The historical and seasonal distribution of schistosomiasis transmitting vectors in the Mpumalanga province, South Africa

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PREFACE

This dissertation represents original work and contains information that was not previously submitted, by the author, for a similar degree at any university. The author of the dissertation collaboratively worked with the supervisors to conceptualise the study, data cleaning and the analysis process. All the information and data used in the study were extracted from publicly available dataset sources which were mentioned in the study.

The dissertation is written in article format and extracts of the study were submitted and presented at the following symposiums and conferences:

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“If I have seen further, it is by standing on the shoulders of giants.”

ABSTRACT

Schistosomiasis is a parasitic disease transmitted by freshwater host snails and is prevalent in tropical and subtropical regions. The spatial-temporal focal distribution and transmission of schistosomiasis are determined by the presence of these vectors in freshwater bodies. The disease has put approximately 40% of the South African population at risk of infection with people living in settings that have poor sanitary facilities having the highest infection rates. Children aged <15 years have the highest prevalence and transmission rates of schistosomiasis. The study aimed to understand the spatial and seasonal distribution of the schistosomiasis vectors, *Biomphalaria pfeifferi* and *Bulinus globosus,* in the Mpumalanga province over 40 years. The first objective was to determine the historical distribution of schistosomiasis transmitting snails using maximum entropy (MaxEnt) and a generalized linear model (GLM). The historical seasonal distribution of schistosomiasis was determined using an interpolation technique, kriging. The second objective was to assess the historic water quality of rivers within the Mbombela and Nkomazi local municipalities. The last objective was to identify rural areas that were vulnerable to schistosomiasis in Mbombela and Nkomazi local municipalities by creating a vulnerability index. ArcMap 10.8.1 was used to prepare the modelling and vulnerability index data which were converted to raster format. IBM SPSS statistics was used to conduct statistical analyses for the water quality assessment. The modelling results showed Mbombela local municipality and areas along the border of the local municipalities provided suitable conditions for the distribution of *Biom. pfeifferi* and *Bul. globosus*. The mapped seasonal distribution within Mbombela local municipality shows that post-rainy followed the trend of the modelled historical distribution, along the Crocodile River and Komati River. There were notable changes in salt, pH and nutrient levels within the Mbombela river systems and this likely affected the water quality in turn negatively affecting the biotic ecosystem where the schistosomiasis vectors are found. The overall vulnerability was observed along areas where models had shown the host snails to be abundant, especially the high and very high vulnerability areas. Vulnerability percentage showed the difference between the vulnerability zones for each snail species. These findings suggest that interventions should consider the dynamic nature of social and environmental factors that contribute to vulnerability in addressing schistosomiasis transmissions. Knowing the historical distribution of schistosomiasis and historically vulnerable areas will aid in predicting areas that may be vulnerable to exposure currently and in the future as it provides a guide for health officials on which areas need fast interventions.

Keywords: Schistosomiasis, species distribution modelling, *Bulinus globosus, Biomphalaria pfeifferi*, local municipalities, vulnerability index, water quality.

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Acronyms and Abbreviations

°C	Degrees Celsius
AUC	Area under the receiver operator curve
CDC	Centres for Disease Control and Prevention
CTA	Classification tree analysis
DALYs	Disability-adjusted life years
DWA	Department of water affairs
DWS	Department of water and sanitation
GIS	Geographic Information System
GLM	Generalized linear models
IARC	International Agency for Research on Cancer
km^2	Square kilometres
KNP	Kruger National Park
MARS	multivariate adaptive regression splines
MaxEnt	Maximum entropy
MDGs	Millennium Development Goals
mm	Millimetres
NFSC	National Freshwater Snail Collection
NICD	National Institute of Communicable Diseases
NTDs	Neglected tropical diseases
PAI	Physicochemical Driver Assessment Index
PCA	Principal component analysis
PES	Present ecological state
RF	Random forest
RS	Remote sensing
SDMs	Species distribution models
SRE	Surface range envelope
SSA	Sub-Saharan Africa
SWV	Soil water volume
TDS	Total dissolved salts
WADI	Water-Associated Disease Index
WHO	World health organisation

CHAPTER 1 INTRODUCTION

1.1 Background

Schistosomiasis is a parasitic disease prevalent in more than 78 countries and has infected more than 250 million people in the world with most inhabiting the southern parts of Africa (Moodley, 2003; WHO, 2008; Chibwana et al., 2020). Schistosomiasis accounts for 10% of the global disease strain caused by the water-associated disease group, and it is associated with high mortality and morbidity rates across the world. All age groups can be infected by schistosomiasis, but it has been noted that children between the ages of 4 and 15 who have contact with local waterbodies are more likely to contract the disease (Appleton & Naidoo, 2012). Haw (1994) submits that children are more exposed to contract the disease in spring, and other studies also note that the most prominent seasons for contracting schistosomiasis are spring and summer (Appleton & Naidoo, 2012; Spencer et al., 2017). The two *Schistosoma* species that are predominantly found or known in sub-Saharan Africa, are, *Schistosoma haematobium*, causing urogenital schistosomiasis and *Schistosoma mansoni*, causing intestinal schistosomiasis (WHO, 2021). In sub-Saharan Africa schistosomiasis is an endemic disease transmitted by intermediate host snails (vectors), mainly *Biomphalaria pfeifferi*, *Bulinus globosus* and *Bulinus africanus* (Manyangadze et al., 2021).

The spatial-temporal focal distribution and transmission of schistosomiasis are largely determined by the presence of intermediate host snails in freshwater bodies and human contact with the ecosystems (Manyangadze et al., 2021). Environmental and climatic factors, such as rainfall and temperature, influence the abundance of intermediate host snails that transmit schistosomiasis (Manyangadze et al., 2016). On a smaller scale, patterns of precipitation play an important role in the decrease or increase in the range of infection of schistosomiasis (Bavia et al., 1999). An increase in rainfall can increase schistosome transmission but heavy rain, which creates fast-flowing water, is not suitable for snail survival (Odongo-Aginya et al., 2008; Xue et al., 2011). Environmental factors are divided into two parts, namely biotic (living) and abiotic (non-living). Biotic factors include aquatic plant density and presence, food availability, competition, and predator-prey interaction, while abiotic factors are related to chemical and physical water properties including pH and water velocity, salinity, turbidity, conductivity, and water temperature (McCreesh et al., 2015). Changes in water temperature influence the schistosome life cycle which affects the rate at which schistosomiasis is transmitted to humans (McCreesh & Booth, 2013). These factors differ between ecosystems, often even in the same ecological zone, with each factor's importance varying from one ecological zone to the next (Stensgaard et al., 2013; Manyangadze et al., 2016).

Changes that take place in climatic factors are major determinants in the development and production of snails, and the development and production time of intermediate host snails in freshwater all depend on climate variability (Adekiya et al, 2019). These climatic factors pose a threat to the fertility of the snails, the hatching of the schistosome eggs, and decreased survival rates (Pedersen et al, 2014). The model below (Figure 1-1) shows some of the climate change factors which have a significant impact on the lifespan and fertility/fecundity rate of both snail and worm transmission during the schistosome life cycle (Adekiya et al., 2019). Factors such as air temperature and rainfall can influence spawning periods, growth rates, and mortality rates of schistosomiasis vectors (McCreesh et al., 2015). Temperature can affect the speed of chemical reactions in the water, aquatic plant photosynthesis rate and the rate of metabolism, and can affect the interaction of pollutants, parasites, and other pathogen creatures with water (Mackey et al., 2013). Long-term rainfall can lead to flooding which can cause water to lose transparency and consequently change the whole environment of the snails. Reduced water transparency leads to greater absorption of solar radiation and heat-trapping at the water surface which can affect the pH and salinity of the water body (Adekiya et al., 2019; Zhou et al., 2021).

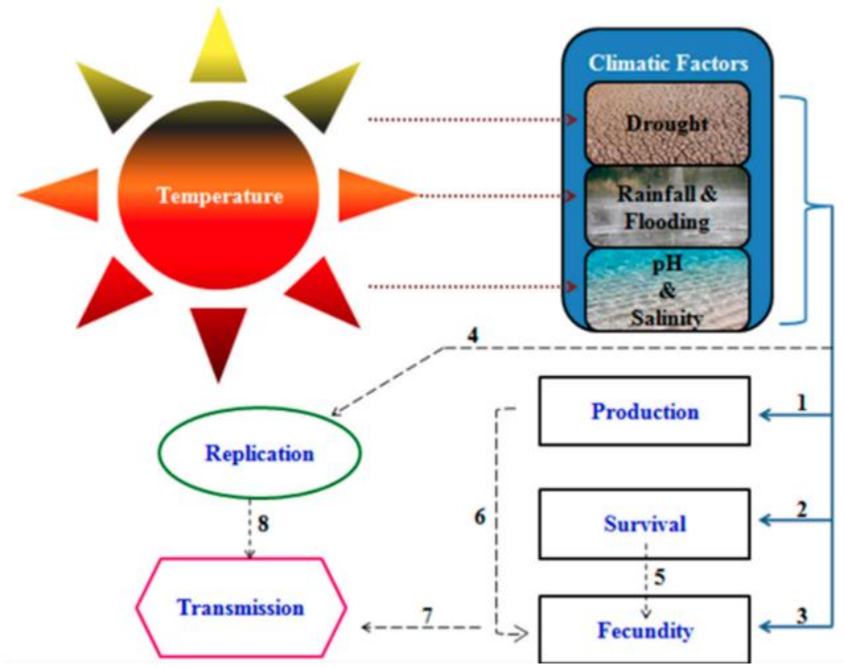

Figure 1-1: Proposed model for effects of change in climatic factors on schistosomiasis transmission by Adekiya et al., (2019).

Human behaviour contact rates and environmental exposure, and snail population dynamics are widely affected by seasonality (Xue et al., 2011; Huang et al., 2022). Human-snail contact and seasonal variation of snail population density make up a seasonal transmission environment that can affect the dynamics of schistosomiasis infections and interventions (Huang et al., 2022). In many areas, there is an observable large seasonal fluctuation for the schistosomiasis intermediate host snail populations with the direction of effect varying by region (Pedersen et al., 2014). Seasonal changes in temperature in temperate and subtropical areas contribute to the seasonality of snail numbers and schistosomiasis transmission. The seasonality of the snails is also affected by the permanence of the waterbodies responsible for transmission in a specific area, and seasonal fluctuations in rainfall have a larger effect on permanent versus temporary waterbodies (McCreesh & Booth, 2013; Pedersen et al., 2014). In a study conducted by Huang et al., (2022), it was found that an increase in seasonal changes makes the endemicity and infection transmission less sustainable, making it easier to apply control strategies in areas with uniform transmission than in areas with seasonal variety. Rainfall and temperature also play a role in the transmission of schistosomiasis (Xue et al., 2011). Changes in patterns of rainfall and temperature in an area have different effects on the seasonality of the transmission of the disease (Figure 1-2), which is why it is important to include seasonality in dynamic models (Figure 1-3) as this will assist in having reliable estimates of the relationship between disease transmission and the environment (Pedersen et al., 2014; De Leo et al., 2020).

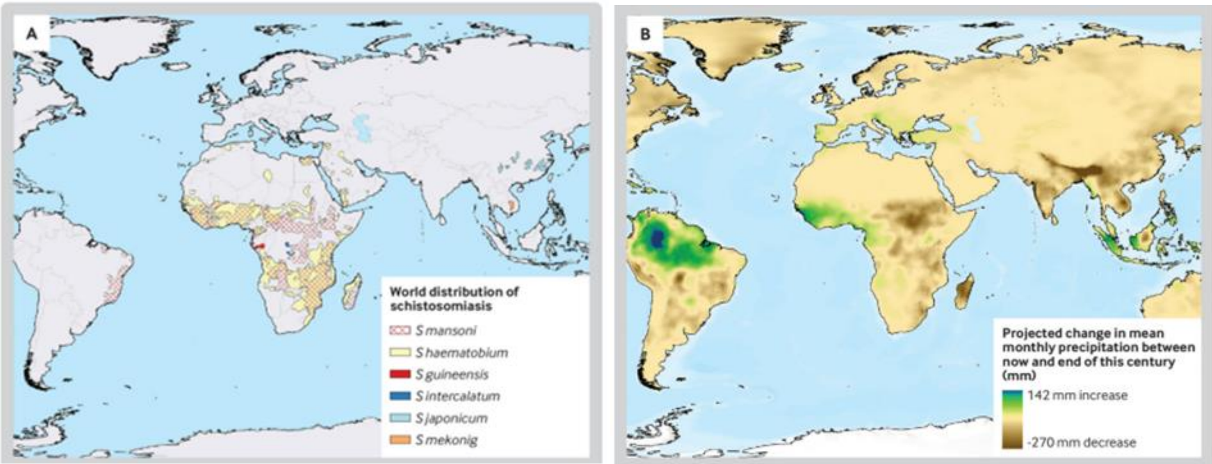

Figure 1-2: Map indicating the distribution of schistosomiasis globally and b) Map indicating the change in mean precipitation that is projected to occur by the end of the 21st century (De Leo et al., 2020).

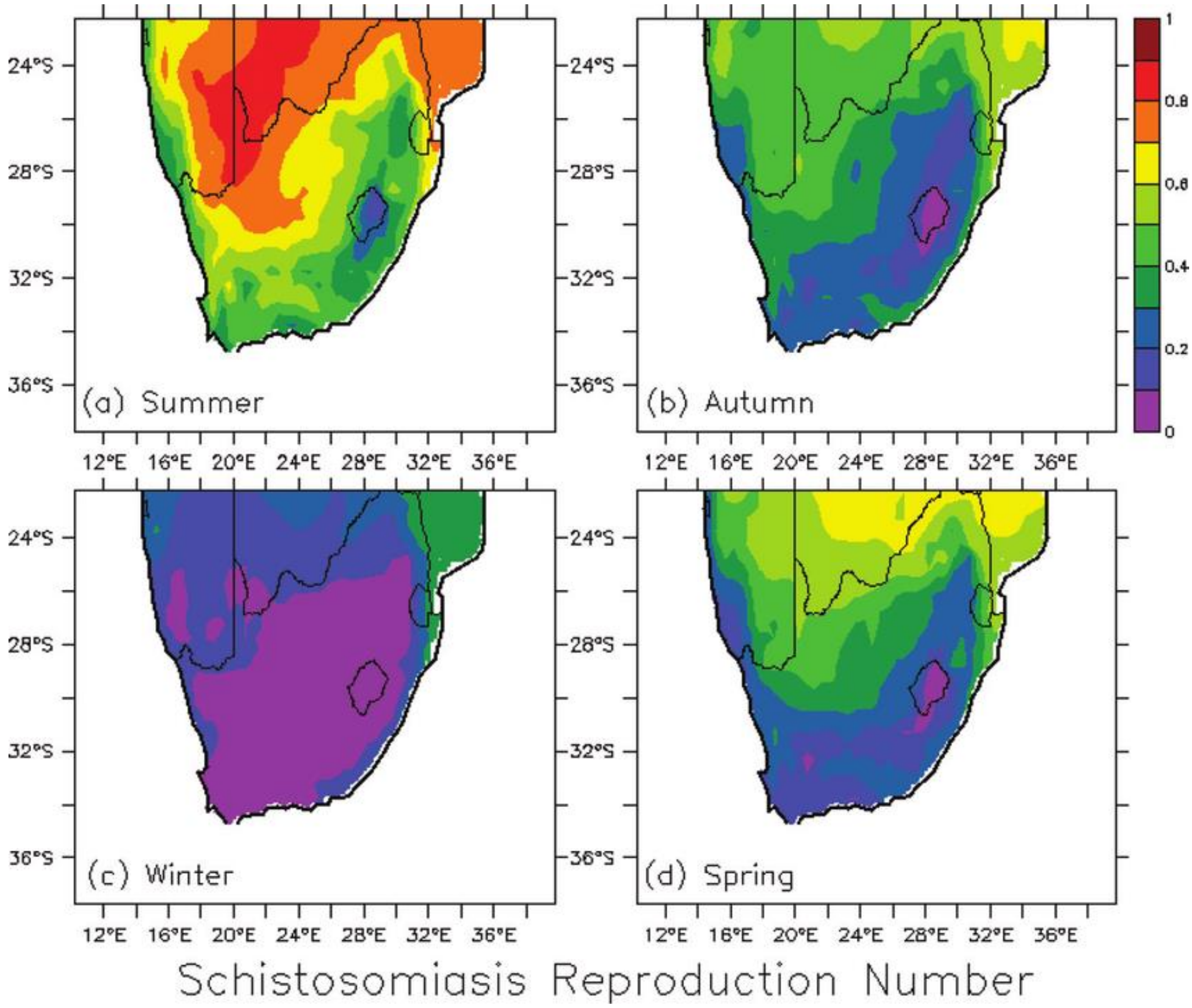

Figure 1-3: Seasonality of schistosomiasis over South Africa. A model by Adekiya et al., (2017) suggests that schistosomiasis transmission is seasonal and indicates climate variability contributes to the increase or decrease in the reproduction number of schistosomes.

According to Quayle et al., (2010), determining whether a habitat is suitable for the intermediate host snails and the water body type, plays an important role as schistosomiasis can be transmitted in a variety of artificial and natural wetland habitats. Schistosomiasis is generally transmitted in habitats that attract contact by infected people; mostly children followed by women (Appleton & Madsen, 2012; De Leo et al., 2020). Intermediate host snails can tolerate water with a wide range of chemical compositions but can be restricted by current velocity (Appleton & Madsen, 2012). In aquatic systems, pH alone is rarely considered a limiting factor in the distribution of schistosomiasis (Mackey et al., 2013). pH is the amount of acid present in the water, is highly dependent on climatic change, and differs greatly from one region to another (Adekiya et al., 2019). *Biomphalaria pfeifferi* has a positive relationship with good water pH of about 7.6-8.5. A recent regression model study conducted by Nwoko et al (2023) noted that pH had a p-value of 0.29 for *Bulinus globosus*. This indicates that *Bulinus* is not mainly affected by changes in pH. No study has yet examined the influence of pH on the *Bulinus* species (Ntonifor & Ajayi, 2007; Marie et al., 2015). Most intermediate host snails can adapt and tolerate various environmental changes (Olkeba et al., 2020). The rate of water flow is particularly important because higher current flow velocity makes host snails vulnerable to being swept out of their habitats and their food dispersed (Appleton, 1978). Waters with a flow velocity below 40 cm/s usually make suitable habitats for the snails, and rainfall can transform often polluted and non-productive sites into breeding habitats by filling standing water habitats (Sulieman et al., 2018). De Kock et al., (2004) express similar views on how stronger currents can limit the distribution of the host snails. Slowly flowing water or standing water is preferable to fast-flowing water, and clear water is preferred over turbid water (De Kock et al., 2004; Appleton & Madsen, 2012). Like water flow velocity, water temperature is influential to the snails' ecology as tolerance is relatively slow (Appleton & Madsen, 2012).

A strong spatial association between variables such as infection, transmission and exposure to water is needed (Appleton & Madsen, 2012). Frequent contact with water by people is also required to facilitate transmission as the presence of snails alone in stable habitats is not enough. The transmission of schistosomiasis has been closely linked with human living conditions with factors such as population growth, housing density, type of water sources and proximity of water sources impacting transmission rates (Adekiya et al., 2019). People who live in semi-rural communities and rural communities frequently have contact with schistosomiasis-infected water (Manyangadze et al., 2016). The continued growth of human populations has likely led to a greater risk of people being in contact with water-borne diseases, especially in rural areas where they have limited access to piped water and appropriate sanitation (WHO, 2021). People who live in large communities usually have an approximately 70% prevalence to schistosomiasis because they live near one or more waterbodies which can lead to large quantities of *Schistosoma mansoni* eggs being washed up into these waterbodies (Pitchford, 1958; Chimmbari et al., 2003; Mujumbusi et al., 2023). It is a different case for smaller communities that use scattered water resources as they live in scattered homesteads. It has been noted that intense transmission can sometimes occur regardless of people's living conditions (McCreesh & Booth, 2013). Wetlands act as contact points for many human activities which involve direct contact with water, and this increases the chances of infection. In rural areas, many activities occur at well-established contact points of wetlands where people contact water, leading to exposure to infection (Appleton & Madsen, 2012). These activities include recreation, swimming, and domestic use such as washing clothes, fetching water, bathing and for irrigation purposes.

1.2 Problem statement

In South Africa, schistosomiasis is a serious public health problem that infects approximately 3 million children while at least 20 million people (approximately 40% of the population) are at risk of infection (Moodley et al., 2003; Manyangadze et al., 2021). People living in settings poor in sanitary facilities and hygiene have the highest infection and disease burden. The Mpumalanga province is among the provinces that have been labelled endemic to schistosomiasis infection by the National Institute of Communicable Diseases (NICD) (Quayle et al., 2010; NICD, 2022). The eastern parts of Mpumalanga, known as the Lowveld, are reported to have a high prevalence of schistosomiasis and are labelled 'High-Risk Areas' (Figure 1-4).

