kenya) and 1 project that shows collaboration between local and international entities (Algeria). The Algerian project (Zikiou *et al.*, 2024) is discussed in section 6.3.4.5.2 and elaborates on the ties between Algeria, Spain and the USA. Projects consisting of only local entity involvement limits the input of collaborating entities. The strongest connecting project is therefore the Algerian one. It integrates local and international entities from various academic institutions, creating a platform for best practice initiatives and further R&D in wildfire mapping activities.

The network in Figure 6.4.4 has multiple connections and projects. Project identification in this section was challenging as wildfire related data is limited in Africa and AI R&D is still in its infancy. Tropical cyclone reduction project examples are even less accessible than wildfire reduction projects in Africa. Even though tropical cyclones are one of the most destructive hazards globally, there is a large gap in African R&D initiatives. In the following section, tropical cyclone reduction project examples are discussed.

6.4.5 Tropical cyclone network connections

Storms and their intensity are increasing in Africa due to climate change, which exacerbate socio-economic stressors (Africa Center for Strategic Studies, 2022). Tropical cyclone project examples are extremely difficult to locate and are limited in this research. A mere 8 reduction project examples are identified in Chapter 5. Nevertheless, this data is coded into a network graph and discussed according to its most dominant network connections. It is important to note that most of the projects mentioned in this section are not designed specifically for African countries but rather for the oceans that affect the coast.

Additionally, not all the places effected by these project examples are African countries but rather consist of a combination of African islands and countries. The islands are worth including in this section as they are heavily affected by tropical cyclones headed for the coast. Furthermore, the network graph compiled from these project examples shows a heavy concentration of nodes in two clusters. This is due to the interconnection between the African islands and countries effected by the Atlantic and Indian Ocean (each consisting of a cluster).

The nodes outside of the clusters primarily consist of AI models, project functions, autonomous agents, and assisting technologies. Due to the exaggerated connection weights shared between most of the nodes in the network, selected connections between the most prominent nodes in the network is discussed. Too many prominent network connections between nodes indicate a CAS that consists of saturated involvement and concentrated influence (see Chapter 2). The network connections discussed includes those shared by Egypt/Mozambique and tropical cyclone predictions, and CNN and Satellite Imagery.

6.4.5.1 Egypt/Mozambique and tropical cyclone prediction

The African countries that have the most project examples in tropical cyclone reduction includes Egypt (4) and Mozambique (4). This may be since both countries have experienced extensive uncertainty in weather prediction and climate change (International Energy Agency, 2023; International Food Policy Research Institute, 2023). Tropical cyclones are extremely complex systems and difficult to predict due to multiple influences on development and behaviour (Roca-Flores *et al.*, 2023).