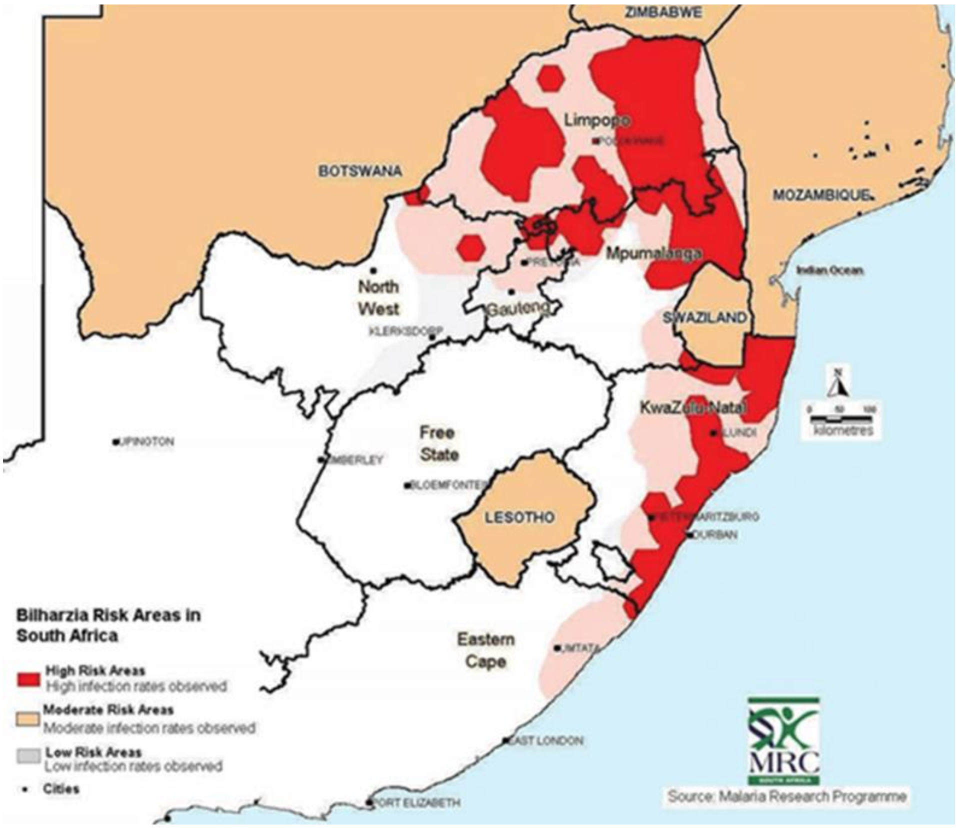

Figure 1-4: map of schistosomiasis distribution adapted from data from the South African Medical Research Council (Quayle et al., 2010).

In Mpumalanga, only 29% of households have access to piped water while the other households are divided between water boreholes or fetching water from rivers with some people having to walk over a kilometre to fetch water. The General House Survey (2018) indicated that a small number of people, about 1.4%, still use open fields or the bush as toilet facilities with an alarming 88.4% of households that drink water without any sort of treatment. Factors that contribute to increased vulnerability include, but are not limited to, age, sex, social roles and economic status, and distance to open water sources (M'Bra et al., 2018). Different socio-economic conditions are associated with occurrences of schistosomiasis which add to the vulnerability and exposure of these communities (Gazzinelli et al., 2006; M'Bra et al., 2018). South Africa as a developing country provides the socio-economic and environmental conditions for a parasitic disease like schistosomiasis to be transmitted (Gazzinelli et al., 2006).

South Africa continues to experience challenges in water and sanitation, especially in rural areas. Individuals in these areas are therefore vulnerable to water-associated diseases such as schistosomiasis (Macnee & Tokai, 2016). Many are left vulnerable and unable to get medical attention due to a lack of basic service delivery. People who live in these communities have little to no knowledge of this parasitic disease which increases exposure and susceptibility as they do not know the dangers (Weerakoon et al., 2015). The health impacts of climate change differ across regions with influences on disease patterns, increase in population dynamics of vector and water-borne diseases, and infectious diseases spreading wider due to migration (De Kock & Wolmarans, 2005). South Africa falls within the sub-Saharan region which, due to climate change, is predicted to have the highest proportion of people who are at risk of schistosomiasis infection (WHO, 2021). In predicting control outcomes, conventional modelling approaches usually restrict seasonal effects by using yearly averaging or ignore the effects of seasonality by using simplified intermediate host modelling (Huang et al., 2022). There is currently a major gap in studies focusing on climate change effects and schistosomiasis, with a handful of studies mainly focusing on the effects of increasing mean temperature and on extreme weather events (McCreesh & Booth, 2013).

1.3 Justification

To understand schistosomiasis transmission dynamics, it is important to identify factors that are significant contributors to transmission in different habitats. Thus, conducting studies at a local scale is important as they will help to identify what factors are significant contributors to the distribution and transmission of schistosomiasis in vulnerable communities. Studies conducted at the local scale will provide information on the temporal distribution, population dynamics and ecology of the snails to enhance present knowledge of the spatial and seasonal distribution of the intermediate host snails *Biomphalaria pfeifferi* and *Bulinus globosus*, which will aid in the development and maintenance of control strategies (Ofulla et al., 2013; Manyangadze et al., 2016). These species are in endemic areas of schistosomiasis in South Africa. *Bulinus globosus* is common in the eastern parts of the country, limited to Mpumalanga, Limpopo and the north-eastern parts of KwaZulu-Natal (Quayle et al., 2010). Studies that have mapped the geographical distribution of *Biomphalaria pfeifferi* showed that the snail is widely distributed along the coastal areas of Eastern Cape, KwaZulu-Natal, Mpumalanga and Limpopo Province (De Kock et al., 2004; De Kock & Wolmarans., 2005).

Few studies on schistosomiasis at a local level have been conducted in South Africa as most have been focused on a broader scale (De Kock et al., 2004; Manyangadze et al., 2016; Kabuyaya et al., 2017; Sacolo-Gwebu et al., 2019). A study conducted by Appleton and Miranda (2015) noted the importance of surveying the transmission of schistosomiasis at local levels as this assists public health personnel in identifying transmission hotspots. The historical distribution of schistosomiasis in Mpumalanga will help in the development of control strategies and programmes that are currently not operational at either local, provincial or national levels in South Africa (Appleton, & Miranda, 2015). At present, schistosomiasis is a non-notifiable disease and thus the geography of the infections encountered, people who have been diagnosed, and treatments administered are not well recorded (Quayle et al., 2010; Appleton & Naidoo, 2012). Baseline information on schistosomiasis prevalence, vulnerability, and maps portraying spatial distribution of intermediate host snails are important for the creation of control programmes as they are resource demanding (Manyangadze et al., 2016). This study was conducted in two local municipalities in Mpumalanga to understand the historical distribution of schistosomiasis and how changes in water quality parameters influence intermediate host snail distribution. This will aid in understanding which areas are endemic (vulnerable), hopefully leading to the creation of control strategies suitable for each community.

1.4 Aim and objectives

This study aimed to understand the spatial and seasonal distribution of schistosomiasis vectors *Biomphalaria pfeifferi* and *Bulinus globosus* in the Mpumalanga province over a period of 40 years (1955-1995). The study will be achieved through the following objectives:

1. Determine the historical distribution of schistosomiasis transmitting vectors (snails) in Mbombela and Nkomazi local municipalities using environmental variables and species distribution modelling.
2. Assess the water quality of rivers within the Mbombela and Nkomazi local municipalities from 1977 to 2009 to understand how changes in water parameters may have influenced the distribution of schistosomiasis vectors within the local municipalities.

3. Identify rural areas that are vulnerable to schistosomiasis in Mbombela and Nkomazi local municipalities by making use of a vulnerability index.

1.5 Study Limitations

The noted limitations in the study were mostly associated with data availability constraints. South Africa is still a developing country and because of this, most of the collected data focuses on a national or provincial rather than local scale. There were no data monitoring stations found in Nkomazi local municipality during the time of this study. As a result, this limited the comparison on how the water quality may have changed for both local municipalities. Due to major data availability limits, the data for the different objectives can be noted to have different years. The study only used a 40-year period for the snail element because data availability allowed it, but for the other objectives, what was available and relevant at the time of the study was used.

The weighting approach was focused more heavily on exposure than susceptibility for the index due to data limitations. In South Africa, this indicates that social drivers are available at a large scale rather than the local level; a data constraint resulting from the highest resolution (De Boni et al., 2021). The national-level data may hide variability in smaller regions. Higher resolution information on susceptibility may enhance the contribution of these indicators to mapping vulnerable areas for schistosomiasis. Furthermore, factors that were not available for the vulnerability index application may be important such as the activity of community schistosomiasis programmes in these local municipalities (Vos et al., 2012). There are other missing factors such as community knowledge and capacity to cope and adapt that may have been a contribution to the study, which were not readily available to download. However, a high score in some susceptibility components such as the number of females suggests a high coping capacity.

1.6 Chapter Outline

This dissertation has been divided into six chapters.

Chapter 1: Introductory overview, gives the background of schistosomiasis and factors that are associated with the distribution of the disease including the problem statement, significance of the study, and the aims and objectives. Also included are limitations noted from the data and results.

Chapter 2: The literature review, which assesses past and present literature on the distribution of schistosomiasis, methods that were used to predict the distribution, and climate factors associated with the historical distribution of schistosomiasis. This chapter also includes literature that has used similar methods to the ones used in this study from geographic information system to maximum entropy.

Chapter 3: This chapter gives a detailed description of the study area, Mbombela and Nkomazi local municipalities. It includes maps of the monitoring stations and land cover within the local municipalities.

Chapter 4: This chapter aims to model the historical distribution of schistosomiasis host snails using historically recorded snail points and environmental variables. also gives a brief overview of the predicted historical seasonal distribution of the intermediate host snails for both local municipalities.

Chapter 5: This chapter focuses on how changes in water parameters affected and affects the distribution of schistosomiasis by assessing the historic water quality of rivers within the Mbombela local municipality.

Chapter 6: This chapter aims to identify areas that are vulnerable to schistosomiasis by making use of environmental and publicly available socio-economic variables for Mbombela and Nkomazi local municipalities.

Chapter 7: This chapter gives a summary of the entire study and conclusions drawn from the results. Additionally, the chapter provides recommendations for future research.

CHAPTER 2 LITERATURE REVIEW

2.1 Schistosomiasis and its vectors

Schistosomiasis, also known as bilharzia or snail fever, is one of the neglected tropical diseases (NTDs) caused by blood flukes (parasitic flatworms) or schistosomes, of the genus *Schistosoma* (McManus et al., 2018). The parasite that causes schistosomiasis infection can result in severe and long-lasting health implications in people.

The disease impact of schistosomiasis is second only to malaria in terms of devastating parasitic diseases (CDC, 2018), and makes up approximately 40% of the disease burden of tropical diseases (Sady et al., 2013). According to the Centres for Disease Control and Prevention (2020), more than 200 million people are infected by schistosomiasis worldwide. Large areas of the subtropics are endemic to human schistosomiasis with sub-Saharan Africa making up 85% of infections due to poverty, poor sanitation, lack of awareness and poor health systems (Fenwick, 2006; Kabatereine et al., 2014). As a result of these factors, rural areas make up a large portion of schistosomiasis infections (Mott et al., 1990). Typical sources of infection include ponds, lakes and natural streams, but over the past few years there have been added factors that contribute to the spread of schistosomiases such as population growth and migration, as well as irrigation systems and man-made reservoirs (Gryseels et al., 2006; McManus & Loukas, 2008).

Six species are of major pathological importance to humans under the genus *Schistosoma*, namely; *Schistosoma mansoni (S. mansoni), S. haematobium, S. guineensis, S. japonicum, S. mekongi, and S. intercalatum* (Webster et al., 2006). Each of these species differs in the type of pathology induced, the intermediate host snail (vector), the final location in the human host, and the size, shape and number of eggs produced. The freshwater snail species that act as the vectors of schistosomiasis include *Bulinus* spp. for *S. haematobium* and *Biomphalaria* spp. for *S. mansoni* (CDC, 2020; Figure 2-1 & Figure 2-2). *Schistosoma mansoni* and *Schistosoma haematobium* infections make up 95% of reported infection cases. In Africa (Figure 2-3), *S. haematobium*, which causes urinary schistosomiasis, and *S. mansoni*, which causes intestinal schistosomiasis, are the most prevalent forms of schistosomiasis (Brooker, 2007).

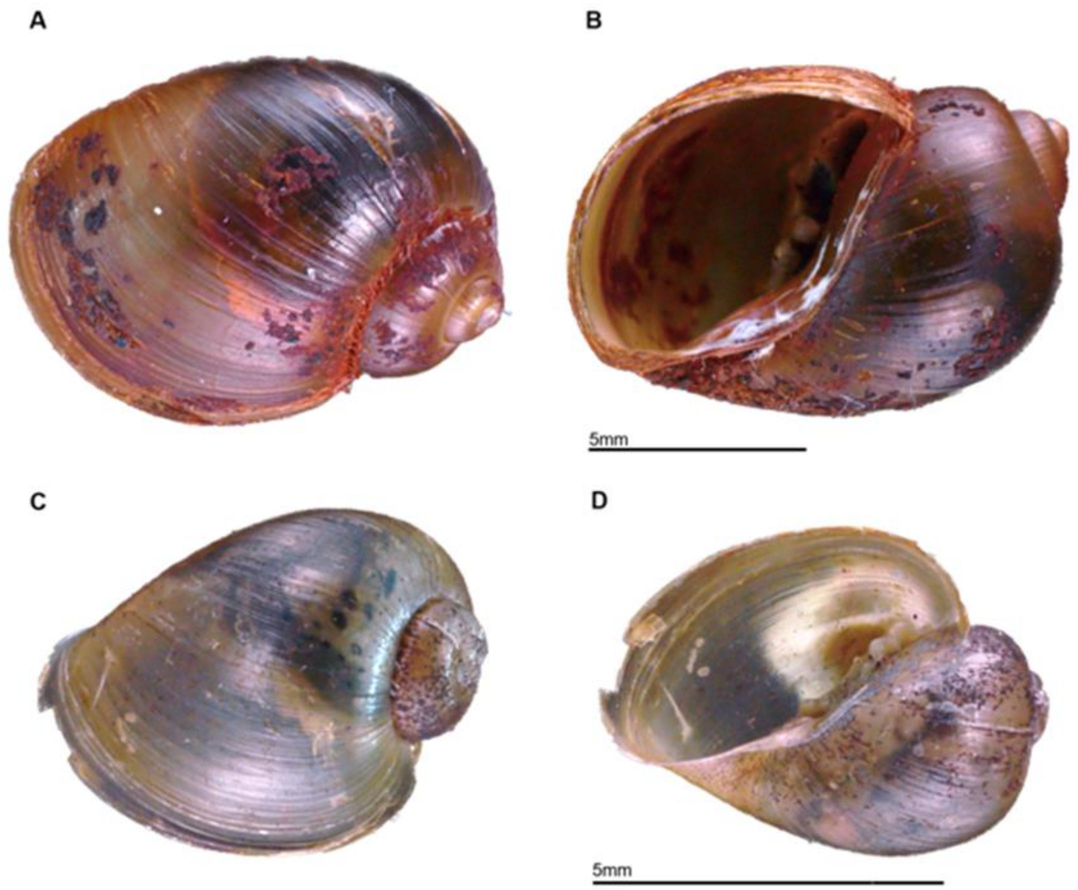

Figure 2-1: Shell morphology of *Bulinus* spp. (Photo Credit: M.H. Le Roux).

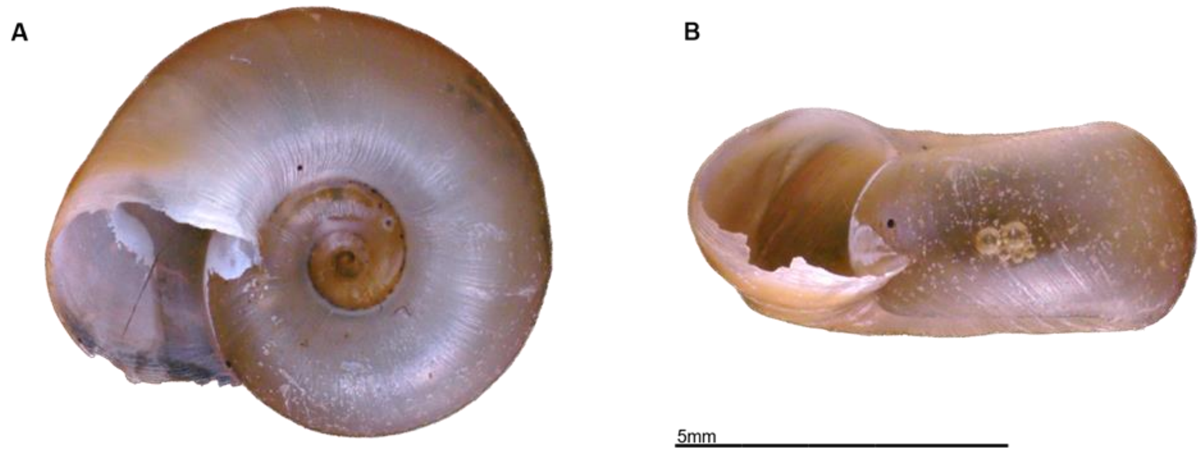

Figure 2-2: Shell morphology for *Biomphalaria* spp. (Photo Credit: M.H. Le Roux).

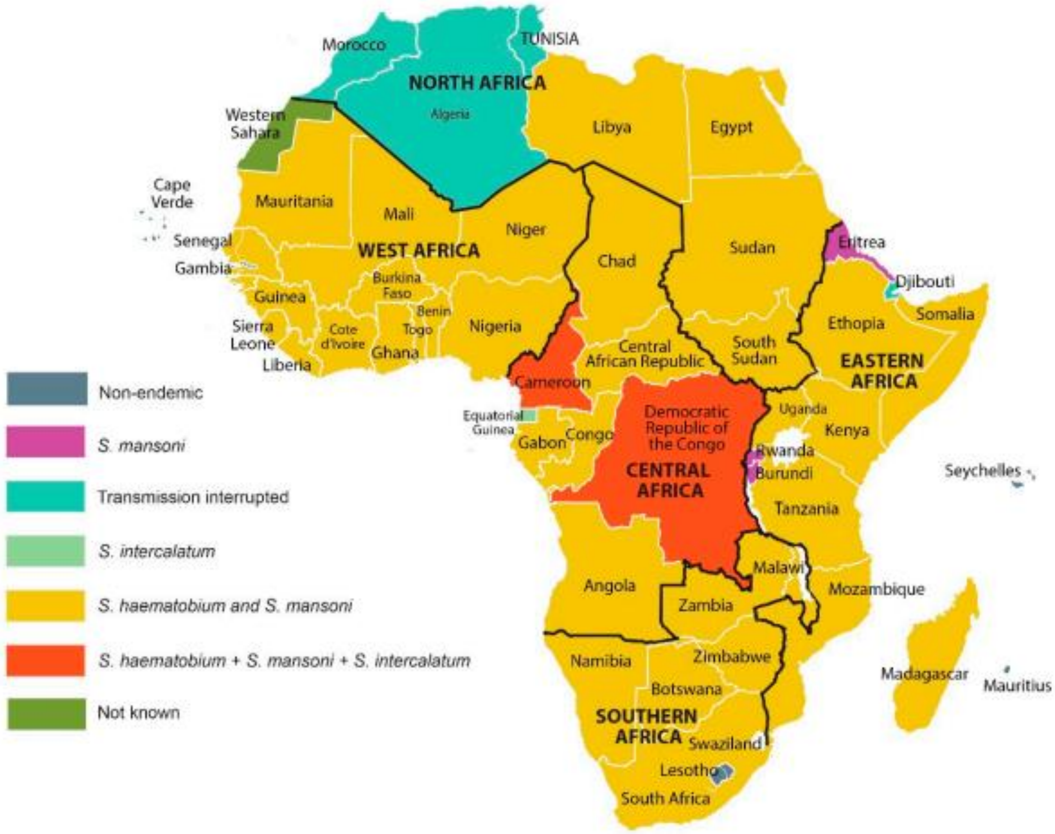

Figure 2-3:The distribution of schistosome infections in Africa (Aula et al., 2021).

2.1.1 Groups at risk

High infection and 'at risk' groups include school-age children, women and specific occupational groups such as farmers, fishermen and irrigation workers, and anyone that uses the infested water for domestic purposes (WHO, 2002; Wepnje et al., 2019). All people are susceptible to the disease, but it is more prevalent in these groups as they have frequent contact with the infested water and are thus more frequently exposed (Appleton & Naidoo, 2012). Infection intensity is different with age, with moderate or high infection intensity occurring in children between the ages of 4 and15 years and lower intensity in adults (Wolmarans et al., 2006). Contamination of fresh water with excretion containing schistosome eggs, the presence of intermediate hosts (snails) and frequent contact with water-infested cercariae by the human host are important factors in maintaining the transmission of schistosomiasis (Jordan et al., 1993). Individuals with the most intense infections usually have a higher risk of developing morbidity (Gryseels et al., 2006). Studies conducted by Clennon et al., (2006) and Kapito-Tembo et al., (2009) indicated spatial relationships between schistosomiasis and the closeness of infected people to open water sources such as rivers. The prevalence of infection decreases when there is less contact with infested water (Kabuyaya, 2017).

2.1.2 Symptoms of schistosomiasis

Schistosomiasis symptoms are not caused by the parasitic worms themselves but by the body's reaction to the eggs produced by the parasites. A rash or itchy skin may develop within days after becoming infected. Within 1-2 months of infection, one may start to develop muscle aches, fever, chills and a cough (CDC, 2020). Inflammation and scarring may occur when adult worms are present and produce eggs that travel to the intestine, bladder or liver and the *Schistosoma* parasite can cause long-term damage to these organs after years of repeated infection. Malnutrition, learning difficulties and anaemia can also develop in children who are repeatedly infected (King, 2010). Eggs are rarely found in the spinal cord or brain, but they can cause spinal cord inflammation, paralysis or seizures if found in these areas. Schistosomiasis has also been associated with a decrease in the ability to perform physical exercises, chronic pain and urogenital schistosomiasis that may further spread HIV (King, 2010; Kjetland et al., 2014; McManus et al., 2018).

McManus et al., (2018) note that the symptoms of schistosomiasis can be divided into three distinct phases of clinical disease progression: (i) *Acute infection* which occurs in travellers to areas that are endemic to schistosomiasis. After primary infection symptoms may include abdominal pain in the right upper quadrant, myalgia (muscle aches and pains), diarrhoea, fever, blood in urine, malaise, and fatigue (ii) *Established active infection* affects individuals mainly from poor rural areas that have long-standing infections (iii) *Late chronic infection* is similar to where the body reacts to schistosome eggs that are trapped in the host tissue, leading to obstructive and inflammatory disease. These stages differ in egg excretion rates, in stool or urine, and in clinical manifestations and symptoms (McManus et al., 2018).