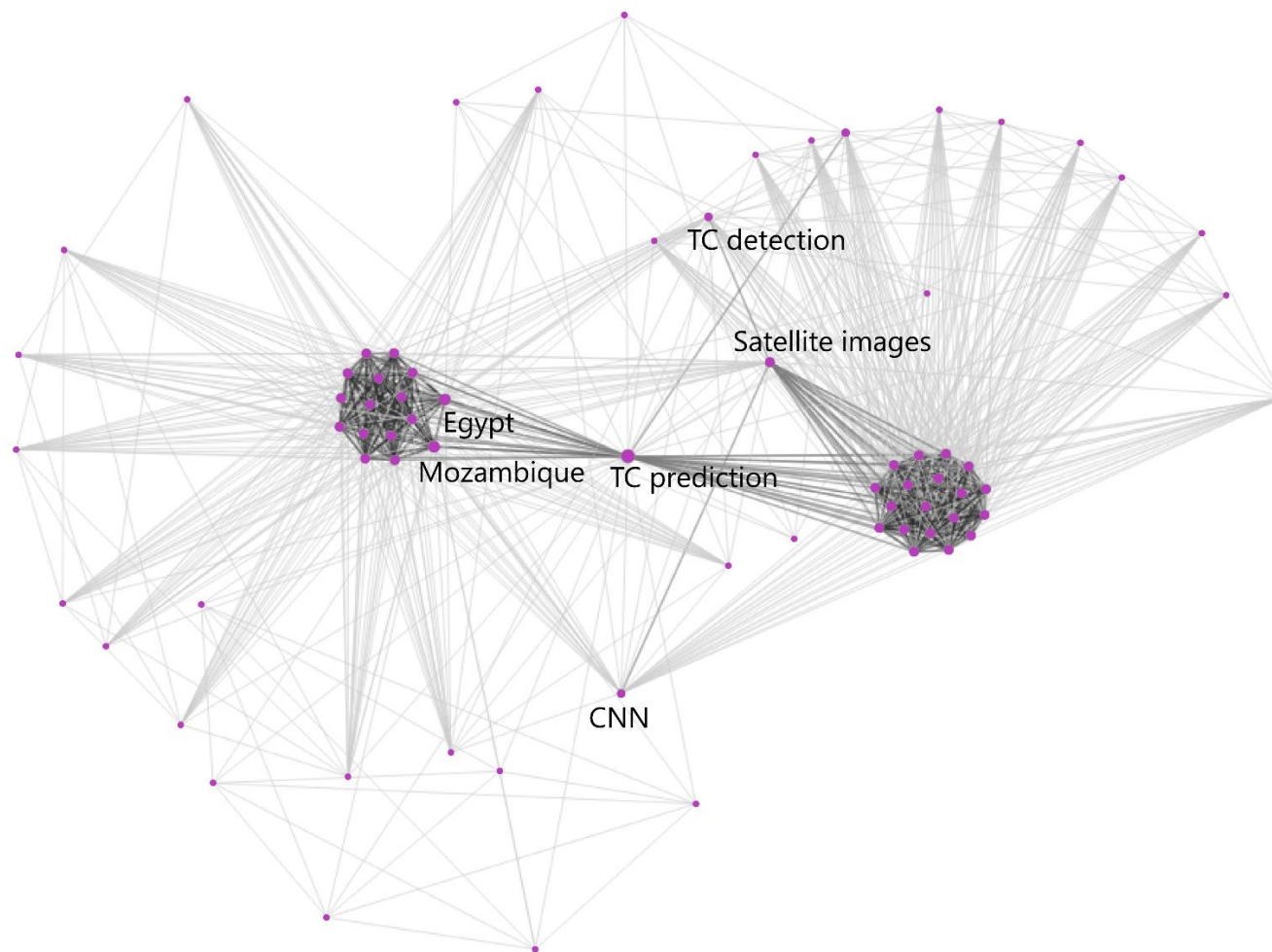


Figure 6.4.5: Co-occurrence network graph of AI for tropical cyclone reduction project examples in Africa.

Tropical cyclone prediction efforts using AI are crucial in DRR for enhancing accuracy in identifying patterns and complex interactions (Sharmin *et al.*, 2023), rapidly processing data for producing real-time updates (Scragg, 2024), improving predictions of rapid intensification processes (Heo, 2024), and assisting in CCA measures (Hao *et al.*, 2024). However, it is important to consider that AI used for predicting tropical cyclones face challenges in data quality (NASA, 2024), computational demands and output data explainability (Duong *et al.*, 2023).

Tropical cyclone prediction in Egypt and Mozambique utilises AI models such as XGBoost, LEGEMP, AR, GED and ANN. These models aid in more accurate assessments of environmental and satellite data to produce efficient tropical cyclone prediction projects (Chan, Wong & Au-Yeung, 2021; Lian *et al.*, 2020; Geetha & Nasira, 2016; Chand *et al.*, 2022). The assisting technologies in these connecting project examples include IBTrACS and NOAA. Both assisting tools are information platforms that aid in determining tropical cyclone position and intensity (Knapp, 2019; AOML Communications, 2023).

Autonomous agents involved in the connecting projects include local agents from Egyptian universities and international agents from universities in India, Netherlands, USA and Saudi Arabia. All these countries benefit from the collaboration between Egypt and Mozambique as they share similar climate change challenges and the drive towards the sustainable developmental goals. The most prominent autonomous agent involved in these projects is India. India is highly vulnerable to tropical cyclones and developed the Indian Meteorological Department (IMD) to actively monitor and predict these hazards using advanced methods (AOML Communications, 2024).

Tropical cyclone prediction efforts are useful to Mozambique and Egypt as they are both vulnerable to these hazards (Anticipation Hub, 2020; WBG, 2021) and experience rapid and uncertain changes due to climate change (Abou-Ali, El-Ayouti & Mohieldin, 2023; Biacuana, 2009). Reducing tropical cyclone project examples in Africa entails a dominant connection between AI model CNN and the assisting technology of satellite images. This connection is analysed next.

6.4.5.2 CNN and satellite images

The CNN model is present in projects impacting the Atlantic Ocean (Griffin, Wimmers & Velden, 2022) and the Indian Ocean (Nair *et al.*, 2021). These projects are focused on predicting the rapid intensification of tropical cyclones and detecting and tracking them. CNN is efficient for single use as it can automatically extract patterns from satellite imagery, allowing for more accurate

estimations of cyclone intensity (Jung *et al.*, 2024). In the Indian ocean project example, CNN is used as a hybrid model with MRCNN.

CNN combines automatic detection of relevant features in satellite imagery (Tong *et al.*, 2022) and MRCNN's analyses images at different scales (Wang *et al.*, 2022c) enabling accurate detection and tracking of tropical cyclones. Therefore, single and hybridised uses for CNN are substantiated for reducing tropical cyclone hazard in Africa. Satellite imagery (3) is the most frequently used assisting technology in the examples. It is used in detecting tropical cyclones, predicting its rapid intensification, and tracking their course (see Table 5.3.6).

Various types of satellite imagery are used for tropical cyclone reduction efforts include infrared imagery, visible imagery, water vapor imagery and microwave imagery (Yang & Cossuth, 2015). Satellite imagery is used with RS. Satellite imagery and RS is used in combination with AI models as both technologies aid in providing detailed information about cyclone movement, intensity and location (Hoque *et al.*, 2017; Yang & Cossuth, 2015). Autonomous agents involved in these connecting projects include universities from India and the USA.

These entities are not directly reducing tropical cyclones in Africa, but rather their projects influence the coastlines of Africa. Both international agents have interest in reducing tropical cyclones because they are extensively susceptible and vulnerable to the hazard. Reducing tropical cyclones using CNN and satellite imagery is a prominent connection in the project examples and show promising results. The network established in Figure 6.4.5 is limited by the inclusion of too few project examples. This saturates the network and creates clusters. The more elaborate the network the less concentrated the systemic structure (see Chapter 2).

Taking into account the different sections of the Chapter and all the different project examples, it becomes easier to understand the holistic representation of these projects. In the following summarising section, all the projects mentioned in this research are indicated on a map of Africa.

6.5 Using AI for reducing hydrometeorological hazards in Africa

Multiple AI project examples used for reducing hydrometeorological hazards in Africa were documented in this research. These project examples were sub-sectioned into various categories to simplify and organise the data. Considering all of these projects together creates a continent filled with AI initiatives. Efforts from various agents and countries create a vibrant AI ecosystem driven by DRR efforts. Figure 6.4.6 indicates the presence of this AI ecosystem in visual format.



Figure 6.5: Map of AI for hydrometeorological hazard reduction project examples in Africa.

Almost the entire African continent is influenced by AI project examples collected in this research. The countries devoid of these examples include the Central African Republic and the Western Sahara. This does not indicate that there are no AI R&D efforts in these countries, just that access and documented accounts are extremely limited. This could be due to many reasons, amongst challenges such as infrastructure, limited documentation, data accessibility, prioritisation, governmental interest and funding.

The country with the most project examples is Nigeria. Nigeria is present in almost all of the sub-categories in this research except for wildfire reduction efforts. Which, once more, does not necessarily indicate that there are no projects in the country, just that the access to these project examples is challenging. Nevertheless, Nigeria is considered a leading African country in AI innovations. It boasts with some of the largest investments and governmental funding in Africa and is home to more than 400 AI start-ups (Agasi, 2024). It is home to the largest AI expo in the world (GITEX tech expo) and has Dubai driving its international investments (Agbetiloye, 2024).

According to Figure 6.4.6 Africa is booming with AI project examples focused of reducing hydrometeorological hazards. This indicates great potential for the continents SDG efforts and sustainable development in the face of climate change. With an ever evolving and growing AI ecosystem in Africa, resilience to climate change and its uncertainties seems more attainable than ever.

6.6 Conclusion

In this Chapter, the data from Chapter 5 was analysed and coded to find dominant nodes and connections between them. This was done to visually represent the extensivity of the various project examples and the complexity involved in the development of AI projects for reducing hydrometeorological hazards in Africa. This Chapter addressed the last two objectives set by the research. The first, to formulate a network of nodes connected by AI projects and identify the most prominent nodes in the network. The second, to discover dominant connections between nodes and establish key contributions to the formation of an African AI ecosystem.

This was accomplished by firstly establishing the dominant nodes identified in the various project examples and tabulating them to indicate key role-players. This helped identify the most weighted nodes in the various networks. Secondly, each sub-section of Chapter 5 was discussed according to the most prominent network connections. These connections were established by considering each connection weight in the graph. They were discussed and analysed according to the various project example dynamics such as AI model use (single or hybrid), assisting technology included, project functions, and autonomous agent relationships. These connections were visually represented in a co-occurring network graph (for each section) to indicate the elaborate formation of a DRR AI ecosystem in Africa.

The most prominent connection discussed in water management was between ANN and predicting water quantity. In LULC, RF and GEE was the most prominent connection in the network. Flood reduction's most prominent network connections included ANN and RF predicting floods, predicting floods and Nigeria, and assessing and mapping floods using RF. Prominent

network connections in drought reduction consisted of RF and monitoring drought. Landslide reduction network connections were between LR and landslide susceptibility, and GIS and landslide susceptibility.

Wildfire reduction's most prominent connections included RF and wildfire prediction, and GIS and wildfire mapping. Lastly the most prominent connections in tropical cyclone reduction examples included Egypt/Mozambique and tropical cyclone prediction, and CNN and satellite images. Lastly, all the mentioned projects were compiled into a geographic map of Africa, indicating the most active countries focused on reducing hydrometeorological hazards and using AI to advance DRR.

This chapter aimed at analysing and identifying prominent nodes and network connections in the project examples listed in Chapter 5. The network formations of each section indicated elaborate relationships between multiple nodes and illustrated the extensivity of complex systemic structures present in the various projects. This ties in CAS theory and the effect of node involvement on a network. In the following section the research is concluded by referring to main arguments raised in each chapter, achieving the various research objectives and listing future research recommendations in the field.

CHAPTER 7 CONCLUSION

The African fourth industrial revolution brings with it many uncertainties and challenges. Simultaneously, it presents the continent with opportunities for immense growth and development. Utilising AI for reducing African hydrometeorological hazards is an extensively complex phenomenon whereby many components interact to create elaborate networks. This research aimed to address this complexity and create a funnel whereby ideas and complex dynamics associated with AI used for African HHR can be better understood.

7.1 Main research discussions

This research was extensively challenging. Not only in terms of finding data for its execution but also structuring it in such a way that non-linear processes and ideas can be understood in a linear manner. The very essence of the research is constructed on the premise of simultaneous and overlapping processes realised in unpredictable systemic behaviours. This idea on its own stretches conventional notions of reality. Creating categories within concepts that lack clear borders was extremely challenging. CAS theory made conceptualising the governing ideas of the research easier to express but at the same time more difficult to define. With uncertainty always lingering behind a concept nothing can be said in complete confidence (see Chapter 2).

This notion is true for most of the components involved in this research. With AI many possibilities are present, but none are definite (see section 4.2.2). There is always a degree of uncertainty involved, be it with data accuracy, processing bias, applicational errors or practical implementation (see section 2.3.1). This uncertainty has become both the rule and problem of conducting a study through the lens of CAS theory. The trick here, it seems, is becoming comfortable with the uncomfortable fact that nothing is certain. The sheer complexity associated with hydrometeorological hazards and their DRR creates additional uncertainty (see section 2.3.4). The processes present in DRR calls for extensive analysis and procedural precautions (see Chapter 3). AI is optimistically integrated into these systems and ignorantly trusted for correct outputs.

AI's ability to address prospective, corrective and residual DR presents various opportunities for African development (see Chapter 3). However, its utilisation towards model adjustments and critical model analysis is still under researched areas (see section 3.3.3). AI can adjust and enhance existing models to produce more accurate projects, but this is not prioritised in the existing efforts of its DRR utilisation. It strikes the researcher that there might be a lack of full awareness among some African stakeholders regarding the implications associated with using AI

for HHR purposes. It seems innovative and exciting; however, its implications can be defining. This is where policy, governance and collaboration efforts become crucial (see Chapter 4).