2.1.3 Schistosomiasis treatment and disease burden

A recommended treatment drug to control schistosomiasis is praziquantel (an oral anti-schistosomal drug), which is a population-based preventive chemotherapy administered to at-risk populations without prior diagnosis (Rollinson et al., 2013). Praziquantel has been the mainstay of schistosomiasis treatment for more than 30 years (McManus et al., 2018). Multisectoral approaches will be required to achieve the elimination of the disease and additional interventions on top of the already existing drug, such as the as development of schistosomiasis vaccines, are needed (McManus et al., 2018).

Although the precise extent is disputed, schistosomiasis can result in substantial morbidity and even mortality if left untreated. A study conducted by Utzinger and Keiser (2004) in support of a study conducted by WHO (2004), suggested that the global burden of schistosomiasis is 1.7 to

4.5 million disability-adjusted life years (DALYs), including factors such as undernutrition, anaemia, and growth faltering in children; partially due to schistosome infection but usually not attributed to schistosomiasis (King et al., 2005). The increase in the prevalence of the disease may not be great but an increase in the disease burden can lead to increased morbidity and mortality (Adenowo et al., 2015).

2.2 Life cycle

2.2.1 Schistosoma mansoni *and* Schistosoma haematobium

The life cycle of schistosomiasis involves an intermediate freshwater snail and a definitive host (Figure 2-4). Freshwater becomes contaminated with the parasite when it is infected with definitive host urine or excreta, eggs hatch in water and seek the snail host, enter the snail host and multiply asexually. Cercaria are then released from the snails and seek the definitive host, penetrate the skin of the host, enter blood vessels and then go to the liver where they become adults and release eggs. From here the eggs go to the bladder or large intestine of the host depending on the species of parasite, and the cycle begins again when excreta or urine enter freshwater where the snail hosts are located (Shebel et al., 2012; McManus et al., 2018; Nelwan, 2019; CDC, 2020). Adult schistosome parasites can be found in blood vessels of vertebrate hosts, humans included. Human infection occurs when contact is made with freshwater-contaminated cercariae, this is the infectious stage of schistosomes released by the intermediate host snail into the water. Freshwater snails form an essential component in the life cycle of schistosomiasis (Brooker, 2007). The parasite can only survive for about 48 hours after leaving the snail and entering the water. Activities such as washing or bathing, swimming and wading can lead to *Schistosoma* parasites penetrating the skins of people (Colley et al., 2014; CDC, 2020).

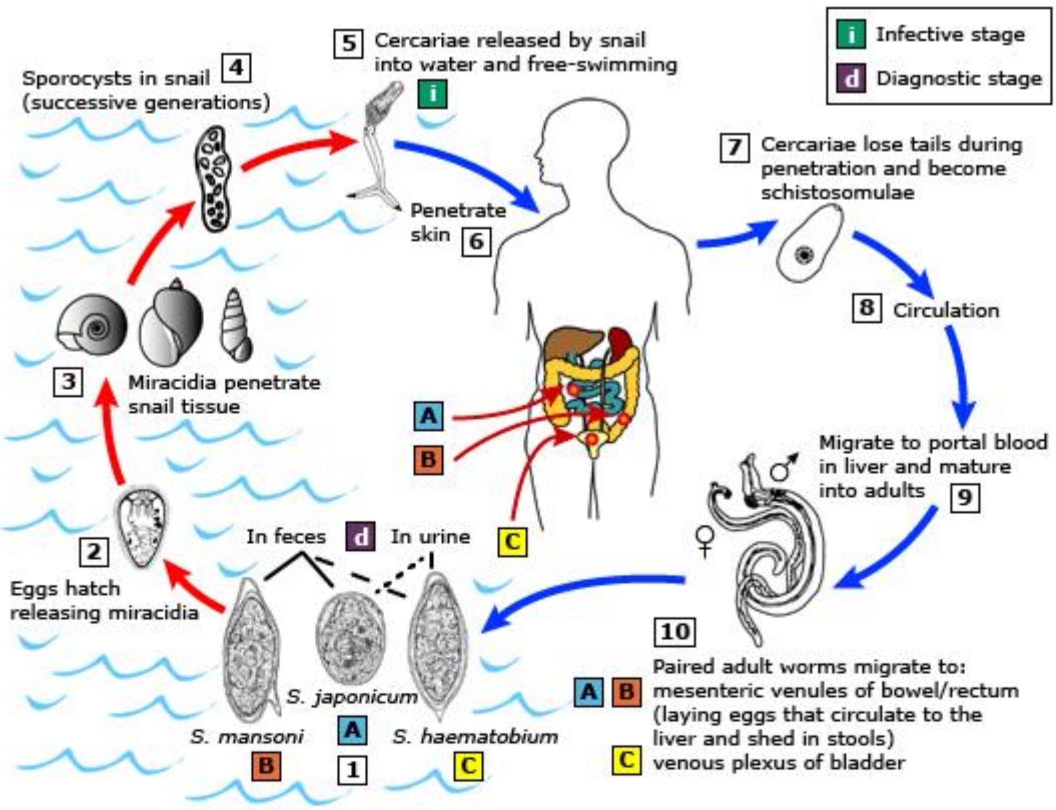

Figure 2-4: Life cycle of schistosomiasis (CDC, 2018).

2.3 Spatial distribution of schistosomiasis

Schistosomiasis occurs across the African continent in numerous geographic landscapes of varied characteristics, in which specific climatic, physical and human characteristics influence the intensity of transmission (Brookers, 2007). Through a knowledge of the characteristics necessary for the transmission of infection, it is possible to understand and predict the spatial and temporal distribution of infection.

The distribution of schistosomiasis can be very focal within countries, regions and villages and this all depends on the variety in human-water contact behaviour and snail populations, and it is important to note that schistosomiasis distribution can be highly uneven across individuals (WHO, 2002; Allan et al., 2020). Transmission and distribution of schistosomiasis are not only limited to the parasite, the intermediate host and the human host but also depends on the environment, culture, biological and socio-economic processes (Salawu & Odaibo, 2014). People situated close to open waters have an increased chance of getting infected by schistosomiasis, making its intensity and prevalence an inverse relationship with the distance from infested waters (proximity to water resources; Adoka et al., 2014). Schistosomiasis distribution and transmission are tied to landscapes where people and snails come together in the same water habitat.

Here, it is worth highlighting an important feature of the transmission dynamics of schistosomiasis relevant to understanding spatial distributions. Overall transmission success depends crucially on the establishment, survival and fecundity of adult schistosomes in the human host and less on the survival and fecundity of the two free-living aquatic stages, the miracidia and cercariae, and the infected snail hosts (Anderson, 1987). For this reason, the most significant determinants of the intensity of transmission are changes in water contact patterns through improved water and sanitation and health education, or changes in parasite mortality through the implementation of population-based chemotherapy (Grimes et al., 2015). However, if these factors remain unchanged, then the rate of parasite establishment and, hence, the patterns of schistosomiasis, are primarily determined by the distribution and abundance of its intermediate hosts, freshwater snails (Brooker, 2007; Grimes et al., 2015).

The earliest geographical distribution of schistosomiasis in South Africa was first described in 1934 and over 40 years later results of parasitological prevalence surveys were published in a detailed *Atlas of Bilharzia in South Africa* (Porter, 1938; Gear et al., 1980). The publications indicated that the north-eastern parts of the country were breeding grounds for intestinal and urinary schistosomiasis (Figure 2-5). Present studies have incorporated this *Atlas* into a Geographic Information System (GIS), which has allowed for the data to be manipulated, updated, and easily accessed (Moodley et al., 2003, Magaisa et al., 2015; De Boni et al., 2021).

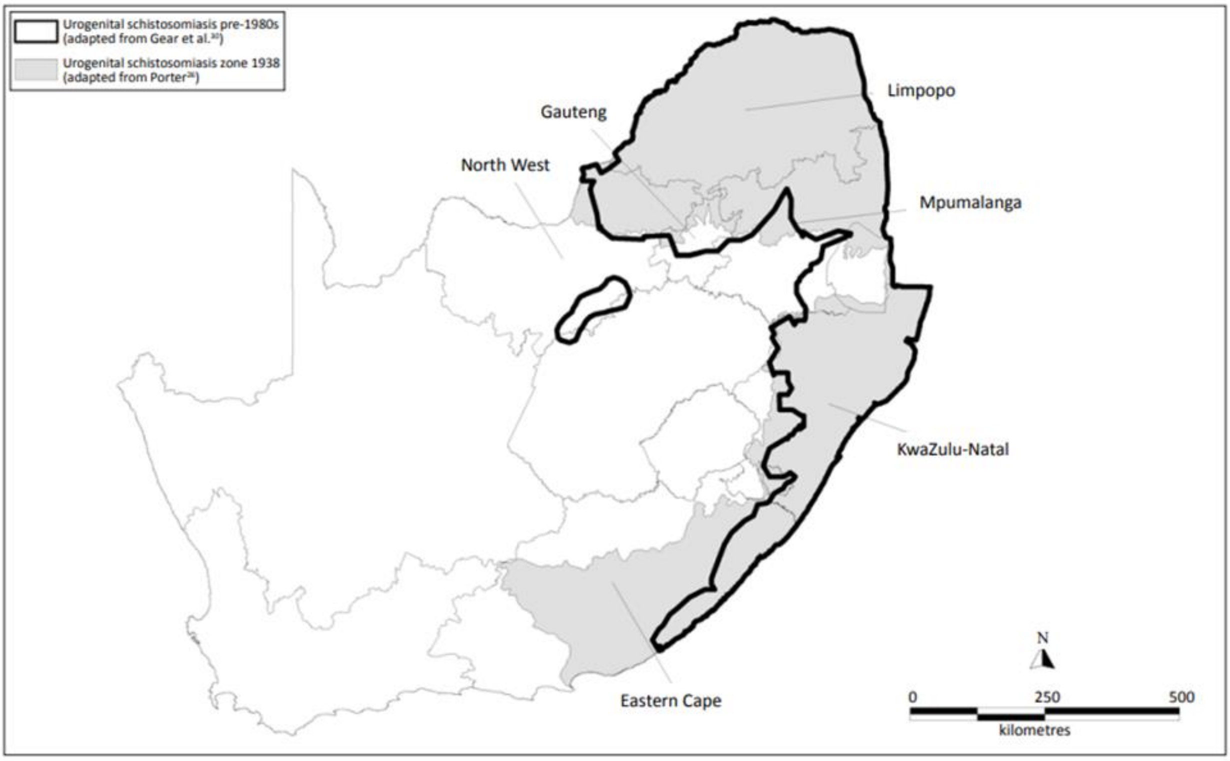

Figure 2-5: Endemic schistosomiasis areas of South Africa mapped by Porter (1938), shaded areas and Gear et al., (1980), solid black line.

2.3.1 Seasonal distribution of schistosomiasis

Seasonal changes influence the transmission and distribution of schistosomiasis as the parasite and its host snails require specific conditions to grow. Most intermediate snail hosts favour warmer conditions of between 25-27 °C, and humid conditions with enough rainfall as these creat a conducive environment for the distribution of the species (Adekiya et al., 2017; Adekiya et al., 2019; Olkeba et al., 2020). Seasonal fluctuations in snail dynamics are of limited significance to overall parasite transmission since adult schistosomes typically have a longer lifespan relative to such fluctuations (Anderson, 1987).

The northern and north-eastern provinces of South Africa provide favourable conditions as well as Mpumalanga, Limpopo, KwaZulu-Natal and North West which receive the most rainfall in summer and have warm temperatures (Kabuyaya et al., 2017). These provinces have a prevalence of schistosomiasis of about 70% in South Africa. Summer floods increase the chances of introducing snails to non-endemic areas as they will be carried away by moving water (Adekiya et al., 2017). Published results on abiotic and biotic factors that affect the survival and distribution of intermediate host snails and schistosomes have been useful in revealing which areas are 'high risk', and conditions are likely to determine habitat suitability on transmission sites (Moodley et al., 2003; Adekiya et al., 2017).

2.4 Factors influencing the distribution of schistosomiasis

Numerous factors act to determine the rate of transmission of schistosomiasis in each location. These include biotic and abiotic factors such as climatic, physical and chemical factors that affect the survival and development of schistosome parasites and snail host populations (Sturrock, 1993; Brooker, 2007). Socio-economic and behavioural characteristics of the human community also contribute to the rate of transmission including water contact behaviour and the adequacy of water and sanitation, which affect the frequency and intensity of exposure to infected water (Bundy and Blumenthal, 1990). In South Africa, the most important determinants of the population dynamics of the intermediate host snails *Biomphalaria pfeifferi* and *Bulinus globosus* are temperature, rainfall, and habitat stability (Appleton, 1978; Sturrock, 1993; Brooker, 2007). Some habitat conditions like silt, organic decomposition, chlorophyll-a, canopy cover, riparian vegetation and freshwater snail abundance have an association with snail infectivity (Coelho et al., 2021). These factors may be contributing to the development of schistosomiasis hotspots and to changes in water quality which affects water suitability for the intermediate host snails and the parasites (Rowel et al., 2015).

2.4.1 Environmental factors

Transmission of schistosomiasis highly depends on environmental factors, especially those that affect the intermediate host snails. These include temperature, rainfall, water pH and conductivity (Adekiya et al., 2019). There is an established link between climatic changes and infectious disease transmission. Schistosomiasis is a typical example of diseases whose local infection and geographical expansion is influenced by climatic changes and global warming (Mas-Coma et al., 2009; Adenowo et al., 2015). Climate change affects the aquatic environment, and this alters the transmission and distribution patterns of water-based and water-borne diseases such as schistosomiasis (McCreesh et al., 2015; McManus et al., 2018). Changes in climatic factors are expected to have an enormous influence on the interactions between pathogens and their hosts (Adekiya et al., 2019). Some of these influences include increased host stress which is a response to changes in the physical environment of the intermediate host; the host range changes as a result of altered habitats which may increase transmission of parasites and increase exposure rates (Cohen et al., 2018). The relevant factors and their importance to distribution of the snail species are discussed below in Table 2-1, which shows the optimal conditions for each factor.

Table 2-1: Optimal conditions that influence distribution schistosomiasis vectors.

Snail species	Influencing factors	Optimal condition	References
Biomphalaria pfeifferi	Temperature	22-27 °C; thermal death occurs at 30 °C as these intermediate host snails cannot stand high temperatures	De Kock & van Eeden, (1986); Kalinda et al., (2017) and Adekiya et al., (2019)
	Rainfall	300 to 600 mm and 600 to 900 mm.	Adekiya et al., (2017)
	Water pH & conductivity	pH 7.2 and 10.9	Marie et al., (2015) and McCreesh & Booth, (2014)
	Slope	10-40 m/km	Schur et al., (2013)
Bulinus globosus	Temperature	25-27 °C; above 35 °C snail mortality increases	Adenowo et al., (2015); Kalinda et al., (2017) and Adekiya et al., (2019)
	Rainfall	300 to 600 mm	Kalinda et al., (2017)
	Water pH & conductivity	pH 7.2 and 10.9	Adekiya et al., (2017)
	Slope	20 m/km	Ajakaye et al., (2016)

- **Temperature**

Water temperature is probably the most influential factor when it comes to the distribution of the host snails. An increase in temperature in sub-Saharan Africa (SSA) may influence growth, distribution, survival and fecundity rates (Adekiya et al., 2019). This creates unfavourable breeding conditions for both freshwater snails and the schistosomes themselves which may, in turn, affect the population dynamics of *Schistosoma* infections in SSA depending on snail types and schistosome species present in the area (Joubert et al., 1990; McCreesh et al., 2014). Local temperature ranges in southern Africa are highly dependent on altitude, which means that provinces such as Mpumalanga will have seasonal transmission due to increased altitude, especially on the escarpment (Pitchford et al., 1969; Moodley et al., 2003).

Air temperature is one of the natural processes that govern water temperature. Increases in air temperature affects the water cycle by increasing water temperatures and this can cause changes in the water quality and river ecosystems (Adekiya, 2017; Yang & Bergquist, 2018). Very low water temperatures can cause immature schistosomes to not develop in the snails (*Biom. pfeifferi and Bul. globosus*). Water temperatures below freezing puts an absolute limit to the host snail survival (Yang & Bergquist, 2018). An increase in water temperature levels may decrease the infectious stage of *Schistosoma* parasites due to a decrease in abundance in snail production and a decrease in the growth and developmental rate of the parasite (Adekiya et al., 2019). A study conducted by Yang and Bergquist (2018) predicted how potential changes in temperature due to climate change can impact distribution and transmission of schistosomiasis vectors (see Figure 2-6 & Figure 2-7). In sub-Saharan Africa, discontinued rainfall may lead to more dry areas which may lead to a shrinkage in transmission rates.

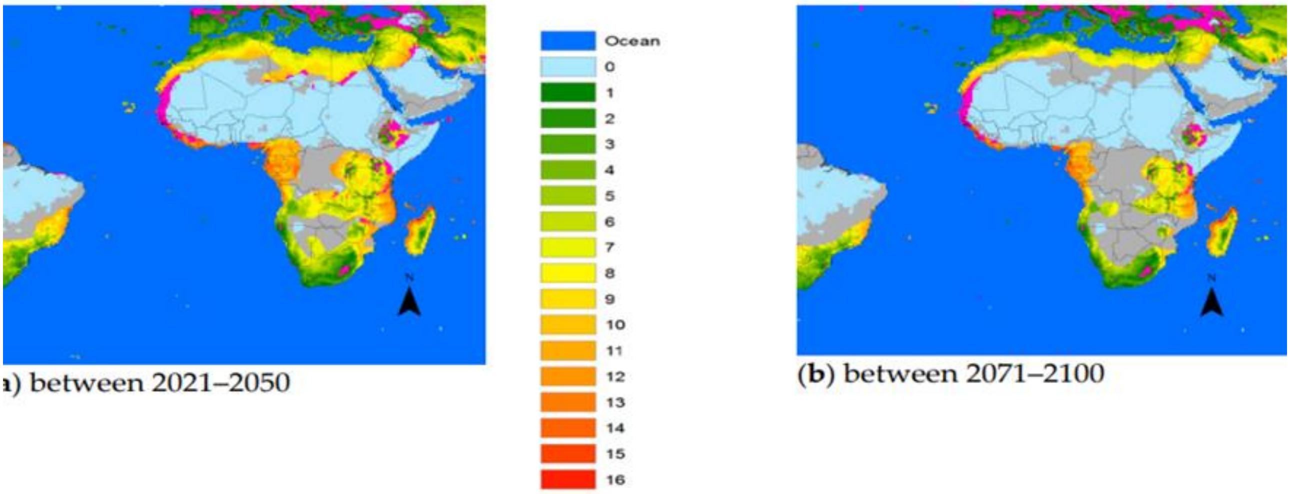

Figure 2-6: Changes in risk areas for *Schistosoma mansoni* in Africa (Yang & Bergquist, 2018). Suitability on the maps varies from less likely light blue over the spectrum to most likely in red. Grey areas signify areas that might potentially have less vulnerability as temperature would become less suited to the specific snails for the different schistosomal species.

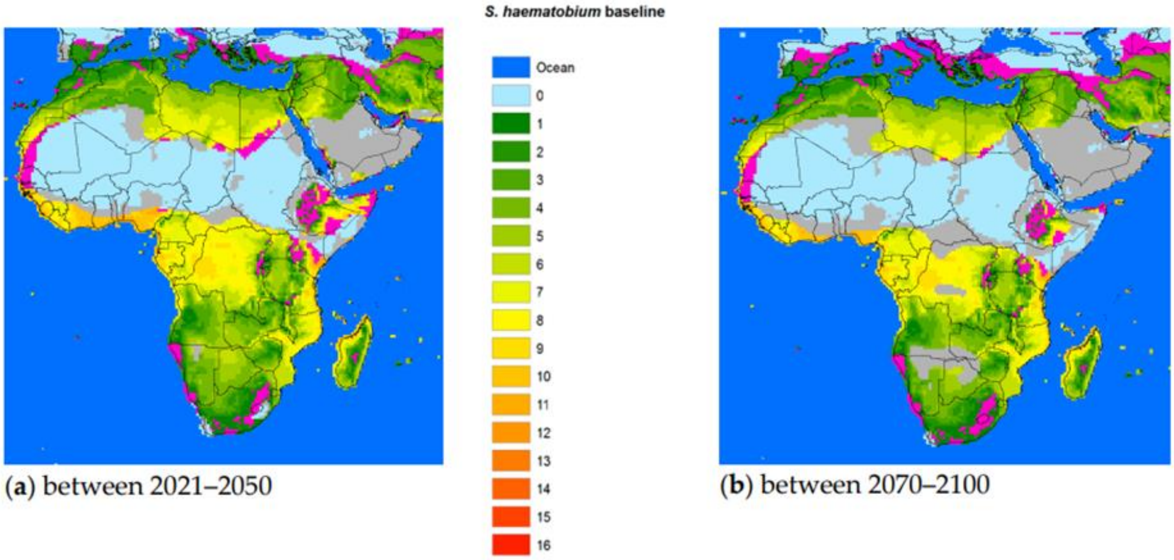

Figure 2-7: Changes in risk areas for *Schistosoma haematobium* in Africa (Yang & Bergquist, 2018). Suitability on the maps varies from less likely light blue over the spectrum to most likely in red. Grey areas signify areas that might potentially have less vulnerability as temperature would become less suited to the specific snails for the different schistosomal species.