Notions of responsible AI and ethical governance drive a sustainable AI ecosystem in Africa (see section 4.2.2). AI integration in Africa shows to be extremely beneficial for economic prosperity and sustainable development (see section 4.3). Integrating AI in economic systems aid in reducing prospective risks associated with hydrometeorological hazards such as lack of facilities, funding, capacity and infrastructure (see section 4.3). Furthermore, to ensure more resilient systems in African AI adaption, public-private collaborations should be encouraged to facilitate adequate funding, investment and R&D initiatives (see section 4.4). CAS theory highlights that the more dynamic and versatile a system, the more resilient and sustainable it becomes.

This creates a platform whereby the DRR AI ecosystems in Africa can flourish and grow. Furthermore, creating AI friendly environments enables more sustainable and resilient AI applications for DRR, driven by best practice initiatives and active collaborations (see Chapter 4). Existing projects using AI for reducing hydrometeorological hazards in Africa involve multiple role-players, AI models, assisting technologies, project functions, countries and autonomous agents (see Chapter 5). The sheer number of available project examples included in this research indicates a growing and evolving AI domain in various African countries. The more involvement in a CAS the higher the uncertainty for emergent behaviours.

AI for water management project examples were some of the most extensive and easiest to locate in the research (see section 5.2.1). these projects focus on using AI to manage water quantity and quality in Africa. The extensivity of these projects are due to the essential role that water management plays in reducing and preventing water related hazards and risks in Africa (see section 5.2). The most prominent connection in the water management network graph was found to be between the AI model of ANN and the project function of predicting water quantity (see section 6.3.1.1). Both nodes are popular in the African water management project examples and play a prominent role in the dense and elaborate water management network (see Figure 6.3.1).

Project examples relating to land use and land cover (LULC) are just as extensive as water management and focus on urbanisation and rural development, and environmental conservation efforts (see section 5.2.2). Driven by the SDG, African land is undergoing heavy development and pose risks associated with environmental degradation, ecosystemic losses, and unplanned urbanisation. Using AI to regulate development in Africa is crucial to its sustainable growth and avoiding certain hazard formations subjected to corrective DRM (see section 3.3).

The study found that the most prominent connection in the LULC project examples network is shared between the AI model RF and the assisting tool of GEE (see section 6.3.2.1). These nodes play a crucial role in the structure of the dense LULC network and facilitate various project examples and their functions (see Figure 6.3.2). Water management and LULC networks are subject to prospective DRM and aid in avoiding the formation of unforeseen hydrometeorological DR (see section 3.2). This is a complex approach to reducing hydrometeorological hazards and assists in creating more adaptive networks and connections between prospective DRM activities (see section 2.3.3 & 3.2).

In this research, project examples focused on specifically reducing existing hydrometeorological hazards and DR included ventures in reducing floods, drought, landslides, wildfires and tropical cyclones (see section 5.3). Hazard specific project examples were notably less and more difficult to locate in this section. Flood and drought reduction project examples are the most common in African AI applications and showed to be the most popular of the corrective DRM categories (see section 3.3 and 5.3). Flood and drought hazards are extremely common in Africa and possess various complexities that influence their reduction (see section 2.2.3).

The flood reduction project examples formed an elaborate network containing many prominent connections (see Figure 6.4.1). These connections include the AI models of ANN and RF connected with the project function of predicting floods. Additionally, Nigeria and flood prediction shares a prominent connection and the AI model of RF and the project function of assessing and monitoring floods (see section 6.4.1). Various prominent network connections indicate a distribution of key role-players and influence in a CAS (see Chapter 2). Drought reduction project examples, just as flood reduction, created a dense and elaborate network (see Figure 6.4.2).

The most prominent network connection was found to be between the AI model RF and the project function of monitoring drought (see section 6.4.2.1). These nodes play an integral part in the CAS structure of the network and contribute towards various African countries efforts to reduce drought (see section 6.4.2). Landslides, wildfires and tropical cyclone reduction project examples were a lot more challenging to locate despite the prominence of these hazards in Africa. Landslides and wildfire reduction project examples are scarce mainly due to limited data and research (see section 6.4.3 and 6.4.4).

The overwhelming focus on the prospective DRM efforts (see section 5.2), and flood and drought reduction projects (see section 5.3.1 & 5.3.2) neglects other, less prominent hazards. Wildfires and landslides are unfortunately no less damaging than flood and drought hazards but are not as popular in African R&D activities (see section 6.4.3 & 6.4.4). Landslide reducing project examples are formulated into a less complex network graph due to the lack in examples (see Figure 6.4.3).

The graph still represents a distributed network with various network connections of which the most prominent includes the AI model of LR and the assisting technology of GIS connected to the project function of landslide susceptibility mapping (see section 6.4.3).

Wildfire reducing project examples are also illustrated in a simpler network graph with the most prominent connections being between the AI model RF and wildfire predictions, and the assisting technology of GIS and wildfire mapping efforts (see Figure 6.4.4). Less complex networks reduce the level of uncertainty and create more appropriate regulatory measures (see Chapter 2). Tropical cyclone reduction project examples were by far the most challenging to locate (see section 5.3.5). This is primarily due to existing projects invested in detecting and predicting tropical cyclones in the Atlantic and Indian ocean (see Table 5.3.5). These projects are not necessarily developed for a certain African country; however, they do influence coastal countries and islands interacting with these oceans.

Therefore, it becomes unnecessary to develop additional projects as existing ones already address the tropical cyclone DR facing Africa (see section 5.3.5). Due to the lack of projects and the focus on the Atlantic and Indian ocean, two prominent clusters are present in the network graph (see Figure 6.4.5). This indicates a concentration of dominant projects and influence on the development of tropical cyclone reduction efforts. The research found that each network of project examples showed extensive involvement from different international countries (see Chapter 5 summary Tables).

The most prominent role-players in using AI for reducing hydrometeorological hazards in Africa includes China, the USA and India (see Table 6.2). China is the most prominent role-player in African water management project examples (see Table 5.2.1), India in tropical cyclone reduction project examples (see Table 5.3.5) and the USA in all the rest (see Table 6.2). The humanitarian aid and mutual interest shared by the USA in Africa plays a crucial role in its overwhelming presence (see section 6.2). Additionally, the USA and China are tech giants and are at the forefront of AI development ventures (see Chapter 6).

The competition between the USA and China and their cooperation with India fuels the evolution of a more complex and resilient DRR AI ecosystem in Africa (see section 2.2.4). The complex interactions between various nodes in a CAS fuels evolutionary changes. Therefore, this enables more AI project development for reducing African hydrometeorological hazards and hopefully a more sustainable and resilient future for the continent.

7.2 Achieving the research objectives

This research was conducted on the premise of various objectives. The first objective was to establish a framework for CAS theory and conceptualize the complexities involved in AI reducing hydrometeorological hazards in Africa. This was achieved by establishing a CAS framework wherein the research commenced. This framework briefly explained crucial aspects of CAS theory for better understanding the way in which the research was structured and what the dynamics of the study entailed. CAS was defined with reference to components of self-organization, interdependence, networks, adaptation, and limitations.

Furthermore, the governing components of the research were conceptualized according to CAS and established the inherent complexity associated with each one. These components included Artificial Intelligence (AI), Disaster Risk Reduction (DRR) and hydrometeorological hazards. The second objective aimed to explore the use of AI in DRR, and the research done on its applications in various countries. This was achieved by discussing AI use in DRR with reference to existing research in different countries. The section was structured according to various DRR processes. These included efforts in prospective, corrective and residual disaster risk management (DRM).

This Chapter aimed to portray the various AI projects implemented for DRR and the different areas of its application. Additionally, it indicated the project development activities present in other countries and the way in which AI is utilized for DRR. The third research objective is intended to investigate the state of AI in Africa and the advantages and challenges faced by its implementation. This was achieved by exploring AI in Africa and addressing the various areas of influence and the implications associated with its application.

Various aspects of this implementation were addressed, for example, the role of government in its growth and development, its influence on key economic sectors, and the opportunities for collaboration and investment initiatives. This was done to create a sense of the larger impact associated with the infiltration of AI, not only for DRR means but also for larger sustainable growth in Africa. The fourth research objective aimed to investigate different AI projects specifically involved in reducing African hydrometeorological hazards and identify autonomous agent involvement.

This was achieved by listing and exploring AI for African hydrometeorological hazard reduction project examples. These projects were described according to two main sections namely climate change adaptation (CCA) and hydrometeorological hazard reduction (HHR). CCA was included in this Chapter to mimic prospective risk reduction measures for future HHR. CCA consisted of AI water management and land use and land cover (LULC) ventures.

On the other hand, HHR was compiled of projects that address existing hazards such as flood, drought, landslide, wildfire and tropical cyclones. These examples indicated existing projects in Africa developed between the year 2020 to 2024. Additionally, each section in this Chapter was summarized using a detailed Table which indicated the key categories of each project example. These categories consisted of were the project reference, the African country of application, the AI model of use, assisting technologies, the project function, and autonomous agent involvement.

The last two research objectives were achieved in the last chapter (6). These objectives are aimed to formulate a network of nodes connected by AI projects and identify the most prominent nodes in the network. Additionally, to discover dominant connections between nodes and established the key contributions to the formation of an African AI ecosystem. This was achieved by analysing the data collected in Chapter 5 using ATLAS.ti 24 which established dominant nodes and connections in various network graphs. Dominant nodes were identified from the data in Chapter 5 and summarized using Table 6.2. This was used to give an overview of key role-players in the different categories of reducing African hydrometeorological hazard project examples.

Furthermore, each category associated with HHR was coded into a network graph which indicated the most weighted connection between nodes. Each graph was assessed and discussed according to its most prominent connections. These connections were analyzed by considering the interactions between African countries, AI models, assisting technologies, project functions, and autonomous agents. Network connections indicated the prominent structures present in a CAS and aided in considering the nodes responsible for creating a dynamic AI ecosystem for DRR purposes.

7.3 Future research suggestions

Pushing AI integration in Africa presents an opportunity for a more sustainable and resilient AI ecosystem focused on reducing DR. However, any system can be subjected to extortion and requires firm and comprehensive ethical boundaries to ensure avoiding negligence. Whilst conducting the research various questions surfaced that require attention. These questions mainly involve the regulation of AI development in Africa, the lack in governmental policy and ethics, the trustworthiness of AI model outputs, the inevitable changes in African labour, and the exacerbation of gender and class inequalities.

These areas must be further investigated to ensure the formation of a sustainable and resilient AI ecosystem in Africa. Addressing these areas of research should help avoid and reduce future risks and their implications. Immense effort is put into developing AI systems for DRR in Africa. The extreme complexity associated with these system dynamics create uncertainty and

vulnerability in the continent. To reduce this phenomenon, it becomes crucial to avoid underestimating these technologies and the challenges associated with their implementation. The African continent possesses immense potential for better DRR and AI can aid in optimising the processes when utilised with caution and understanding.