Snails are less sensitive to low temperatures than their associated schistosome parasites. Uninfected snails can therefore be found in high altitude areas of endemic countries where low temperatures inhibit parasitic larval development in snails. The optimal temperature for snail development and survival is around 25-27 °C (De Kock & van Eeden, 1986; Kalinda et al., 2017; Adekiya et al., 2019). Above 30 °C snail mortality increases, and thermal death occurs at 40 °C as these intermediate host snails cannot stand high temperatures (Adenowo et al., 2015). Temperature can affect the speed of chemical reactions in water, and aquatic plant photosynthesis rates can influence snail abundance and parasite production within infected snails as snails feed on the aquatic plants and affect the interaction of pollutants and other pathogens with water (Oloyede et al., 2016; Zhang et al., 2018). Aquatic plants such as the genus *Ceratophyllum* spp. have been found in endemic areas in Africa and is also associated with a high per capita cercarial release that increases potential human exposure risk to *S. mansoni* and *S. haematobium* where the plant is dominant (Senghor et al., 2015; Haggerty et al., 2020). This plant grows in temperatures that are suitable for intermediate host snails. *Ceratophyllum* spp. increases the food source of *Bulinus* spp. and *Biom. pfeifferi* snails (Haggerty et al., 2020). The plant is found in the eastern provinces of the country, KwaZulu-Natal, Mpumalanga and Limpopo (Figure 2-8).

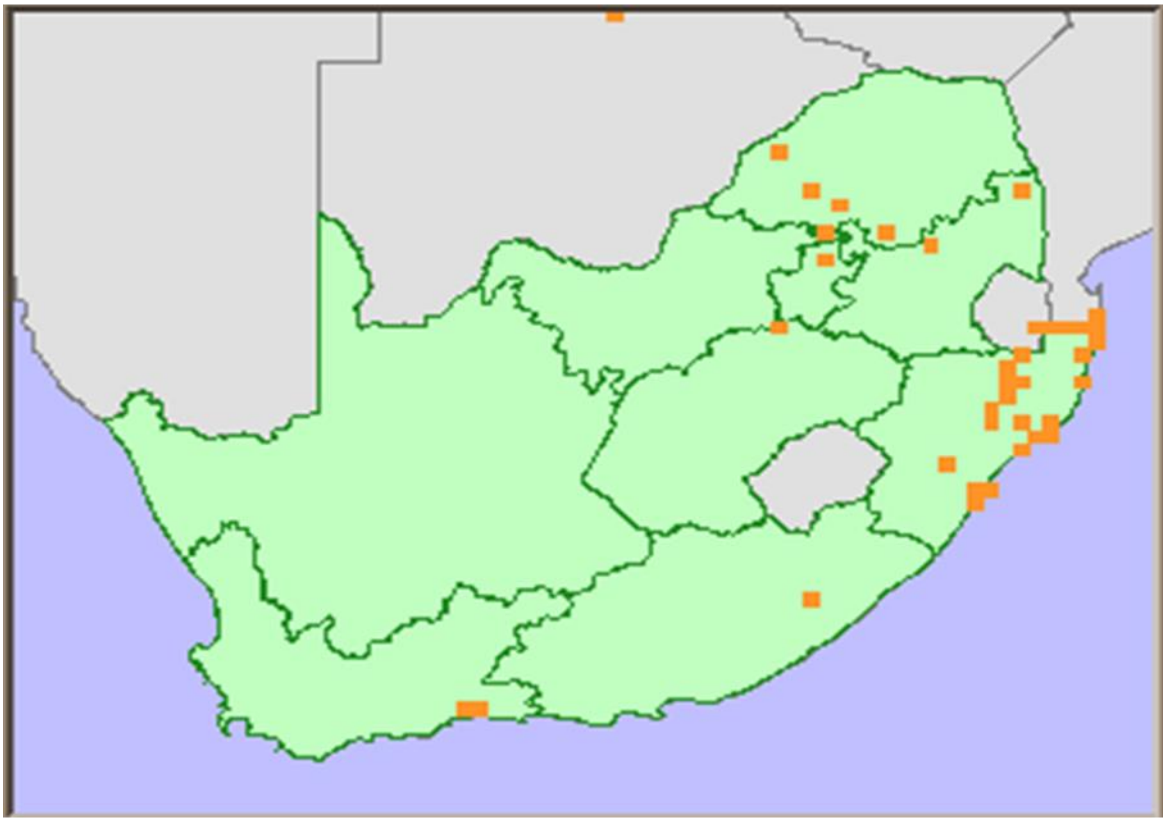

Figure 2-8: Distribution of Ceratophyllum spp. in South Africa (South African Biodiversity Institute; Cholo & Foden, 2006).

- **Rainfall**

It is difficult to quantify the precise spatial relationship between rainfall and snail population dynamics and transmission of schistosomiasis as rainfall effects vary according to the geographical location and snail species (Brooker, 2007). Rain may have a cooling effect on aquatic ecosystems by lowering the near-surface air temperature. Several studies have demonstrated marked spatial and temporal heterogeneity in snail population dynamics owing to fluctuations in rainfall (Woolhouse & Chandiwana, 1990; De Kock et al., 2004; Brooker, 2007)

An increase in rainfall provides a breeding space for the snail population due to an increase in the volume of runoff waters that are channelled through irrigation canals (Adekiya et al., 2019). This may, in turn, increase flow velocities, thereby promoting contact between the parasite and its intermediate host. An increase in water levels due to high rainfall may also cause greater water turbulence which may increase the flow rates of water that, in turn, disturb snail habitats as well as the decreased survivability of cercariae (Xue et al., 2011, Adekiya et a., 2019).

The effect of changes in rainfall on population dynamics or in the transmission of schistosomiasis in SSA cannot be overemphasised. It is believed that an increase or decrease in water levels occurs because of rainfall patterns which influence the transmission of schistosomiasis (Adekiya et al., 2019). A study done by Codjoe and Larbi (2016) in the Ga District in Ghana showed that the total rainfall and number of rainy days positively correlated with the prevalence of schistosomiasis in the area. De Kock et al., (2004) found that high snail densities can be found within two intervals of mean annual rainfall, ranging from 300 to 600vmm and 600 to 900vmm. Furthermore, it was shown that years with reduced amounts of rainfall correlated with a low prevalence of schistosomiasis, while years with moderate as well as high rainfall correlated with a high prevalence of schistosomiasis (Stensgaard et al., 2013). Lack of rainfall will lead to drought which may cause infected snails to die off. This disturbs the transmission of schistosomiasis in areas that are drought-stricken as there is no source of infection (Stensgaard et al., 2013; Mutuku et al., 2014; Senghor et al., 2015; Adekiya et al., 2019).

- **Water pH and conductivity**

Climatic factors in relation to physico-chemical parameters such as pH and conductivity are known to have a considerable influence on the population dynamics of schistosomiasis transmission in sub-Saharan Africa (Adekiya et al., 2017). pH is the presence of hydrogen ions in water or soil, and the amount of acidity in water is measured by the pH. The acidity or pH of water differs greatly from one region to another, is dependent on the landscape and land-use activities and can be altered by climate change (Porcal et al., 2009; McCreesh & Booth, 2014). A study conducted by Rowel et al., (2015) in Uganda showed that physico-chemical factors such as pH and conductivity influence *Biomphalaria* populations and infections. A disparity in the population dynamics of *Biomphalaria* from one location to another was observed but depended on the river factors such as flow and the pH. The pH ranges that harbour snail production fall between pH 7.2 and 10.9 (Marie et al., 2015, Adekiya et al., 2019).

The ionic strength of the concentration of dissolved solids including calcium and magnesium is determined by water conductivity (Cormier et al., 2013). Conductivity has been identified as a determinant for *Bul. globosus* mortality and thus poses an important constraint on its occurrence (Brown, 1994; Marie et al., 2015; Tabo et al., 2022). Several factors can increase the conductivity of aquatic ecosystems including certain substances from anthropogenic sources such as fertilisers, chloride salts, industrial effluents, and organic pollutants (Bellos & Sawidis, 2005; Pal & Chakraborty, 2017). An increase of conductivity in aquatic habitats could have negative effects on aquatic plants and snails such as *Biom. pfeifferi* and *Bul. globosus* (Romero-Blanco & Alonso, 2019). A reduction in individual number and thin-ness of the snail shells occurs as a result of waters with low conductivity which may have low calcium to stimulate shell development for snail species (Coelho et al., 2021; Tabo et al., 2022). Conductivity is thus a limiting factor to snail growth and the abundance of a snail population (Njoku-Tony, 2011). When the water levels are high during the rainy season the seasonal variation in conductivity lies between 500 and 3000 µs/cm, and under such conditions the salt content of the water may have little effect on the transmission of schistosomiasis (Porcal et al., 2009).

The effect of slope on the transmission of schistosomiasis is not well documented yet. Studies on snails' host vectors of schistosomiasis show that snails prefer a slope of less than 20 m/km (20%) (Birley & WHO 1991; Ajakaye et al., 2016). A study conducted by Ajakaye et al., (2016) showed that there is a positive relationship between prevalence of schistosomiasis and slopes with high-risk areas found on gentle and moderate slopes of 10-40 m/km (Schur et al., 2013; Ajakaye et al., 2017). This factor is termed a negative predictor of schistosomiasis infections as steeper slopes correspond with lower odds of infections. Higher altitude is associated with steeper slopes and less stagnant water, which in turn leads to less temporary waterbodies and to less suitable habitats for the host snails, leading to decreased *S. haematobium* and *S. mansoni* infections (Brooker & Michael, 2000; Manz et al., 2020). Slope also influences the velocity of the water; the higher the slope the faster the water will travel which decreases snail population as the snails prefer water that is slow flowing (Zhu et al., 2015).

2.4.2 Socio-economic factors

There are other factors that increase the risk of infection and influence the distribution, intensity of infection, prevalence, morbidity and mortality of schistosomiasis. These risk factors include living in proximity to open waterbodies and activities, immune response of the host, household clusters, behaviour, and genetic factors (IARC, 1994; Bethony et al., 2001; Quinnell, 2003).

Schistosomiasis has been labelled the disease of the poor as it is more endemic in rural communities than in urban populations. Neglected tropical diseases (NTDs) (Parker & Allen, 2011), including schistosomiasis, have profound negative effects on the development of children, outcome of pregnancy and agricultural productivity and is thus a key reason why the 'bottom 500 million' inhabitants of sub-Saharan Africa continue to be in poverty (Hotez & Kamath, 2009). This has led to the concern for the elimination of NTDs as a major element of the Millennium Development Goals (MDGs). King (2010) predicts a vicious cycle between poverty and schistosomiasis. He explains that poverty compels individuals to utilise contaminated water sources for domestic activities thereby getting infected with the disease and becoming unable to engage in activities to earn a livelihood which means that poverty persists.

Lack of access to clean water, poor sanitation and hygiene, and activities involving contact with water, whether domestic (for example washing clothes and dishes in open freshwater bodies), recreational (playing and swimming in ponds, lakes and rivers) or professional (car washing and sand collection), puts children, adolescents and adults at risk of schistosome infection by exposure to contaminated waterbodies (King et al., 1988; Grimes et al., 2014). Availability of safe water and sanitation are necessary for reducing the incidence and prevalence of schistosomiasis, but many inhabitants of sub-Saharan countries have limited access to potable water for domestic use, leaving them with the option of using natural waterbodies such as lakes, rivers, ponds, and other water sources contaminated with developmental stages of the schistosome parasite (Kanwai et al., 2011; Adenowo et al., 2015). South Africa has many recreational sports catered for by dam facilities. This is where people can take part in activities such as fishing, swimming, sailing, skiing and diving and, in most cases, the people indulging in these activities are usually unaware of the risk of contracting schistosomiasis (Pretorius et al., 1989). Due to the rapid increase in population, there is a shortage of basic delivery services such as formal houses, proper sanitation and clean water. This has forced many of people to live in slums which are usually situated close to a waterbody used for recreational and domestic purposes (Wolmarans et al., 2006). These conditions contribute to the increased risk of schistosomiasis infection for people living within these communities.

- **Proximity to water sources**

The schistosome parasite requires an avenue that gives direct contact between the molluscan intermediate snail and the definitive human host for transmission of schistosomiasis to take place. In sub-Saharan Africa, including South Africa, it is estimated that 76% of the population is situated in proximity to open waterbodies that are possibly infested by intermediate host snails that carry the disease (Adenowo et al., 2015; Woldegerima et al., 2019). Various studies have established a direct association between the intensity of the disease and proximity of infected individuals to natural water sources such as lakes, rivers, and ponds (Clennon et al., 2006; Kapito-Tembo et al., 2009). A study carried out by Kapito-Tembo et al., (2009) in Blantyre district in Malawi, showed that children whose schools were closer to open waterbodies had an increased risk of infection as they may take part in activities involving the use of the water.

2.4.3 Agricultural impacts

Ecological changes due to man-made construction of irrigation schemes, reservoirs, and dams for agricultural purposes and electricity generation are also responsible for the continued transmission of schistosomiasis in some sub-Saharan African countries (Fenwick et al., 2006). Movement of people also plays a major role in the distribution of schistosomiasis. Water development projects, mostly agricultural, may cause people from rural areas that are endemic to schistosomiasis to move into neighbouring communities (non-endemic) which leads to introduction of schistosomiasis to these areas (Kabuyaya et al., 2017). In South Africa, schistosomiasis is not only associated with a lack of proper water supplies, sanitation and recreational facilities (such as swimming pools) in resource-poor settings but also occurs around irrigation schemes and dams in some more affluent areas where there are relatively good infrastructures (Gear et al., 1980).

Schistosomiasis transmission is linked to agricultural expansion which can expand the suitable habitat for intermediate host snails and can affect the distribution of predators capable of suppressing snail populations (Steinmann et al., 2006; Sokolow et al., 2015). In the same environments, agrochemical pollution might cause similar ecological disruptions that increase snail resources, kill snail predators, or affect schistosomes directly (Hoover et al., 2020; Figure 2-9). The effects of agrochemicals on schistosomiasis transmission have not been systematically investigated (Rohr et al., 2019). Schistosomiasis-endemic regions of sub-Saharan Africa, where more than 90% of schistosomiasis cases occur, have historically had low agrochemical use, owing to the predominance of small-scale farming (Hoover et al., 2020). However, due to industrialisation, global agrochemical use is increasing quickly as agrochemical inputs become more readily available and developing economies rely on less labour-intensive methods of agricultural production (Ciceri & Allanore, 2019). The scarcity of local production of agrochemicals has suppressed their widespread application in schistosomiasis endemic areas of sub-Saharan Africa.

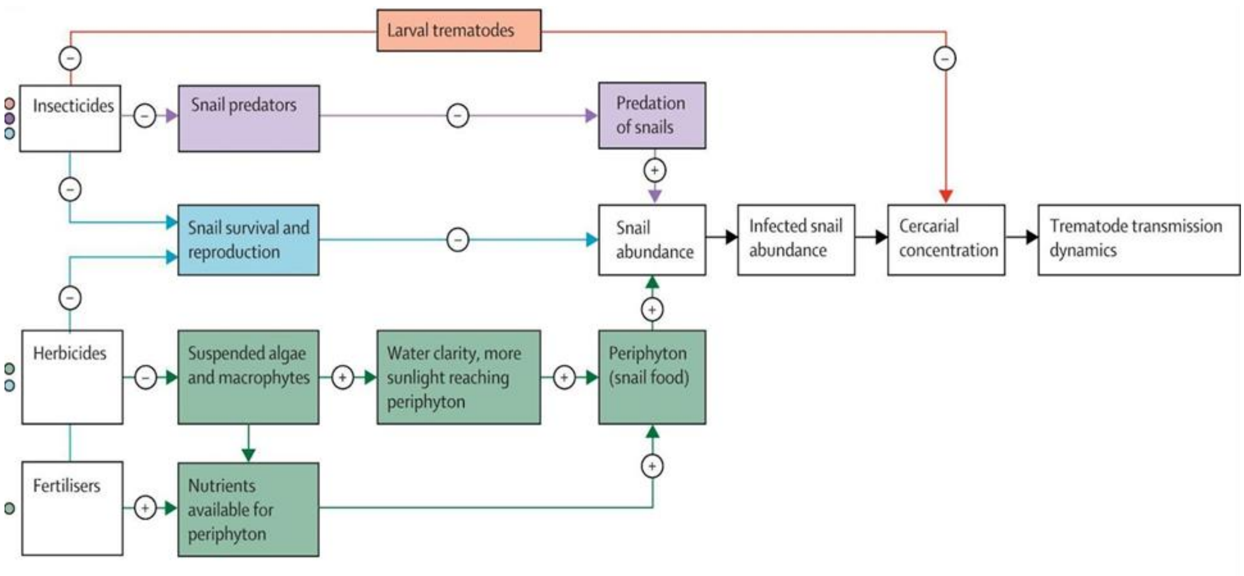

Figure 2-9: Summary of agrochemical effects on the schistosome life cycle (Hoover et al., 2020).

Several sources of published literature have shown that agrochemicals affect the transmission of non-human trematodes through direct effects on the parasites and their associated intermediate snail hosts and through indirect trophic cascades (Rohr et al., 2008; Blaustein et al., 2011; Halstead et al., 2018). Fertilisers and herbicides trigger bottom-up trophic cascades by altering algal dynamics to benefit periphytic algae, a key food resource for snail populations (Perez et al., 2007; Rohr et al., 2008). Insecticides cause top-down trophic cascades, whereby snails are released from predation due to the high toxicity of insecticides to aquatic arthropods that prey on snails (Hoover et al., 2020). Additionally, all three types of agrochemicals directly affect snail survival and reproduction, schistosome egg viability, cercarial survival, and miracidial survival (Halstead et al., 2018). It has been suggested that certain agrochemicals can increase the risk of human schistosomiasis, but the array of agrochemical effects on human schistosomiasis transmission has not been systematically investigated (Rohr et al., 2019).

2.5 Modelling schistosomiasis

The disease burden and the need to control schistosomiasis remains greater in Africa compared to other continents and the introduction of spatial modelling has improved the understanding of the disease (French et al., 2018). The geographical distribution of schistosomiasis across Africa was first comprehensively mapped in the 1960s through a synthesis of historical records, documents, and published reports, including hospital-based data (Doumenge et al., 1987). However, this traditional cartographic approach has the disadvantage that the derived maps cannot be easily updated, and are therefore unable to reflect recent epidemiological trends. For instance, changes in transmission have occurred because of (i) man-made ecological changes such as the construction of large dams and irrigation schemes and (ii) the successful implementation of intervention programmes (Fenwick et al., 2006). Numerous studies have been undertaken using satellite-derived environmental data to predict the distribution, abundance and prevalence of diseases and their vectors, including malaria (Hay et al., 2000; Rogers et al., 2002) and schistosomiasis globally (Brooker et al., 2001; Malone et al. 2001; Brooker et al., 2002; Moodley et al., 2003; Kabatereine et al., 2004), but so far none have attempted this for South Africa.

2.5.1 Geographic Information System (GIS)

A geographic information system (GIS) is a computer system that allows the user to capture data and manage it, including maintenance and storage; to manipulate and analyse data; and to present the data as a final product in the form of a map (Huisman & de By, 2009). The software allows the user to use different coordinate systems and provides options to analyse georeferenced data. A geographic information system is a sophisticated tool that can predict the pattern of diseases and the relationship between parasites and ecological processes using geo-static algorithm spatial analysis and model making (Fletcher-Lartey & Caprarelli, 2016). One of the ways geographic information systems are used is to find environmental distinctions in the population and the need for healthcare among people, providing a foundation to analyse and plan health services (Brooker, 2002; McLafferty, 2003).

The scientific study of the spatial epidemiology of schistosomiasis has been greatly enhanced by the use of GISs and remote sensing (RS) over the past few years. Geographical information has enabled data to be georeferenced, stored, extracted, integrated in new ways, and displayed by the user (Robinson, 2000), whilst RS has provided high-resolution data on climate and land cover features (Hay et al., 2006). Since Cross et al (1984) first used Landsat satellite data to predict the occurrence of schistosomiasis in the Philippines and the Caribbean (see Cross and Bailey, 1984), an increasing number of studies have employed GIS/RS to predict the distribution of schistosomiasis on the basis of associations between infection and large-scale environmental variables (Malone et al., 1994; Brooker et al., 2001; Malone et al., 2001; Moodley et al., 2003; Clements et al., 2006; Raso et al., 2006). The emphasis of most of these studies has been to develop more accurate and statistically robust risk models, increasingly adopting a Bayesian inferential platform. Less emphasis has been given to assessing either the uncertainties inherent in geographical data (Agumya & Hunter, 2002) or the practical application of models in the context of large-scale control activities (Brooker et al., 2002).

The World Health Organisation (WHO) along with its Partners for Parasite Control coordinate a worldwide programme that aims to control schistosomiasis by using GIS to plan, monitor and control the disease (Fletcher-Lartey & Caprarelli, 2016). South Africa has made developments in technologies dealing with spatial mapping by using GIS technology. For example, the health department has made use of this tool which has been useful in disease control (Breetzke, 2006). Using GIS and RS contributes to understanding the expansion and distribution of schistosomiasis in endemic areas as well as understanding schistosomiasis transmission spatial dynamics and temporal interaction, thus aiding in controlling the infection and understanding transmission better (Simoonga et al., 2009; Santos et al., 2017). Aside from the obvious benefits of data capture and visualisation, the integrated use of GIS and RS, coupled with geostatistical techniques, has allowed for robust quantification of spatial heterogeneity in schistosome infection patterns (Hay et al., 2000).

The application of GIS and RS technologies in determining environmental features such as land surface temperature, rainfall and freshwater bodies, has been utilised for schistosomiasis risk profiling and estimating treatment needs with the anti-schistosomal drug praziquantel following the guidelines and treatment thresholds put forth by the WHO (Simoonga, et al., 2009; Schur et al., 2012; Lai et al., 2015). In South Africa, GIS has been applied in studies on tuberculosis (Beyers et al., 1996) and malaria (Craig et al., 2004). Countries such as Brazil have made use of GIS and climate data derived from satellite images to spatially define the relative suitability of habitats for intermediate host snails and the transmission of schistosomiasis parasites to determine vulnerable areas (Bavia, 1996).