7.4 Conclusion

In this Chapter the research findings were presented and discussed. The main research discussions considered how the overarching theme of CAS theory creates a framework for better understanding the complexities and ventures associated with using AI for combatting hydrometeorological hazards in Africa. The primary challenges identified in conducting this research stem from the prominence of uncertainty and incomplete documentation. Although the CAS approach highlights these challenges, conducting research within these limitations were unexpectedly difficult. Research is still inherently linear and requires a logical flow to present an argument efficiently. When a phenomenon is evidently non-linear or complex, portraying its components and dynamics in a linear fashion becomes confusing.

The research aimed at considering the phenomenon of ‘AI used for hydrometeorological hazards reduction’ as a complex and dynamic system, adapting and evolving within the context of African DRR ventures. Each research aim and objective was met by the study and produced a clear and contextually relevant picture of existing AI applications in Africa. Evidently, the amount of project development examples identified in this phenomenon, compared to the actual reduction of hydrometeorological hazards in Africa indicate a mismatch to the system. CAS mismatches pose a threat to the development of a resilient and sustainable system.

Although extensive measures are put in place to ensure the development and growth of AI in Africa, many challenges and limitations create setbacks for its efficiency. This is evident from the difficulties still present in African hydrometeorological hazard reduction efforts and the toll these hazards persistently take on the region. Efforts in more comprehensive policy development and extensive research could increase the efficiency of AI technology used for reducing hydrometeorological hazards in Africa. However, the approach to its implementation must consider CAS theory and the extensive complexity of the phenomenon to construct practical and viable ways forward.

Therefore, further research becomes crucial to formulating a more comprehensive and contextually relevant plan in utilising AI models for reducing hydrometeorological hazards in Africa. With proper consideration and comprehension of the phenomenological complexities

presented, future development of more sustainable and resilient CAS in Africa can become a reality.

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ANNEXURE

Ant-Colony Algorithm (ACA)	A probabilistic technique for solving computational problems. The model uses multi-agent methods inspired by the synchronisation of biological ants.
Adaptive Boosting (AdaBoost)	An Ensemble learning algorithm that uses weighted errors to build a strong classifier from a series of weak ones.
Adaptive Neuro Fuzzy Interface System (ANFIS)	A kind of artificial neural network that is based on the Takagi-Sugeno fuzzy interface system which can increase AI model accuracy and reduce the time needed to train models.
Algorithm	A complex set of rules that drive AI programs, determining their steps and ability to learn.
Analytical Hierarchy Process (AHP)	A type of multi-criteria assessment technique for analysing complex decisions.
Application Programming Interface (API)	The code that enables software programs to communicate.
Area Under Curve (AUC)	Is a methodology used in machine learning to evaluate several used AI models to determine which one has the highest level of performance.
Artificial Intelligence (AI)	The theory and development of computer systems able to perform tasks normally requiring human intelligence such as visual perception, speech recognition, decision-making, and translation between two languages.
Artificial Neural Networks (ANN)/ Neural Networks (NN)	A computational model inspired by the human brain's neurons. Comprised of multiple nodes and connections, starting with an input of nodes, a hidden layer of connections and ending in an output of nodes.

Assessment	A quantitative or qualitative approach to determine the nature and extent of disaster risk by analysing potential hazards and evaluating existing conditions of exposure and vulnerability.
Autonomous Agent	Is a system that can act independently and purposefully in a complex and dynamic environment.
Auto-regressive (AR)	A linear predictive model that uses historical data to predict future trends.
Autoregressive Integrated Moving Average (ARIMA)	A statistical analysis model that uses time series data to predict future trends or understand datasets.
Bayesian Negative Binomial (BNB)	A classification technique based on the Bayes Theorem with the assumption of independence among predictors.
Binomial Logistic Regression (BLR)	A statistical test for predicting the likelihood of an observation belonging to one of two possible categories of a binary dependent variable.
Boosted Regression Trees (BRT)	Also known as Gradient Boosted Trees, combine two powerful algorithms namely Boosting and Regression trees to optimise the model.
Cellular Automata (CA)	A fully discrete dynamical model that has received much attention due to simple setup expressing highly complex phenomena.
Cellular Automata-Markov (CA-Markov)	A hybrid model consisting of cellular automata and Markov algorithms.
Classification	The supervised machine learning process of categorising data into distinct classes or categories and involves predicting the class of given data points.
Climate Change Adaptation (CCA)	The process of adjusting to the effect of climate change. It aims to moderate and avoid harm and may include current or expected hazards.

Complex Adaptive System (CAS)	A complex system consisting of many parts of interconnected agents. Creating an unpredictable source of emerging behaviour, governed by adaptive and evolutionary forces.
Convolutional Neural Networks (CNN)	A type of artificial neural network mainly used to analyse visual data such as image recognition and face detection. Unlike an artificial neural network CNN does not have fully connected layers.
Decision Tree Regression (DTR)	Tree-like model used for classification and regression. They are used to determine the relationship between a single dependent variable and a series of independent variables that split off from the initial dataset.
Deep Learning (DL) / Deep Neural Networks (DNN)	The branch of AI based on artificial neural networks which, without explicit programming, is capable of learning complex patterns and relationships within data.
Deep Reinforcement Learning (DRL)	The sub-field of machine learning that combines deep learning and reinforcement learning. It is used to solve multi-layered problems and perform sophisticated decision-making tasks.
Detection	AI usually involves object detection related to image processing and computer vision; set on detecting instances of specific objects that are classified into videos and images.
Dynamic Ensemble Selection (DES)	An ensemble model used for automatically selecting a subset of ensemble members when making a prediction.
Disaster Risk (DR)	The potential or probability of harmful consequences or losses that occur to a system due to human induced hazards, vulnerable conditions and exposed environments.
Disaster Risk Reduction (DRR)	Is aimed at reducing existing disaster risk, preventing new disaster risk and managing residual risk; all of which contribute to strengthening resilience and achieving sustainable development.
Electro-Kinetic Remediation Technology (EKRT)	An environmentally friendly method that uses electric currents to extract pollutants from soil and sediment.