2.5.2 Species Distribution Models (SDMs)

Species distribution models (SDMs) correlate occurrence of species with environmental factors to predict spatiotemporal habitat suitability (Guisan & Thuiller, 2005; Elith et al., 2006). Species distribution models can be a useful tool for incorporating climate change into natural resource decision making (Araújo & Peterson, 2012; Schwartz, 2012; Guisan et al., 2013), including choices of species and source locations for restoration (Havens et al., 2015). Simply put, SDMs use spatial occurrence data together with broadscale environmental data to predict spatial patterns of environmental suitability for species. Most SDMs types have different measures that can help to assess how well a model fits the data. It is worth becoming familiar with these and understanding their roles because they help to assess whether there is anything substantially wrong with your model (Hernandez et al., 2006). Species distribution models use computer algorithms to generate predictive maps of species distributions in geographic space. Complexity control has a direct impact on the choice of the optimal model that is used (Elith et al., 2006).

- **Maximum Entropy (MaxEnt)**

Maximum entropy (MaxEnt) has recently been applied to vector-borne diseases and was the first-choice model for this study. Entropy is described by Shannon (1948) as “a measure of how much ‘choice’ is involved in the selection of an event”, thus more choices and less constraints are involved in a higher entropy.

According to Stensgaard et al., (2016), the MaxEnt is used to estimate the distribution of species by finding the maximum entropy (largest spread) of the geographical presence of the species in comparison to a set of climatic and environmental variables. The ecological model only requires presence data (i.e., snail data) and environmental information that covers the study areas to achieve high predictive performance (Phillips & Dudik, 2008; Phillips & Elith, 2011). It is a widely used machine learning algorithm that estimates the species’ probability distribution of maximum entropy, constrained by incomplete information about the species’ distribution and environmental factors (Phillips et al., 2006; Araújo et al., 2018).

Maximum entropy is a method that uses incomplete information to make predictions; the most spread out or closest to uniform, subject to specific constraints which represent the incomplete information about the target distribution (Jaynes, 1957). ‘Features’ are a set of real-valued variables which contain available information about the target distribution, and constraints are the value expected for each feature that should match the average value for a set of sample points taken from the target distribution. This is called the empirical average (Jaynes, 1990; Phillips et al., 2006). Features include environmental factors such as soil category, vegetation type and elevation and climatic variables such as rainfall. Pixels with known species occurrence records make up the sample points and the space on which the MaxEnt probability distribution is defined, is made up of pixels of the study area (Phillips et al., 2006; Tang et al., 2021). Manyangadze et al., (2016) made use of MaxEnt to determine the impact of seasonal changes on the distribution of *Bul. globosus* and *Biom. pfeifferi* in the Ndumo area, KwaZulu-Natal, (see Figure 2-10 for the results).

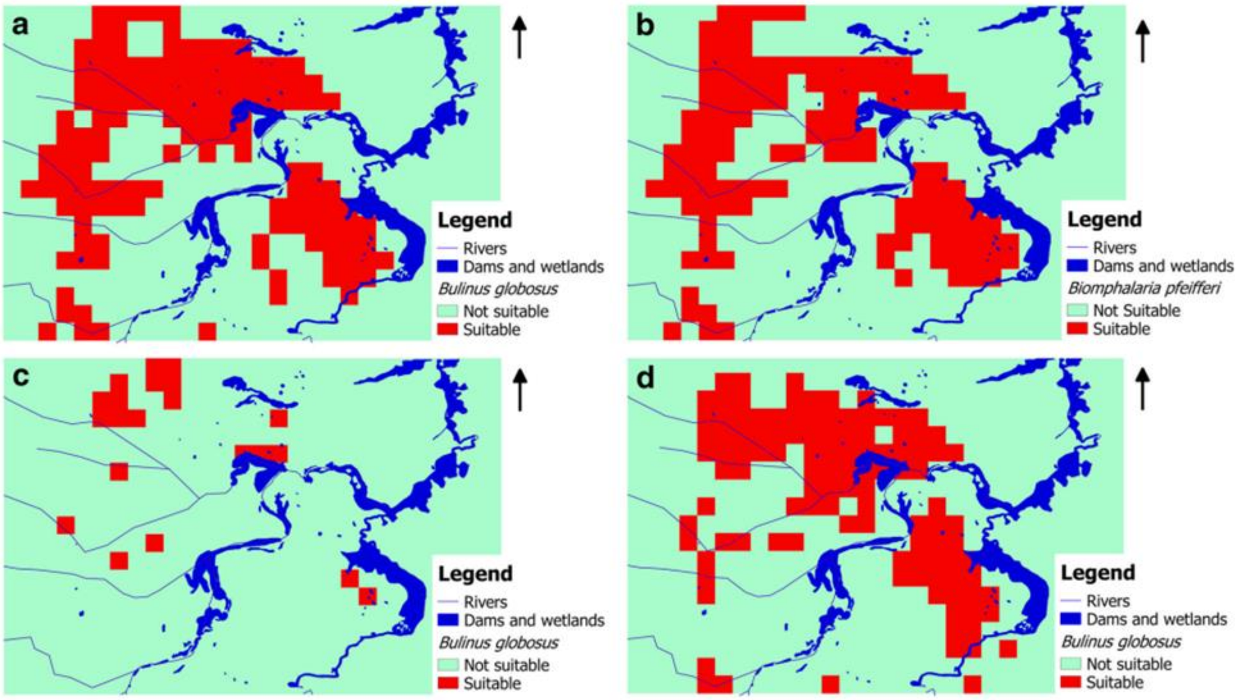

Figure 2-10: Seasonal distribution of *Bulinus globosus* and *Biomphalaria pfeifferi* in Ndumo area (Manyangadze et al., 2016). (a) Bulinus globosus in the cold season (June to August). (b) *Biomphalaria pfeifferi* in the cold season (June to August). (c) *Bulinus globosus* in the hot season (September to November). (d) *Bulinus globosus* in post-rainy season (March to May).

Although useful benchmarks for future applications of disease mapping in Africa using accessible and practical methods, these approaches could be improved on by assessing uncertainty, which is inherent in all aspects of disease mapping, including the data, models, analyses and predictions (Elith et al., 2002) and by incorporating the spatial structure of the data. Maps that include estimates of uncertainty in model outputs can allow more informed and objective decision-making in relation to targeted disease control as the control programme managers gain greater appreciation of decision risk. The use of maximum entropy to model habitats of intermediate snails could help to improve current understanding of the spatiotemporal distribution of schistosomiasis risk and create possibilities to improve its management and control (Simoonga et al., 2009; Manyangadze et al., 2016).

A few limitations stand out when using the MaxEnt, such as the possibility of over-fitting which limits the capacity for the model to generalise well to independent data (Arnold et al., 2014). The model has a 'regularisation multiplier' parameter that aims to address this problem by limiting the complexity of the model and generating less localised predictions (Phillips & Dudík, 2008). Another limitation of MaxEnt is biases in the occurrence localities which affects the accuracy of presence only modelling (Guillera-Arroita et al., 2014). The model is difficult to compare output with other algorithms, as MaxEnt output gives environmental suitability rather than predicted probability of occurrence. MaxEnt's logistic output relies on an assumption of prevalence and not an estimation (Yackulic et al., 2013).

- **Generalized linear models (GLM)**

A generalized linear model (GLM) was used in this study to compare the effectiveness and resolution to the MaxEnt. Linear models are generally made of random (error) and systematic components; the errors are usually assumed to have a normal distribution (Nelder & Wedderburn, 1972). The associated analytical technique is least squares theory, which in its classical form considers only one error component. There are extensions for multiple errors to use with the models, developed mainly for survey data and analysis of designed experiments (Hastie, 2017). The GLM is a combination of systematic and random components. It is also a way to link together systematic elements with random elements in a model (McCullagh, 2019).

According to Smith and Warren (2019), there are three elements that make up generalized linear models: (i) the predictor function, covariates used to predict the response variable (ii) the link function which describes the linear relationship between the model covariates and the mean of the response variable and (iii) the distribution error terms. A major assumption of GLM is that the observation dataset is independent of others. The risk of non-independence can be reduced by careful sampling (Extence et al., 1999). A study by Ponpetch et al., (2021) made use of different SDMs to find the potential distribution of *Schistosoma mansoni* in endemic areas in Ethiopia. The models used in the study included GLM, generalized additive models (GAM), multivariate adaptive regression splines (MARS), classification tree analysis (CTA), random forest (RF), gradient boosting machine (GBM), surface range envelope (SRE) and MaxEnt. The results showed that GLM was among the models that indicated a wider distribution of the disease compared to RF and MaxEnt which had predicted a small range of the distribution (see Figure 2-11).

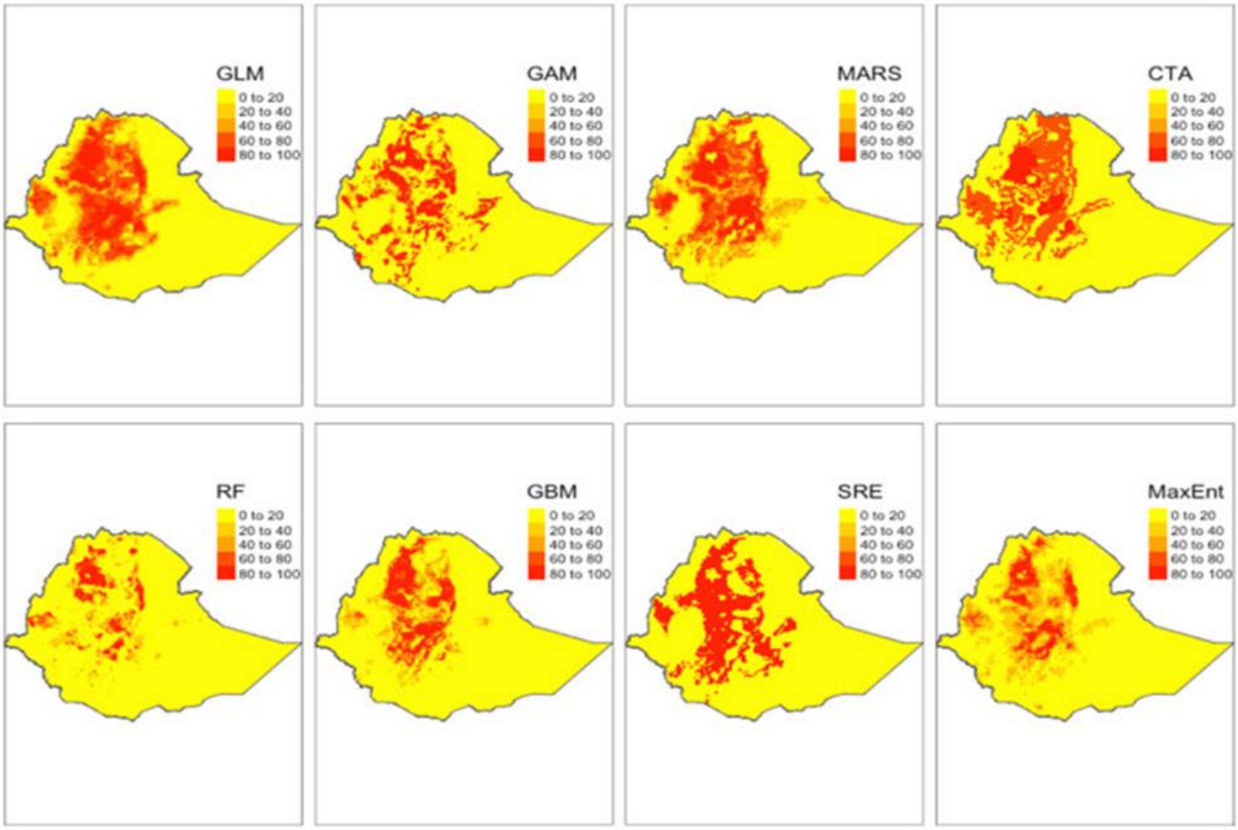

Figure 2-11: Potential distribution of *Schistosoma mansoni* using different Species distribution models in endemic areas in Ethiopia (Ponpetch et al., 2021). The probability of occurrence given the environmental suitability is shown in a scale of 0 to 100 with low suitable areas represented by yellow shading and high suitable areas represented by red shading.

Generalised linear models are mathematical extensions of linear models which allow for non-linearity and non-constant variance structures in the data by not forcing it into unnatural scales (Hastie, 2017). These models are based on a link function or an assumed relationship between the linear combination of the explanatory variables and the mean of the response variable. According to Guisan et al., (2002), data may be assumed to be from several families of probability distributions, which includes gamma, negative binomial, Poisson, normal and binomial distribution. This makes GLMs better suited and more flexible to analyse ecological relationships such as intermediate host snails and environmental variables. Due to its extrapolative nature, GLM can overpredict areas where the species is present (McCullagh, 2019). The model was chosen for this study because it has a high predictive performance for the test data but low specificity compared to MaxEnt that is extrapolative (predictable) and interpolative (complex) in nature and tends to make more specific predictions (Phillips et al., 2006).

CHAPTER 3 STUDY AREA

Mpumalanga Province is located in the eastern part of South Africa (SA) and is the second smallest province after Gauteng with a surface area of 76 495 km^2 (2,366,353 ha). The province is divided into several distinct physiographic regions (Mpe, 2018). In the west, the Highveld is characterised by a plateau with an elevation ranging from 1200 to 1800 metres. The Drakensberg mountains make up the eastern boundary of the province with an elevation over 2300 metres (Hopkins, 2011). The Lowveld makes up the north-eastern parts of Mpumalanga with a bush-clad plain sloping upwards towards the Lebombo mountains (Ferrar & Lötter. 2007; Hopkins, 2011). Although Mpumalanga mainly falls within a grassland biome, there is a transitional zone formed by the Lowveld and the escarpment between the Savanna biome and the grassland. The varying elevation causes Mpumalanga to experience different temperatures and precipitation. The mean temperatures range from 16 °Cs in the Highveld to 23 °C in the Lowveld (Maponya et al., 2013). Precipitation increases from west to east with parts of the Lowveld receiving rainfall of over 1000 mm compared to the Highveld which receives about 510 to 760 mm annually (Maponya et al., 2013).

The population of the province is over 4 million, making it the sixth most populous province in SA, and the primary languages are siSwati (27,7%), IsiZulu (24,1%) and Xitsonga (10,4%) (StatsSA, 2018). Mpumalanga is divided into three districts. Ehlanzeni district is divided into four local municipalities, namely Bushbuckridge, Thaba Chweu, Nkomazi and the City of Mbombela local municipality which houses the business centre for the Lowveld and is the capital city of the province (MTPA, 2014; StatsSA, 2018). Gert Sibande district has seven local municipalities, namely Chief Albert Luthuli, Dipaleseng, Dr Pixley Ka Isaka Seme, Govan Mbeki, Lekwa, Mkhondo and Msukaligwa. Nkangala District is divided into six local municipalities, namely Dr JS Moroka, Emakhazeni, Emalahleni, Steve Tshwete, Thembisile Hani and Victor Khanye (MTPA, 2014; StatsSA, 2018). This study mainly focuses on the Mbombela and Nkomazi local municipalities (Figure 3-1) that fall under the Ehlanzeni district municipality located in the north-eastern parts of Mpumalanga. The district is situated in the summer rainfall region and is regarded as a moist tropical to subtropical region, receiving most of its rainfall during the rainy season which usually occurs from October to March (Lötter, 2013). The Ehlanzeni district receives an average mean precipitation of 750 mm-860 mm, which is less compared to the high Escarpments areas (receiving about 1500 mm) and the eastern areas that receive about 450 to 550 mm (Lötter, 2013). Ehlanzeni district has a population of about 168 8615 and although 16.4% of people have access to piped water, there are many who depend on water from tankers and rivers (StatsSA, 2011).

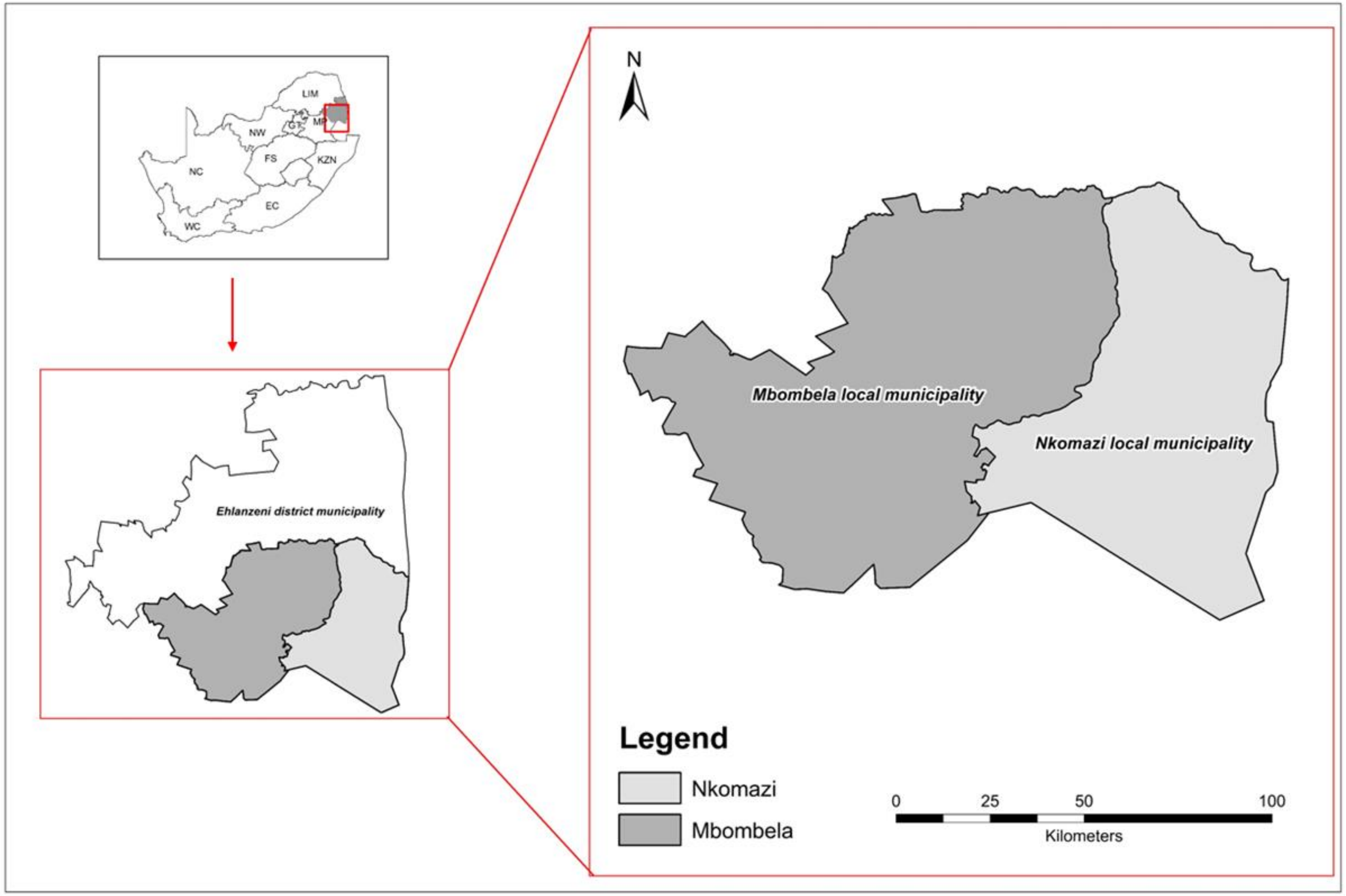

Figure 3-1: A map showing Mbombela and Nkomazi local municipalities in the Ehlanzeni district located in Mpumalanga, South Africa. The dark grey area is Mbombela and light grey is Nkomazi.

The Mbombela and Nkomazi local municipalities are located in the eastern part of South Africa in the Mpumalanga Province and forms part of the Ehlanzeni district. Mbombela is one of the four municipalities in the district, making up approximately a third of its geographical area with a surface area of 7152 km² (Adams & Moila, 2004). Mbombela is a regional centre catering for people from as far as Bushbuckridge in the north, Mozambique (Maputo) in the east, the Kingdom of Eswatini (Mbabane) in the south-east and Lydenburg in the west (Mbombela IDP, 2012; Magagula et al., 2022). The rural nodes include Hazyview, Mganduzweni, Ngodwana, Luphisi/Mpakeni, Nsikazi and Elandshoek in the planning areas (Mbombela IDP, 2012). The municipality is one of four in the district of Ehlanzeni and is endowed with several advantages, notably fertile land, a strategic location, great infrastructure and a beautiful environment (Mpumalanga SDF, 2011). The municipality also serves as a gateway to some of the best eco- and adventure activities in southern Africa. The moderate climate within the local municipality makes it a preferred tourist destination all year round (MTPA, 2011; Botai et al., 2018).

The Nkomazi local municipality is the smallest of the municipalities within the Ehlanzeni district making up 17% of the geographical area with a surface area of 4785 km² (Stats SA, 2011). The municipality is bounded by the Mbombela local municipality to the west and the Kruger National Park north of the area. Urban areas within the municipality include Hectorspruit, Malelane, Komatipoort, Kamhlushwa, Kaapmuiden and Tonga (Ubisi et al., 2020). There are eight traditional authorities located in the southern section of Nkomazi, which is where most of the low-income communities are found. Nkomazi makes up the region that has the lowest flushing toilets within the Ehlanzeni District with about 10.8% compared to Mbombela that has the highest percentage of flush toilets of about 55.06% (Nkomazi Local Municipality, 2020). Some of the important indicators identified for each local municipality are summarised in Table 3-1.

Table 3-1: Summary of important indicators: area, urban/rural, population, unemployment rate, poverty rate, water sources, sanitation, public health facilities, climate and vegetation for Mbombela and Nkomazi local municipalities in Mpumalanga, South Africa.