Ensemble Empirical Mode Decomposition (EEMD)	A noise assisted technique which is meant to be more robust than Empirical Mode Decomposition. The technique can perform better decompositions on noisy/slightly perturbed signals.
Entropy	A measurement of disorder and impurities in the information process; it is the average level of information/surprise/uncertainty inherent in random variable outcomes.
Evaluation	The methods used to assess the performance and accuracy of AI models and algorithms.
Evapotranspiration	The combined processes through which water is transferred to the atmosphere from open surfaces such as bare soil, open water, ice surfaces and vegetation.
Extra Trees Classification (ETC)	Short for extremely randomized trees, is an ensemble learning algorithm that combines multiple decision trees to create a robust classifier.
Extreme Gradient Boosting (XGBoost)	The algorithm repeatedly builds new models and combine them into ensemble models. It is superior compared to gradient boosting algorithm since it offers a good balance between variance and bias.
Extreme Learning Machine (ELM)	Feed forward neural networks with different training approaches used for classification, regression, clustering, sparse approximation, compression, and feature learning.
Feed Forward Neural Networks (FFNN)	A multi-layered network of neurons with information only travelling from the input through the hidden layers producing the output. Data only travels in one direction.
Forecasting	The application of AI to analyse large datasets, spot trends, and produce predictions with extensive accuracy.
Frequency Ratio (FR)	The AI model estimates the likelihood of an event occurring based on relative frequency of that event in different conditions and the influence of certain factors such as land use, soil type, elevation etc.

Fully Convolutional Neural Network (FCNN)	A neural network that exclusively performs convolutional operations and are mainly used for semantic segmentation.
Fuzzy Analytic Hierarchy Process (Fuzzy-AHP)	Hybrid AI model making use of fuzzy logic and analytic hierarchy process models.
Fuzzy Interface System (FIS)	An AI framework used to connect and produce maps of any data input into its output using fuzzy logic reasoning.
Fuzzy Logic	Is a way to model logic reasoning in a way where the truth of a statement is not binary but rather ranging between absolutely true or absolutely false.
Gated Recurrent Units	A type of RNN architecture designed to process sequences of data for tasks like natural language processing, time-series prediction, and speech recognition.
Gaussian process modelling	A data driven method that is a powerful tool for non-linear function regression without much prior input. The model provides a mean prediction and a measure for model fidelity.
Gene Expression Programming	An evolutionary algorithm that creates models and programs. These programs are complex tree-like structures that adapt and learn by changing their composition, size and shape, much like a living organism.
Genetic Algorithms	Adaptive search algorithms that belong to larger evolutionary algorithms inspired by the process of natural selection.
Geno-fuzzy Interface System (GENOFIS)	A novel predictive model developed for determining rainfall patterns in Rwanda. It combines genetic algorithms, neuro network systems and a comparative support vector machine tool.
Geographic Information System (GIS)	A computer system that captures, stores, analyses, and displays data related to positions on earth's surface.

Google Earth Engine (GEE)	The random forest cloud-based platform uses satellite imagery and geospatial datasets with planetary-scale analysis capabilities to detect changes, map trends, and quantify differences earth's surface.
Gradient Boosting Classifier (GBC)	A group of machine learning algorithms that combine many weak learning models together to create a strong predictive model. Decision trees are usually used for gradient boosting classification.
Gradient Tree Boost (GTB)	A methodology applied on top of another machine learning algorithm. The technique involves two types of models, a weak decision tree model and a strong model composed of multiple weak models.
Group Method for Data Handling (GMDH)	A group of AI algorithms that can be used to solve different tasks. It combines parametric, clustering, alternatives complexing, binarization and probability algorithms.
Hierarchal Clustering (HC)	Method used for cluster analysis which seeks to build a hierarchy of clusters and group similar objects into clusters that are more related to each other than objects in other clusters.
Hydrological Model (HM)	The Google Flood Hub AI system predicts water flow based on weather data.
Hydrometeorological hazards	Processes or phenomena of atmospheric, hydrological or oceanographic nature that may cause loss of life, injury or other health impacts, property damage, loss of services and livelihoods, social and economic disruption, or environmental damage.
Image Classification (IC)	A computer vision task that involves assigning labels or tags to images based on pre-existing labelled training data.
Inundation Model (IM)	The Google Flood Hub AI system uses HM information alongside satellite images to forecast flood hazard.
Internet of Things (IoT)	A network of physical objects embedded with sensors, software, and other technologies that enable collection and exchange of data with other devices and systems over the internet or other communication networks.