Indicators	**Mbombela local municipality**	**Nkomazi local municipality**
Area	7152 km^2	4787 km^2
Urban/Rural	Predominantly Urban	Predominantly Rural
Population	Total population: 655 950 Females: 51% (334 535) of the population Males: 49% (321 415) of the population	Total population: 393 030 Females: 52% (204 376) of the population Males: 48% (188 654) of the population
Population density	110 persons/km^2	82 persons/km^2
Unemployment rate	25.85%	32.10%
Poverty rate	40.35%	48.10%
Water sources	Draws water from different water management areas such as the Sabie River and Crocodile River. About 83% of households have access to free basic water from taps.	The municipality draws water from two dams, Mbuzini and Driekoppies, and from the Crocodile, Mlumati and Nkomati rivers. About 75.3% of households have access to free basic water from taps.
Sanitation	55% of households have flushing toilets connected to the sewage and 29% have access to waste removal services.	76.9% of the population is connected to proper sanitation services and most of the population in low-income areas use pit latrines.
Public health facilities	Six 24-hour clinics Twenty-four 8-hour clinics Nine mobile units	Four 24-hour clinics Twenty-eight 8-hour clinics Eight mobile clinics
Climate	Moderate climate, humid and subtropical all year round. Average summer temperatures: 27-28 °C and in winter 23-25 °C during the day. Annual rainfall: 400-600 mm most of which occurs in summer.	Subtropical climate; a summer rainfall region. Mean annual temperature is 28°C. Annual rainfall ranges between 750-860 mm, receives most of its rain during summer with dry winters, especially July.
Vegetation	Grassland and savanna	Savanna

Mbombela local municipality is responsible for the huge former homeland trust area known as Nsikasi. The northern Nsikasi area receives chlorinated/disinfected (not purified) water from the Sabie, Crocodile and Komati rivers with a few water monitoring stations located along these river systems (Brown, 2005; see Figure 3-2a). Although several monitoring stations occur on the rivers flowing through the Mbombela municipality, no data from the monitoring stations is available from the Nkomazi municipality (Figure 3-2a). The main economic activities within Nkomazi are agriculture, mining and tourism. The river systems that flow through Nkomazi include the Crocodile River which supplies to Hectorspruit, Malelane, and Marloth Park. Nyathi and Langeloop water schemes are primarily supplied by the Mlumati River, and the Nkomati River supplies water to areas around Tonga, Madadeni, Magudu and Sibange (DWS, 2013; Nkomazi Local Municipality, 2020). The municipality does not have enough capacity to monitor pollution, caused by run-off from agricultural land, of the local rivers (Adeola et al., 2016). Water uses have a major impact on the environment due to the unsustainable use of resources that has compromised the ability of the municipality to deliver enough quantity and quality water to the communities (Ubisi et al., 2020). The lack of sustainable resources within Nkomazi has led to the few communities not being catered for in terms of proper water and energy resources (Adeola et al., 2016).

The main river systems within Mbombela and Nkomazi local municipalities are main tributaries to the Incomati basin. The main sub-catchments are Komati, Crocodile and Sabie which contribute about 94% of the natural discharge within the basin (van Eekelen et al., 2015). The basin falls within the summer (October–March) rainfall region with a mean annual precipitation of about 740 mm per annum, which generally increases from east to west (Mogebisa, 2021). The mean annual potential evaporation for the basin is about 1900 mm per annum, which generally decreases from east to west. Consequently, the deficit between rainfall and potential evaporation increases from west to east, irrigation becoming more important for crop production towards the east including exotic forest plantations (van der Zaag & Carmo Vaz, 2003). The most important anthropogenic changes in the river environment are caused by dams and reservoirs, water abstractions from these, and inter-basin transfers. The resulting modified river flow regime affects structural and functional attributes of the biotic communities (van der Zaag & Carmo Vaz, 2003). In terms of land and water use and economy, two crops dominate the basin, namely rain-fed commercial tree plantations (some 340 00 ha) and irrigated sugarcane cultivation (42 800 ha). Excluded from this is 10 800 ha in the Umbeluzi basin which is irrigated with Incomati water and the related sugar industry (Smithers et al., 2001; van der Zaag & Carmo Vaz, 2003). Other water and land uses include domestic, municipal, and industrial use as well as water for livestock and game (Figure 3-2b).

The Mbombela area has also become a destination for approximately 40.67% of all immigrants coming into the Ehlanzeni district municipality (Stats SA, 2011) meaning that the municipality is greatly challenged to ensure that communities are getting appropriate water channels that offer quality water (Calfucoy et al., 2009). Small communities in Mbombela mainly use water for activities such as subsistence farming, but due to the large population growth caused by immigrants there is a great deal of pressure on the region and water availability (DWS, 2013). Due to limited water resources such as taps, people in the area make use of dams and rivers to access water, and this has increased exposure to water-related diseases such as schistosomiasis (Wolmarans et al, 2006; Bakre & Dorasamy, 2021). The municipalities provide favourable socio-environmental conditions for distribution and transmission and have a high prevalence of schistosomiasis host snails which make the communities vulnerable.

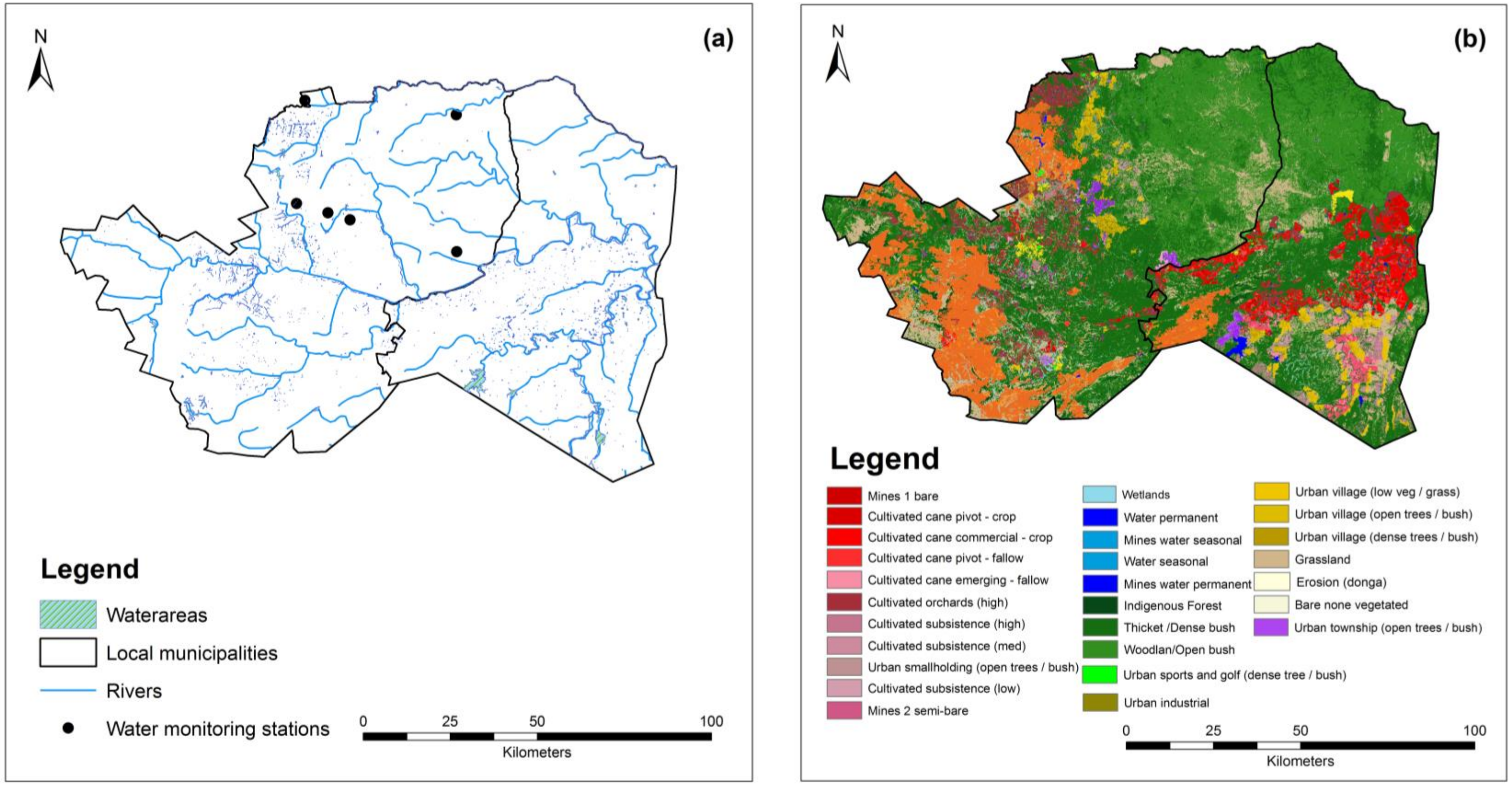

Figure 3-2: Maps showing (a) water areas, rivers and monitoring stations within Mbombela and Nkomazi local municipalities and (b) land cover and use within Mbombela and Nkomazi local municipalities.

CHAPTER 4 DETERMINING THE HISTORICAL DISTRIBUTION OF SCHISTOSOMIASIS TRANSMITTING SNAILS

4.1 Introduction

Schistosomiasis is endemic in sub-Saharan Africa and is transmitted by intermediate host snails such as *Bulinus* spp. and *Biomphalaria* spp. (Ofulla et al., 2013; WHO, 2021). Approximately 40% (20 million) of the South African population is at risk of schistosomiasis infection, with 2 to 3 million children infected (Appleton & Miranda, 2015). The distribution and transmission of schistosomiasis within sub-Saharan African (SSA) countries is significantly different from one region to another. Transmission is dependent on the presence of various snail species from one ecological region to the other (Picquet et al., 1996). The focal distribution of schistosomiasis is spatially and temporally restricted to waterbodies inhabited by intermediate host snails and human-water contact (Ofulla et al., 2013; Moser et al., 2014).

Scientists have noticed an increase in global temperatures of 2-3 °C (Gosling et al., 2011; Perkins-Kirkpatrick & Gibson, 2017), which negatively affects ecosystems and alters the known distribution and transmission of water and vector-borne diseases (Brosse et al., 2022). Three key aspects of climate change that have been noted to historically influence disease patterns such as schistosomiasis are: (i) Changes in precipitation patterns (ii) temperature increases and (iii) a surge in the occurrence and intensity of extreme climate events including floods and droughts (Seneviratne et al., 2012; IPCC, 2013). Studies, such as McManus et al., (2018), have shown that species distribution has already been historically altered due to climate change and may continue to be altered as climate change effects increase. Therefore, forecasting the effects of climate change on the distribution of schistosomiasis intermediate host snails, such as *Bulinus globosus* and *Biomphalaria pfeifferi,* will play a vital role in understanding future conditions and in warning health authorities of possible areas at risk (Moodley et al., 2003; Appleton & Miranda, 2015).

In South Africa, the distribution of *Bulinus globosus* is mainly influenced by water flow rates or waterbody type and temperature, and with ongoing climate change these factors are expected to affect the geographical range of the snails (Adekiya et al., 2019). A change in the geographical range of schistosomiasis intermediate host snails will have an impact on the dynamics of the disease. Climate change may lead to the creation of favourable conditions in the environment, and this would create the conducive conditions for infectious disease transmission (Stensgaard et al., 2016). According to a study conducted by De Kock et al., (2004), there are several climatic and environmental factors affecting the distribution of *Biomphalaria pfeifferi* in South Africa. This includes the salinity levels of the waterbody that the species is found, the temperature of the water, water speed, and the geological composition of the waterbody (Manyangadze *et al.,* 2016). Other chemical water factors are water turbidity, conductivity, and pH (Younes et al., 2017). Changing precipitation patterns and increasing water temperatures related to climate change could significantly affect the prevalence and dispersal of schistosomiasis, leading to a change in disease dynamics and transmission to humans (Ofulla et al., 2013; De Leo et al*.,* 2020).

In order to efficiently design, execute, and assess programmes to manage schistosomiasis, a thorough understanding of the historical distribution of intermediate hosts for schistosomiasis is essential (Kloos et al., 2008. A better understanding of the local dynamics of snail populations remains crucial for large-scale drug management under a global strategy, as recognised by the WHO. This is useful in periods when re-infection is very low for reducing the likelihood of re-emergence, even when relying on cheap and effective medications (Manyangadze et al., 2016). However, the sustainability of such a control strategy is questionable because re-infection can be rapid even after implementing deworming initiatives, and the focus on morbidity control has since shifted to transmission control and local elimination (Manyangadze et al., 2016). There is a stronger focus on snails and transmission sites along with primary prevention tailored to specific socio-ecological systems (Manyangadze et al., 2016; Gurarie et al., 2018; Yigezu et al., 2018). An understanding of the abundance and distribution of snail vectors is important in designing control strategies.

In order to plan successful interventions against the disease and target communities in high-risk areas, it is important to be able to determine the past spatial and seasonal distribution of schistosomiasis infections at a reasonably fine scale, including the distribution of parasites and host species (Manyangadze et al., 2016; Aula et al., 2021). This will help to determine current distribution to create suitable intervention programmes.

4.2 Data and Methods

4.2.1 Snail data

The historic snail dataset from 1955 to 1995 was obtained from the National Freshwater Snail Collection (NFSC) of South Africa. Two host snails were chosen for this study, namely *Biomphalaria pfeifferi* and *Bulinus globosus*. The reason these snails were chosen is that they are dominant in the eastern parts of Mpumalanga, which is the north-eastern part of South Africa where these snails are more prevalent and transmission rates are high (Joubert et al., 1990). The data was stored in quarter-degree grids and to refine the sampling points, they were manually digitised to get the X and Y coordinates plotted in ArcMap 10.8.1. After digitising, a total of 962

Biomphalaria pfeifferi and 1193 *Bulinus globosus* snail points were recorded across the Mbombela and Nkomazi local municipalities (Table 4-1).

Table 4-1: Digitised snail records of *Biomphalaria pfeifferi* and *Bulinus globosus* from sample sites within the Mbombela and Nkomazi local municipalities.

Snail species	Mbombela	Nkomazi
Biomphalaria pfeifferi	755	207
Bulinus globosus	1038	155

4.2.2 Environmental variables

Climatic indicators from 1950 to 2020 were obtained using ERA 5-Land data provided by the Copernicus Climate Change Service. Bioclimatic indicators as in WORLDCLIM were also obtained using the Copernicus Climate Change Service as ERA 5 reanalysis data from 1970 to 2018. In total, 19 bioclimatic and 13 climatic variables were downloaded for this study. These indicators were used to describe the influence of climate on the species' habitats. The variables were downloaded with a spatial resolution of 0.5° x 0.5°. The data for both the climate and bioclimatic variables was downloaded in NetCDF-4 files and using ArcMap 10.8.1 were converted to raster files for model use. Some highly intercorrelated variables were removed for each species because multicollinearity may violate statistical assumptions and may alter model predictions (Fourcade et al., 2014).

4.2.3 Principal component analysis (PCA)

Principal component analysis (PCA) is based on a linear response model which relates a single variable, namely the water data, to a site (Jolliffe & Cadima, 2016). The technique enables one to reduce the dimensionality of a system by representing it in a new space (Solidoro et al., 2004). A diagram of the study area is visualised on a two-dimensional basis (de Necker et al., 2019). Fourcade et al., (2014) used cluster analysis to show how biased data problems can be solved in modelling. Biased datasets typically lead to spatial autocorrelation of records and artificial spatial clusters of observations thus violating the assumption of independence (Dormann et al., 2007; Fourcade et al., 2014). This bias can be circumvented by sampling one point per cluster in environmental space (Rödder et al., 2009; Stiels et al., 2011). A PCA was performed on the climatic variables of occurrences using the XLSTAT package in Excel to define independent axes in the environmental space (Dray & Dufour, 2007). One record per class was randomly sampled, and the models were run on these subsampled datasets. Climatic, elevation and bioclimatic data was used with the snail data to determine which variables are highly correlated to the snail sampled points. A PCA with a Pearson's correlation was conducted to reduce multicollinearity in the climate and bioclimatic datasets. Variables that had a correlation > 0.8 were excluded. Only 7 Bioclimatic variables and 5 climatic variables were selected. Table 4-2 shows the selected variables used in the species distribution models for each host snail.

Table 4-2: Suitable bioclimatic and climatic variables from Principal Component Analysis used to model the historical distribution of *Biomphalaria pfeifferi* and *Bulinus globosus* within Mbombela and Nkomazi local municipalities.

Species	**Environmental Variables**	**Description**
Biomphalaria pfeifferi	BIO 1	Annual mean temperature
	BIO 2	Mean diurnal range [mean of monthly (max-min) temperature]
	BIO 3	Isothermality
	BIO 8	Mean temperature of wettest quarter
	BIO 13	Wettest month
	BIO 14	Driest month
	SWV1 layer	Soil water volume
	SRO layer	Surface runoff
Bulinus globosus	BIO 1	Annual mean temperature
	BIO 2	Mean diurnal range [mean of monthly (max-min) temperature]
	BIO 3	Isothermality
	BIO 4	Seasonality (standard deviation)
	BIO 8	Mean temperature of wettest quarter
	BIO 13	Wettest month
	Elevation	Elevation
	SWV1 layer	Soil water volume
	SRO layer	Surface runoff
	TP layer	Total precipitation

4.2.4 Modelling procedures and data analysis

The following species distribution models were used to predict and model the historical distribution of *Biomphalaria pfeifferi* and *Bulinus globosus* in Mbombela and Nkomazi local municipalities.

- **Maximum Entropy (MaxEnt)**

Species distribution models correlate the occurrence of species and snail data with environmental factors to predict spatiotemporal habitat suitability (Guisan & Thuiller 2005; Elith et al., 2006). Maximum entropy is used to estimate species distribution by finding the maximum entropy and most extensive spread of geographical presence of the species in comparison to a set of climatic and environmental variables (Stensgaard et al., 2016). The model requires presence data, snail points, environmental information, and climatic and bioclimatic variables. This model uses features to store information on the target distribution (Phillips et al., 2009). Features include environmental factors such as soil category, vegetation type, and elevation and climatic variables such as rainfall.

The model is difficult to compare the output with other algorithms, as MaxEnt output gives environmental suitability rather than predicted probability of occurrence. MaxEnt's logistic output relies on an assumption of prevalence and not estimation (Yackulic et al., 2013). Another limitation of MaxEnt is bias in the occurrence localities which affects the accuracy of presence-only modelling (Elith et al., 2002). There are many factors in addition to climate that affects the distribution of species, for example interspecific interactions, microtopography and local microclimates. Therefore, the MaxEnt model represents the theoretical maximum possible species distribution, and the suitable areas are often shown to be much wider than the actual areas occupied (Booth et al., 2014). Using maximum entropy to model habitats of intermediate snails could help improve the current understanding of the spatiotemporal distribution of schistosomiasis risk and create possibilities to improve the management and control of schistosomiasis (Simoonga et al., 2009; Manyangadze et al., 2016).

- **Generalized Linear Models (GLM)**

Generalised linear model (GLM) is a modern quantitative method that uses statistics. The model is a package that can be accessed through R Studio which is an open-source programming language. Generalised linear models simulate the relationship between responses and predictors using parametric functions like higher-degree polynomials or linear functions (Valavi et al., 2022). The models can be fitted for a variety of distributions since they are based on so-called parametric functions, which allow the shape of the curve to be explained by functions (Binomial, Poisson, Gaussian, Bernoulli and Gamma) (Gastón & Garcia-Vinas, 2011). Contrary to non-parametric types of regression, which allow the use of the same distributions but do not produce parametric parameter estimates, this parametric shape fitting produces non-parametric classification trees or local smoothing functions along gradients of predictor variables (CT) (Gastón & Garcia-Vinas, 2011). It is crucial to remember that in GLMs, the model is fitted to the converted dependent variable, and the parameters thus represent the transformed dependent variable in the data space (Shabani et al., 2016).

Presence can be expressed as 1 (exists) or 0 (is missing), and not intermediate values or values above 1 or below 0 are possible (Valavi et al., 2022). A study done by Collins and McIntyre (2015) which reviewed approximately 30 studies on species distribution modelling across the world, found that 43% used GLM, 33% used MaxEnt and approximately 20% used other models. Logistic regression, used in this study, is the most popular GLM that has been applied in species distribution modelling. There is not yet an application study of the GLM focusing on schistosomiasis intermediate host snails in South Africa. The model requires the environmental variables to not be highly correlated with one another as this can cause problems in estimation (De Leo et al., 2020).

- **Models' evaluation and performance**

To model the historical distribution R Studio, which is an open-source programming language, was used to access GLM and MaxEnt modelling packages. The following are settings used to run and evaluate GLM and MaxEnt. The sorted distribution point data bioclimatic and climatic variable data was imported into R Studio. The models were calibrated using 70% of the available records for each species as training (calibration) data and the remaining 30% were used for model validation as test data. This was done to evaluate the accuracy of the two models. A bootstrap method was implemented with 15 repeats and a maximum of 5000 iterations, and the default selected parameters with a maximum of 10 000 background points (Yan et al., 2020). Running the models 15 times along with withholding 30% of the data for testing allows one the ability to test the performance of the model without having an independent dataset (Young et al*.,* 2011). Additionally, performing multiple runs also provides a way to measure the amount of variability in the model (Young et al*.,* 2011). In order to reduce the model over-fitting, the regularisation number was set to 1 (Merrow et al., 2013).

The performance of the models was evaluated based on the area under the receiver operator curve (AUC), which ranges between 0 and 1 (Wang & Li, 2017). The closer the AUC score to 1, the greater the probability and predicted accuracy of the species distribution in the area (Gao et al., 2021). Area under the receiver operator curve scores are divided into four different categories: high suitability; moderate suitability; low suitability; and no suitability. It is generally understood that AUC < 0.7 indicates low accuracy of the model. Prediction results can be adopted when AUC is 0.7– 0.9, and AUC >0.9 indicates that the prediction results are accurate, which can be used for subsequent analysis (Dai et al., 2022). For this study, values >0.8 were considered satisfactory (Wiley et al., 2003, Phillips & Dudik, 2008). Jack-knife testing was used to evaluate the most important environmental variables which determined the potential distribution (Phillips et al., 2006). To visualise the modelling results, colours were used to indicate predicted historical distribution. Red indicates a high probability of suitable conditions for the species, yellow indicates conditions typical of those where the species were found, and shades of blue indicate a low predicted probability of suitable conditions.

The following Interpolation method was used to predict and map the seasonal distribution of *Biomphalaria pfeifferi* and *Bulinus globosus* in Mbombela and Nkomazi local municipalities.

- **Kriging Interpolation**

Interpolation is the process of predicting values at unknown locations using values at measured locations (Maris et al., 2013). Many interpolation methods are based on topological and similarity relations of nearby sample points, and the value of the variable that needs to be measured. Interpolation can be achieved by simple methods such as Inverse distance weighting or complex methods such as kriging interpolation (Park et al., 2019). Kriging, which is a method derived from geostatistics, has been used for fitting the model of deterministic outputs as the realisation of a random process (Kiš, 2016). The interpolation method can be applied when there is uncertainty and the variation depends on the distance between the measurements as it has a statistical base (Kiš & Malvić, 2014). It is important to understand the principle of spatial autocorrelation when using kriging.

There are different types of kriging such as universal kriging and ordinary kriging. Ordinary kriging is a spatial estimation method where the error variance is minimised and is recommended for most datasets as it is highly reliable (Maris et al., 2013). This error variance is called the kriging variance (Maris et al., 2013). It is based on the configuration of the data and on the variogram, hence it is homoscedastic. This means that it is not dependent on the data used to make the estimate (Yamamoto, 2005). It is mostly used when variation in the data is so irregular that simple interpolation methods produce unreliable predictions. Optimal predictions are produced under the assumption that the process is normally distributed and second-order stationary (Daly et al., 2002). Since the weights of the kriging interpolation depend on the modelled variogram, kriging is quite sensitive to misspecification of the variogram model (Oladejo & Ofoezie, 2006). The accuracy of interpolation by kriging will be limited if the number of sampled observations is small, the data is limited in spatial scope, or the data is not spatially correlated.

Kriging interpolation was used to determine the historical seasonal distribution of *Biomphalaria pfeifferi* and *Bulinus globosus* within the Mbombela and Nkomazi local municipalities. Ordinary kriging was applied to the digitised snail data using the spherical semi-variogram model in ArcMap 10.8. The digitised data was divided into different seasons, summer, autumn, winter and spring, by using the dates that were recorded on the available data for each snail species.

4.3 Results

4.3.1 Historical distribution of *Biomphalaria pfeifferi* and *Bulinus globosus*

- **Model performance**

The models were evaluated through jackknife tests, the AUC score, and the contribution rate of the main environmental variables. Overall, MaxEnt provided high performance results for both snail species. The mean AUC score for *Biomphalaria pfeifferi* using MaxEnt was 0.939 (Figure 4-1a). The resulting AUC score using GLM for *Biom. pfeifferi* was 0.892 (Figure 4-1b). Among the environmental variables used in MaxEnt and GLM, the precipitation of the wettest month (BIO 13) and precipitation of the driest month (BIO 14) had the highest relative variable importance as they had the highest contributing value that affected the distribution of *Biom. pfeifferi*. Other important variables in the predicted historical distribution of *Biomphalaria* using MaxEnt were the; the precipitation of the driest month (BIO 14) and the mean diurnal range (BIO 2), and for GLM included annual mean temperature (BIO 1) and soil water volume (SWV1).

The jackknife test results for *Biom. pfeifferi* (Figure 4-2a) showed that these variables provided high gains for both MaxEnt and GLM when used independently. This indicates that these environmental variables were the most contributing to the distribution of *Biom. pfeifferi* within the local municipalities. The variables that had low gains when used independently in MaxEnt included surface runoff (SRO) which had very little contribution to the model's historical predictions (<0.1) and BIO 3 (Isothermality, >0.2). The highest relative importance scores in MaxEnt were produced by BIO 2 (>0.6) and BIO 14 (>0.7). Precipitation of the wettest month (BIO 13) had the highest relative importance (>0.8) when modelling for *Biomphalaria* using the GLM Figure 4-2b). Annual mean temperature (BIO 1) was the second highest contributor when using GLM with a score >0.6. Surface runoff was the least contributing variable to the historical distribution when using the GLM (<0.1) and BIO 2 (<0.1) was also the least contributing variable.

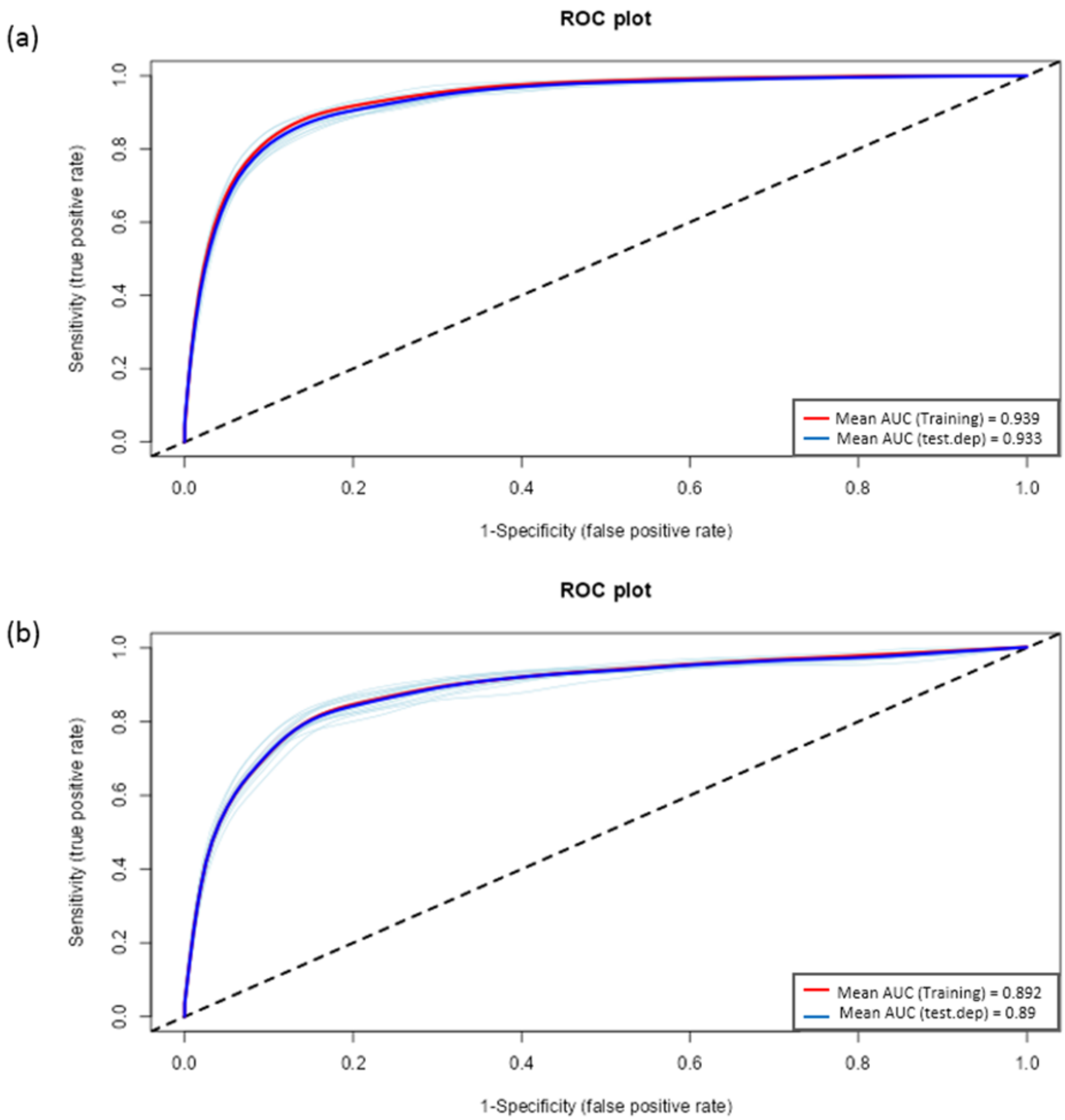

Figure 4-1: The operating curve for both training and test data are shown for *Biomphalaria pfeifferi*. The blue indicates the test of the model's predictive power. The red line shows the fit of the model to the training data. (a) Maximum Entropy and (b) Generalised Linear Model.

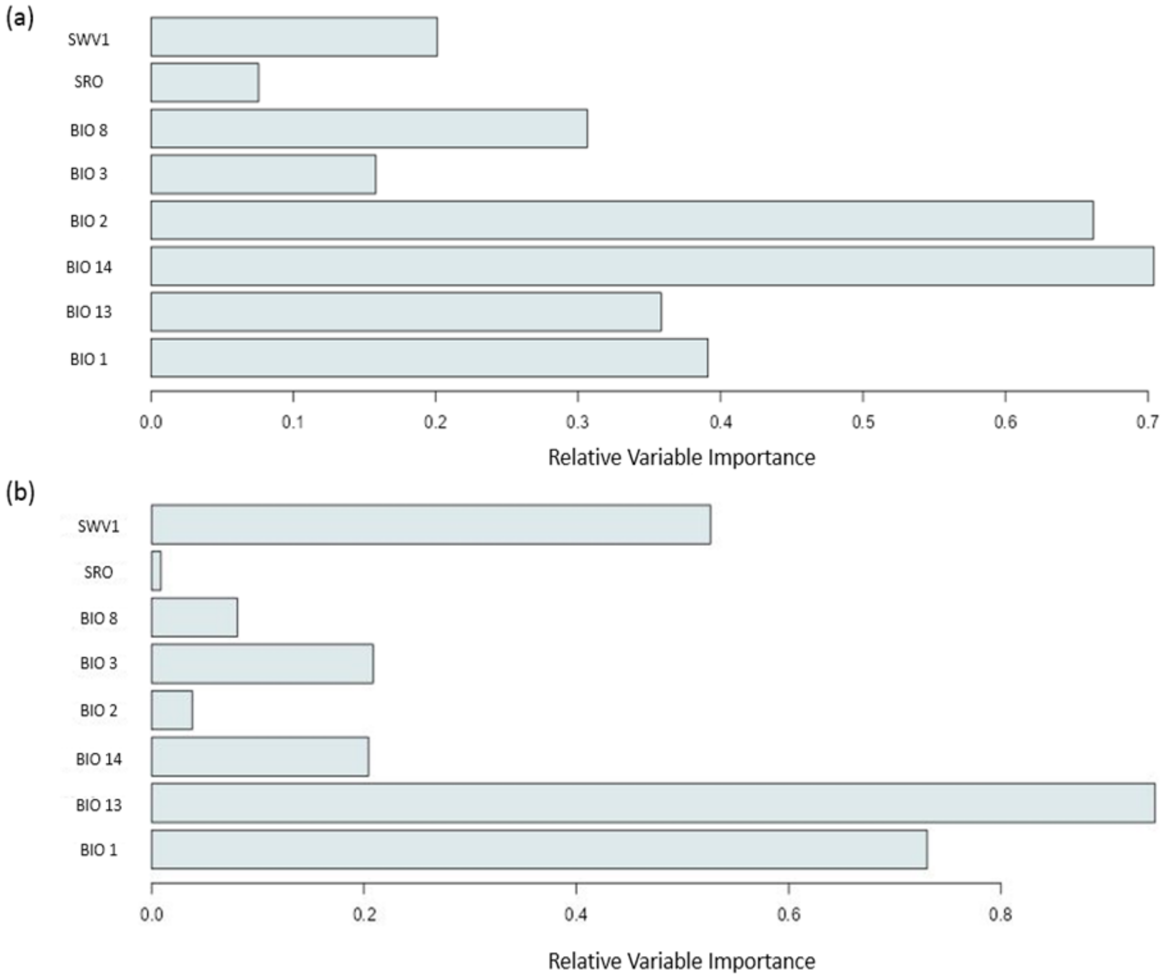

Figure 4-2: Jackknife test for *Biomphalaria pfeifferi* snail species with estimates of important variables when running the (a) Maximum Entropy and (b) Generalised Linear Model.

The AUC sore for *Bul. globosus* was 0.942 using MaxEnt suggesting that the model predicted the distribution of *Bul. globosus* with high accuracy (Figure 4-3a). The mean AUC score for the combined model output in GLM for *Bulinus globosus* was 0.856 (Figure 4-3b). Generally, the most significant variables for *Bul. globosus* prediction was the mean diurnal range (BIO 2), Precipitation of the wettest month (BIO 13), annual mean temperature (BIO 1), and mean temperature of wettest quarter (BIO 8) and elevation.

The variables that were found to have high contribution to the historical distribution when using Maxent included BIO 2 (>0.7) with other variables, such as BIO 8 and BIO 13, having a score of >0.5 (Figure 4-4a). The jackknife results for *Bulinus globosus* also showed that BIO 13, elevation, BIO 4 and BIO 2 had high predictive power when using GLM with a score >0.8 (high test gain; Figure 4-4b). Other important variables included BIO 1 and BIO 8 (>0.6). These variables, according to the models, were important contributors of the distribution of *Bul. globosus* within the local municipalities. Surface runoff and SWV1 were found to be among the least contributing variables for the *Bulinus globosus* historical distribution.

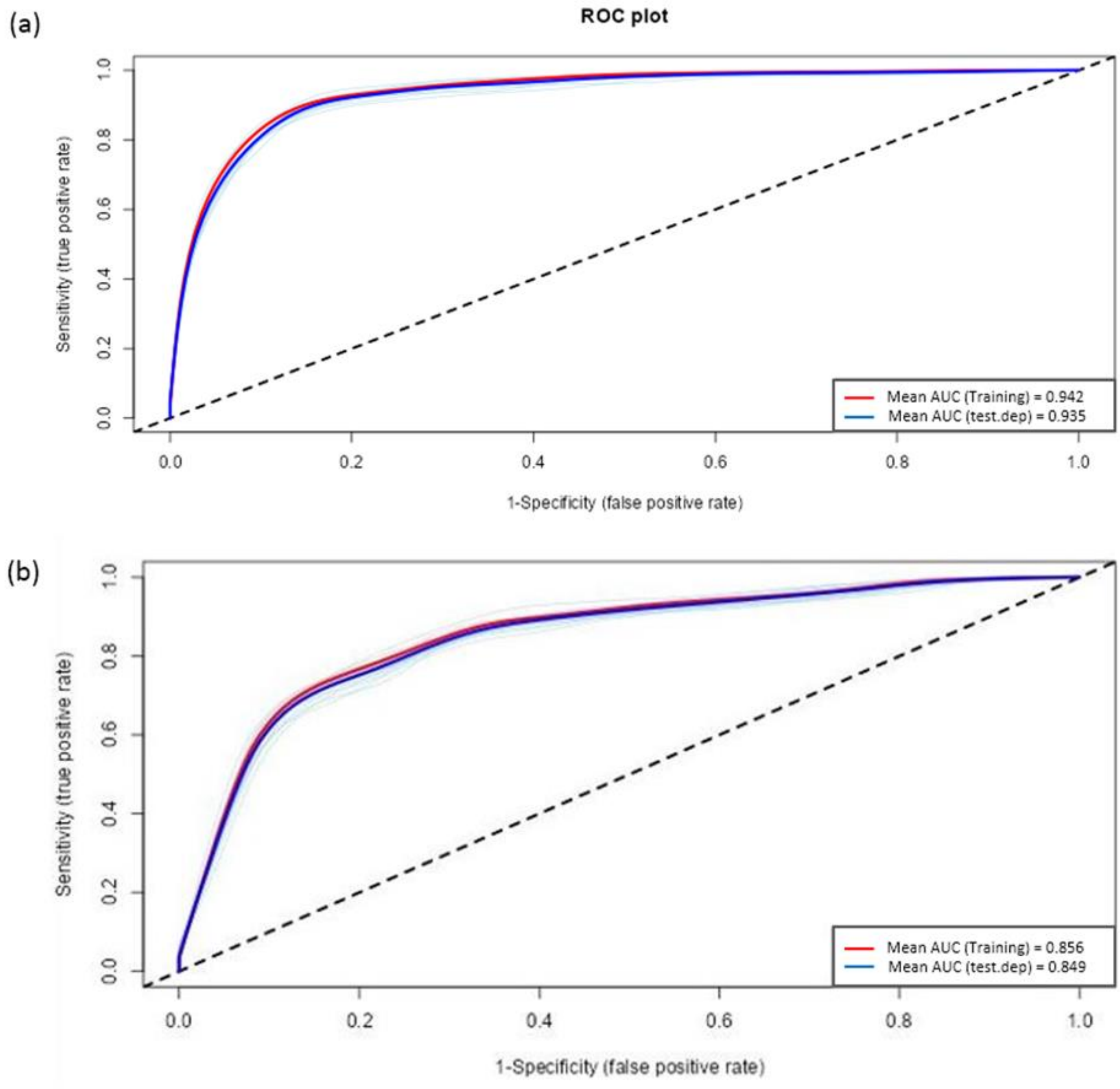

Figure 4-3: The operating curve for both training and test data are shown for *Bulinus globosus*. The blue indicates the test of the model's predictive power. The red line shows the fit of the model to the training data. (a) Maximum Entropy and (b) Generalised Linear Model.

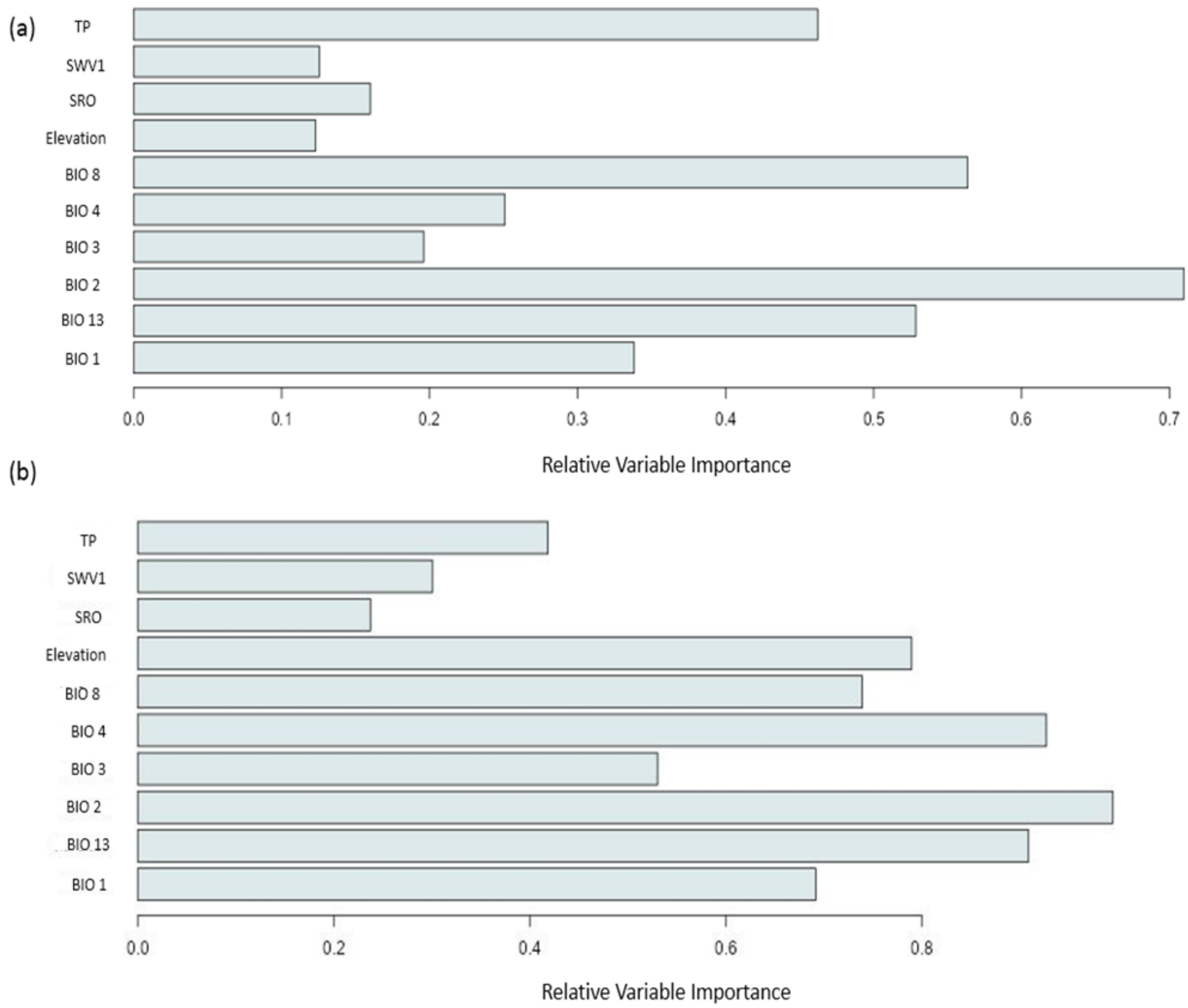

Figure 4-4: Jack-knife test for *Bulinus globosus* snail species with estimates of important variables when running the (a) Maximum Entropy and (b) Generalised Linear Model.

- **Maximum Entropy and Generalised Linear Model Maps**

Maximum entropy and GLM were used to model the distribution of intermediate host snails within the Mbombela and Nkomazi local municipalities, and the results were visualized using ArcMap 10.8.1. The results for the historical distribution of *Biom. pfeifferi* and *Bul. globosus* indicated that the species react to climate variables differently due to the difference in favourable conditions for each host snail species. The Mbombela local municipality was found to provide suitable conditions for the historical distribution of *Biom. pfeifferi and Bul. globosus* in both MaxEnt and GLM.

The high suitable areas for the species were almost similar but GLM predicted the *Biomphalaria pfeifferi* distribution was high around the Crocodile River, Kaap River, Komati River and along the border of the local municipalities for both models (Figure 4-5). Although the historical distribution of *Biom. pfeifferi was* found along permanent water sources, GLM showed high distribution on the southern end of Nkomazi and MaxEnt showed a small part on the northern parts of Mbombela to have moderate to high distribution. MaxEnt predicted the high historical distribution of *Biom. pfeifferi* to extend to the northern parts of the Nkomazi area but overall, the municipality was largely predicted to have a moderate to low distribution of the snail species.