K-Means	An unsupervised machine learning algorithm used for clustering and aims to split data into different clusters and report the location of mass for each cluster.
K-Nearest Neighbors (K-NN)	The supervised machine learning method is a non-parametric model employed for classification and regression problems.
Logistic Model Tree (LMT)	A classification model with a supervised training algorithm that combines LR and DTR.
Logistic Regression (LR)	A supervised machine learning algorithms used for classification tasks where the goal is to predict probability of an instance belonging to a given class and the relationship between two data factors.
Long Short-Term Memory (LSTM)	A type of recurrent neural network that is specifically designed to handle sequential data and more effectively imitate human thought.
Machine Learning (ML)	The branch of AI that imitates the way in which humans learn through experience and automatic improvement the from input data.
Mapping	In robotics mapping is used for floorplans in autonomous robot development. In artificial neural networks, mapping involves simulating connected neural units.
Markov	A stochastic model used for temporal and sequential data modelling. It is based on the idea that future systemic states depend only on the current state and not on the events that occurred in the past.
Maximum Entropy (ME)	The principle states that when trying to determine a probability distribution based on partial information, one should select the distribution with the highest level of entropy.
Maximum Likelihood Classification (MLC)	A popular supervised image classification model and assigns each cell in the input raster to the class it has the highest probability of belonging to.

Model	An AI program that has been trained on a set of data to perform specific tasks like recognizing certain patterns or making certain decisions.
Moderate Resolution Imaging Spectroradiometer	A satellite-based sensor used for earth and climate observational measurements.
Monitoring	The tracking of specialised metrics and data specific AI operations.
Multi-Criteria Decision-Making (MCDM)	Branch of operations research that aims to determine the best alternative to conflicting criteria in decision making. It is used to assist AI models in computational assessment.
Multi-Layer Perceptron (MLP)	A neural network connecting multiple layers of fully connected nodes in a directed graph. It has the advantage of learning from non-linear models and train models in real-time.
Multi-Layer Perceptron Neural Network (MLP-NN)	The hybrid model combines multi-layer perceptron and neural network models for classification and regression problems.
Multi-Linear Regression (MLR)	A statistical technique that uses two or more independent variables to predict the outcome of dependent variables.
Multiple Decision Tree (MDT)	Simply, it is more than one decision tree regression model being utilised for modelling and evaluation.
Multivariate Discriminant Analysis (MDA)	Is a multivariate dimensionality reduction technique used in ML. It is used to predict signals from diverse domains.
Naïve Bayes (NB)	The supervised machine learning algorithm uses the Bayesian Theorem with an assumption of independence among predictors.
Naïve Bayes Trees (NBT)	A hybrid classifier algorithm composed of NB and RT algorithms.
Natural Language Processing (NLP)	A branch of AI that provides a framework for computers to understand and interpret human language.

Non-Parametric model	A type of AI model used in statistics and machine learning that does not assume any specific form for the relationship between independent and dependent variables.
Object Based Image Analysis (OBIA)	The segmentation of an image by grouping pixels together into vector objects.
Parametric model	A class of machine learning methods in the field of statistics that summarize data with a fixed number of parameters.
Prediction	Is the use of machine learning to identify patterns in past events and make predictions about future events.
Principal Component Analysis (PCA)	A dimensionality reduction technique used in AI that converts the observations of correlated features into a set of linearly uncorrelated features.
Product Quantized k-means (PQk-means)	Is a hybrid technique used to efficiently approximate high dimensional vectors, making the k-means search faster and more applicable.
Project	A software-based initiative that utilises AI techniques, technologies, and methodologies to develop intelligent programs.
Random Forest (RF)	A supervised machine learning algorithm that grows and combines multiple decision trees for classification and regression problems.
Random Tree (RT)	A tree formed by a stochastic process and include uniform spanning tree and random forest.
Recurrent Neural Networks (RNN)	A type of artificial neural network that uses sequential or time series data for tasks such as speech recognition and language translation.
Regression	The mathematical approach to find the relationship between two or more variables in machine learning.
Regression Trees (RTs)	A variant of decision trees that are used to predict continuous valued outputs instead of discrete outputs and have no leaf nodes which represent real values.

Remote Sensing	The process of detecting and monitoring the physical characteristics of an area by measuring its emitted and reflected radiation at a distance.
Reinforcement Learning (RL)	A machine learning paradigm that focuses on how intelligent agents can learn to take actions in an environment to maximise a cumulative reward.
Resilience	Is the ability of a system to resist, absorb, adapt to, transform, recover and 'bounce back' from the effects of hazards.
Response Surface Methodology (RSM)	A general strategy for combining designed experiments and regression analysis to explore the relationship between one or more responsive variables and set of factors thought to affect responses.
Self-organisation	The process by which individuals organize their communal behaviour to create global order by interactions amongst themselves rather than through external instruction or intervention.
Sentiment Analysis (SA)	Also known as opinion mining and emotion AI, is the process of analysing large volumes of text to derive a positive, negative or neutral sentiment.
Sentinel-1	Is a high-resolution radar imagery satellite, providing a day-and-night, all-weather supply of earth surface images.
Sentinel-2	An earth observational mission from the Copernicus Programme that systematically acquires optical imagery at high spatial resolution over coastal waters and land.
Stacking (ST)	An ensemble model used for combining multiple ML models to achieve better predictive performance.
Support Vector Machine (SVM)	A powerful machine learning tool used for linear and non-linear classification, regression, and outlier detection tasks.
Support Vector Regression (SVR)	An instance based supervised learning algorithm that extends the capacities of SVM to regression problems.

Susceptibility	The state or fact of being likely or liable to be influenced or harmed by a particular hazard.
Sustainability	The avoidance of the depletion and degradation of natural resources to maintain ecological balance.
Vector Auto Regressive (VAR)	The workhouse multivariate time series model relates current observations of a variable with its past observations and past observations of other variables.
Urban Sprawl	The rapid expansion of low-density urban housing with single use zoning and increased reliance on private automobile transportation.