For both models, suitable conditions for *Bulinus globosus* were highly probable and scattered in the Mbombela local municipality and along the border of the two municipalities. The species was found to be distributed on the eastern areas of the municipalities extending to the northern parts of Mbombela. The Mbombela local municipality presented conditions where the host snails would typically be found. Maximum Entropy predicted the historical distribution of *Bul. globosus* to be almost similar to that of *Biom. pfeifferi,* but less distribution was noted on the north of the Nkomazi area.

The GLM results for the historical distribution of *Bul. globosus*, showing some south-western areas in Nkomazi had moderate distribution of the snails. The model also indicated that a small area on the southern parts of Mbombela had moderate to high distribution of *Bul. globosus*. Compared to *Biom. pfeifferi*, *Bul. globosus* was found by the GLM to be historically distributed beyond the main river systems as it can survive shallower waters (Figure 4-6). For both snail species, *Biom. pfeifferi* and *Bul. globosus,* MaxEnt was found to produce satisfactory results for the historical distribution within the Mbombela and Nkomazi local municipalities.

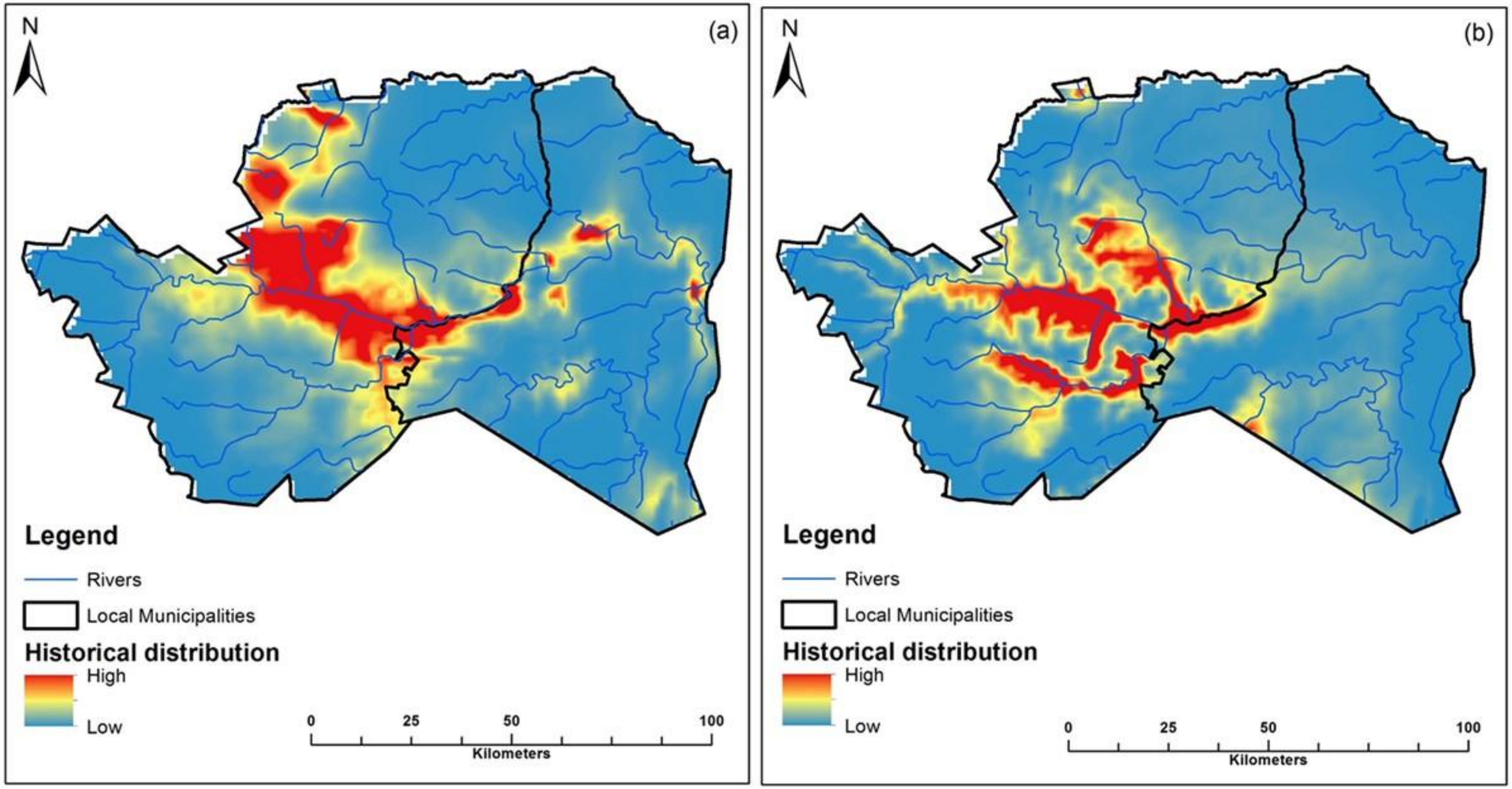

Figure 4-5: Predicted historical distribution of *Biomphalaria pfeifferi*. (a) Maximum Entropy and (b) Generalised Linear Model results within Mbombela and Nkomazi local municipalities.

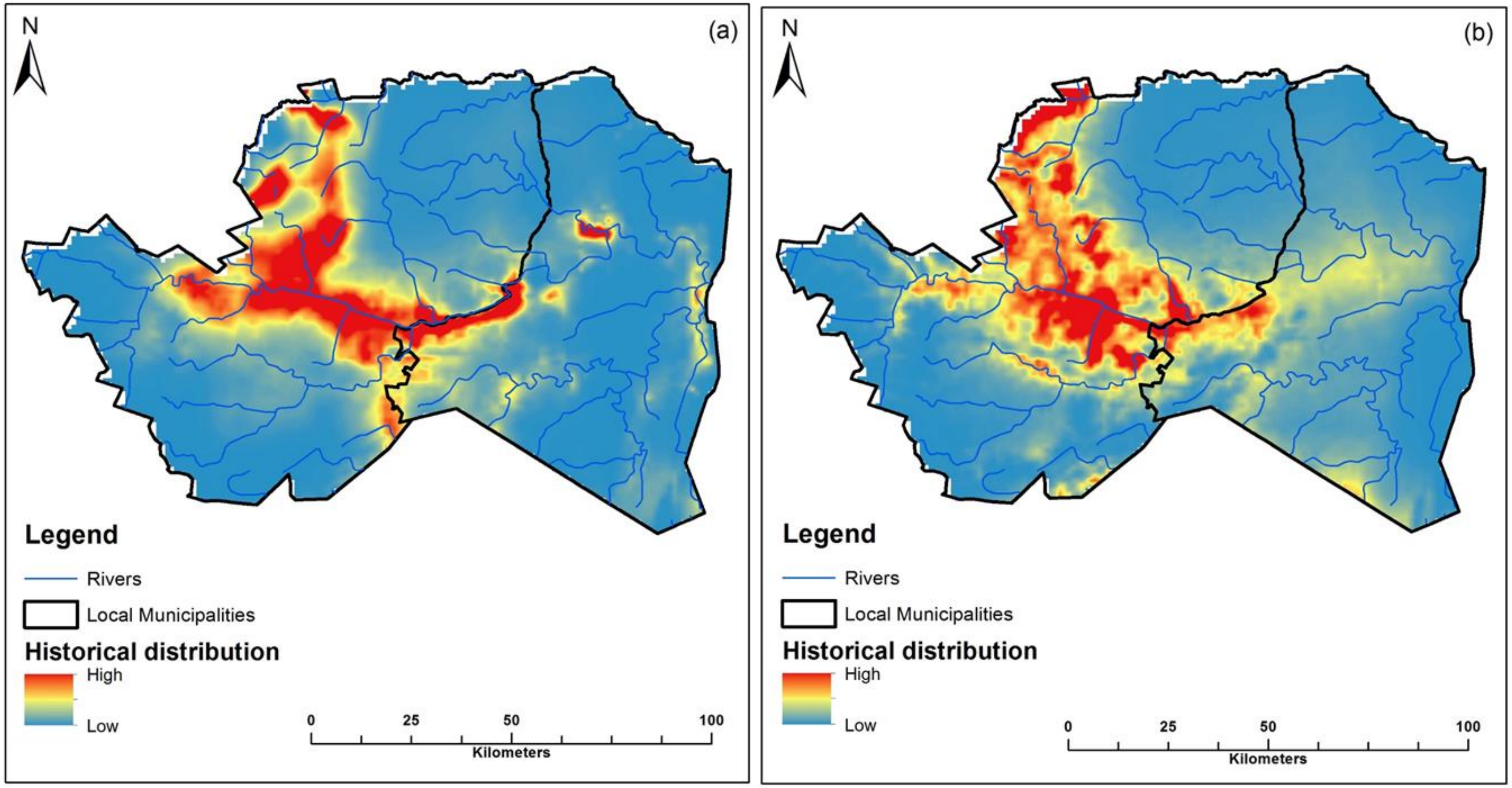

Figure 4-6: Predicted historical distribution of *Bulinus globosus*. (a) Maximum Entropy and (b) Generalised Linear Model results within Mbombela and Nkomazi local municipalities.

Additional species response curves show how each environmental variable affected the predictions of GLM and MaxEnt for each snail species. The curves depict the predicted probability of presence changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. The response curves showing how each environmental variable affected MaxEnt and GLM prediction are shown in Appendix A to D, with the probability of the host snails' presence based on individual response curves for the major environmental factors.

The probability of *Biom. pfeifferi* occurrence was negatively correlated with BIO 3. Increases in isothermality caused the historical distribution of the snail species to decline. The probability of *Biom. pfeifferi* presence increased with the increasing precipitation of the wettest month (BIO 13), and after it reached a peak there was a decline which remained constant. There was a similar trend with *Bul. globosus* and BIO 3, with sharp decreases in species distribution as isothermality increased. The *Bul. globosus* snails can handle changes in elevation, compared to *Biom. pfeifferi,* as the response curve shows they can maintain a certain level and stay constant.

4.3.2 Seasonal Distribution

The results were obtained by making use of kriging interpolation in ArcMap 10.8. Seasonal variation was observed for both species. Rainfall was negatively associated with both *Biom. pfeifferi* and *Bul. globosus* snails. The summer and winter seasons showed a high distribution of the *Biom pfeifferi* snail within the Nkomazi local municipality (Figure 4-7a & c). During the autumn season (Figure 4-7b), high distribution of the *Biom. pfeifferi* snail was predicted on the northern and eastern areas of Mbombela with Nkomazi having a low distribution. The results predicted that in spring there was a high distribution along the border of the local municipalities and on the north-eastern parts of Mbombela (Figure 4-7d). During the summer season, *Biom. pfeifferi* was found to be highly distributed on the northern parts of the local municipalities (including Kruger National Park).

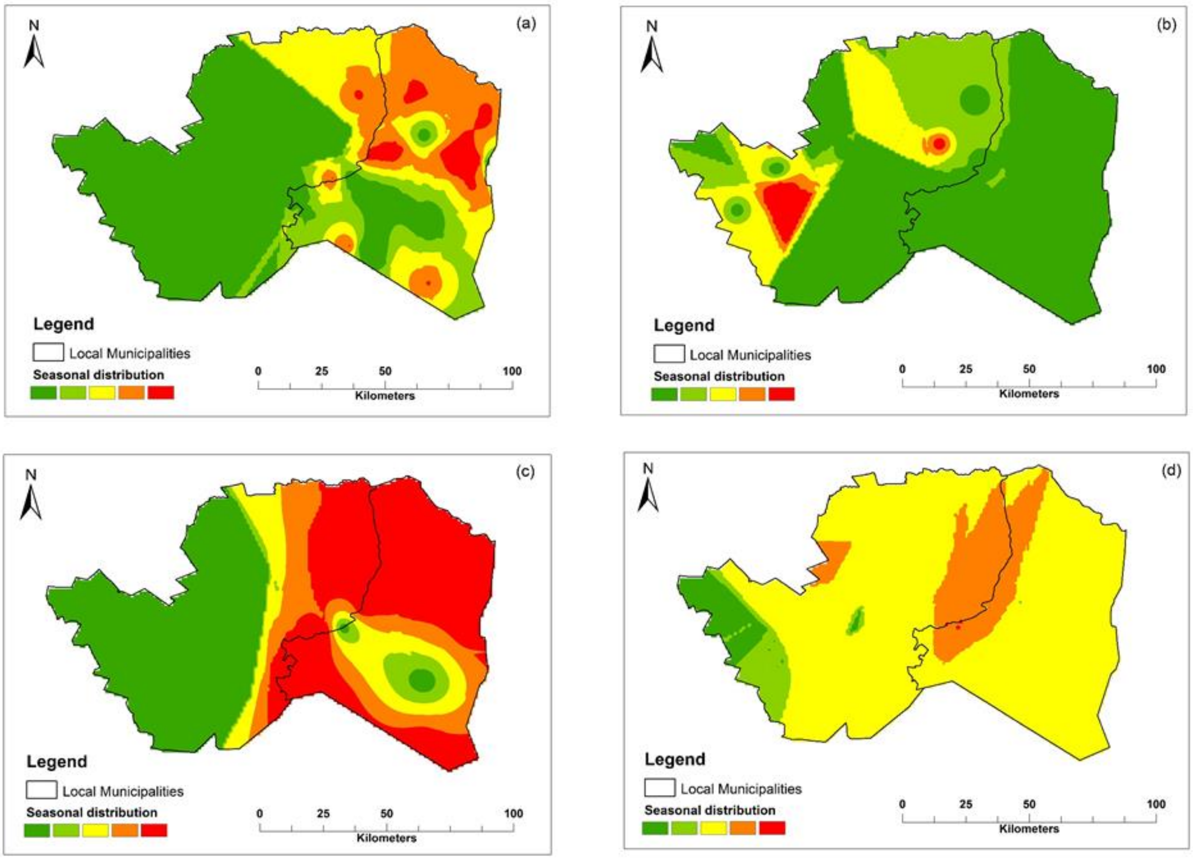

Figure 4-7: Predicted seasonal distribution of *Biomphalaria pfeifferi* within Mbombela and Nkomazi local municipalities for (a) summer, (b) autumn, (c) winter and (d) spring. Dark green represents a very low distribution and red represents very high distribution.

The *Bul. globosus* populations were relatively variable in inland locations, mostly occurring during and shortly after the wet season. The seasonal maps results predicted the distribution of *Bul. globosus* during the hot season, summer, was moderate and high within the Nkomazi local municipality and high in communities in the centre of Mbombela (Figure 4-8a). A few areas indicated high distribution of *Bul. globosus* during the autumn season within the Mbombela local municipality and Nkomazi having mostly low distribution (Figure 4-8b). *Bulinus globosus* showed low distribution in the Mbombela region during the cold and dry season (Figure 4-8c), while the opposite was true for the southern reaches of Nkomazi. Most of Mbombela and Nkomazi showed low and very low distribution of *Bul. globosus* in the spring except for some parts of Mbombela which showed moderate to very high distribution of the snail (Figure 4-8d).

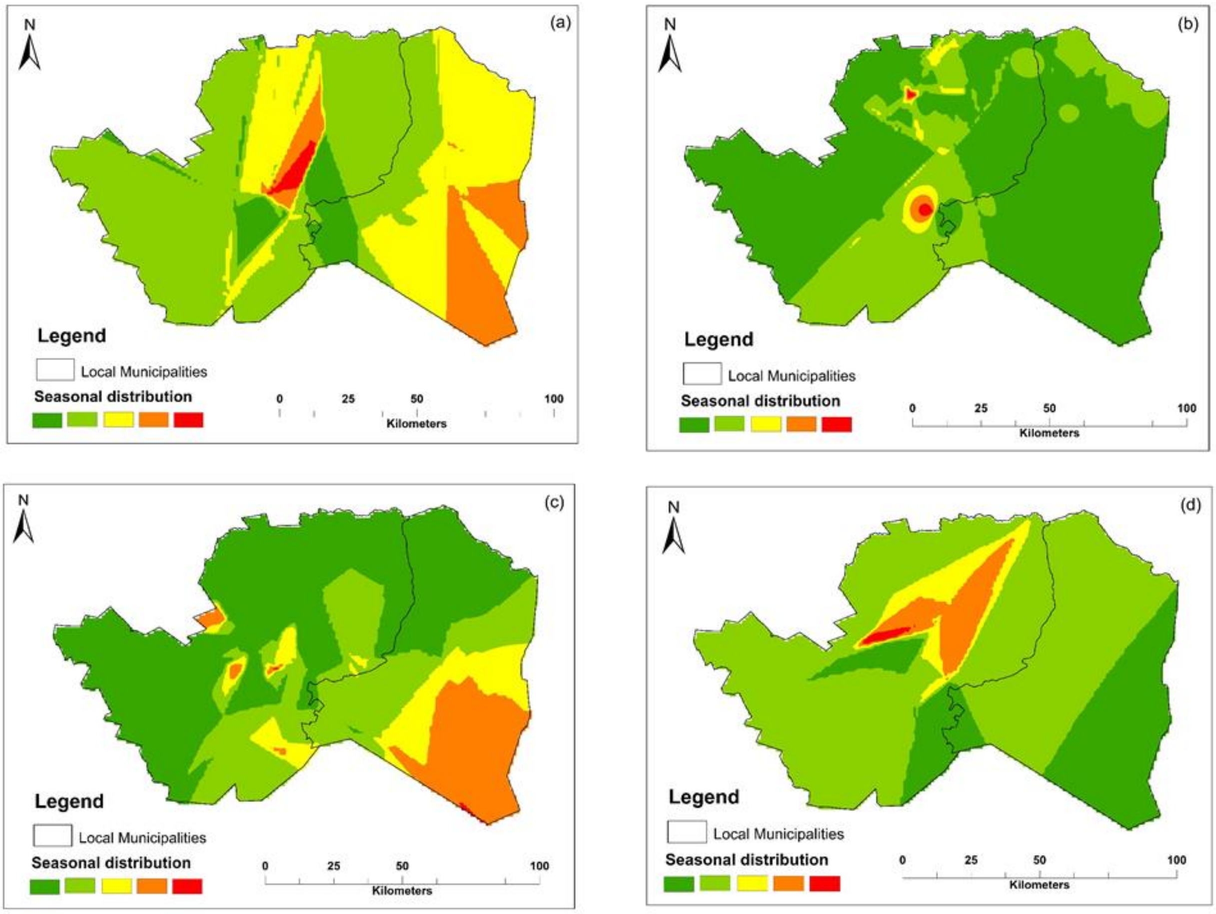

Figure 4-8: Predicted seasonal distribution of *Bulinus globosus* within Mbombela and Nkomazi local municipalities for (a) summer, (b) autumn, (c) winter and (d) spring. Dark green represents very low distribution and red represents very high distribution.

4.4 Discussion

Model predictions in this study indicated a good prediction of the historical distribution of suitable habitats of *Bulinus globosus* and *Biomphalaria pfeifferi* in Mbombela and Nkomazi local municipalities based on bioclimatic and climatic variables. The study made a comparison of two species distribution models, MaxEnt and GLM. The AUC scores for both species indicated that the GLM utilized in this study performed satisfactorily. The MaxEnt generated high AUC scores which showed that the model had the best occurrence probability for the historical distribution. The results suggest that the model generated by MaxEnt is much more restrictive as it specifies the distribution range for the species, while GLM is much more open. The results indicate that when there is no absent data, MaxEnt can infer the distribution of the species in an acceptable way. There are many factors that determine the ability of a model to run successfully such as the spatial extent of study area and sample size. For many species the sample field data are insufficient to characterise the geographic distribution of species in the study area and, often, must be supplemented by digital species information. However, the distribution records of some species must be confirmed by Google Earth due to the lack of detailed latitude and longitude information. Some distribution sites have been collected over long periods and their environment has changed over time. Using these distribution data for simulation often weakens the model's niche definition, resulting in a decline in the simulation ability and accuracy of the distribution model.

4.4.1 Distribution Patterns of *Bulinus globosus* and *Biomphalaria pfeifferi*

Compared to the actual distribution, it is found that the range predicted by the model is in general agreement with the actual distribution. Although there are minor deviations, the core distribution area is consistent with the historical distribution. Based on the results of the MaxEnt model, the key factors affecting species' geographical distribution are not completely consistent as it was seen that the variables contributed differently for each species. This is also true of the generalised linear model.

Distribution modelling was employed to stimulate the distribution of highly suitable areas for intermediate host snails for Mbombela and Nkomazi. The model predictions indicated that precipitation was the main environmental variable affecting species distribution. This was also supported by Manyangadze et al., (2021) who found similar results in a study looking at the spatial and seasonal distribution of *Bul. globosus* and *Biom. pfeifferi* snail species in KwaZulu-Natal. In summer, the seasonal distribution predicted *Biom. pfeifferi* snails to have low to moderate historical distribution within Mbombela local municipality, which may be due to the high rainfall the municipality receives during the rainy season. This was also observed in a study conducted by Utzinger and Tanner (2000) in Tanzania. High distribution in the cold and dry season in the Nkomazi municipality may be because of the dams and pools along the streams which provide suitable habitats for host snails. Seasonal fluctuations in rainfall affect temporary and permanent waterbodies in which intermediate host snails are found. Seasonal precipitation can also be used to measure the availability of suitable temporary waterbodies that host snails are known to inhabit (Dai et al., 2022).

The seasonal distribution maps showed that *Biom. pfeifferi* snails were highly distributed during the dry season, especially within the Nkomazi local municipality. This can be accounted for by the distribution patterns on the model results for MaxEnt and GLM where the snail species is distributed to the parts of the local municipalities which are known to have low rainfall ranges.

Several studies have shown that the distribution, abundance and infection rates of *Biomphalaria* snails were higher during the dry season than in the wet season (Abdulkadir et al., 2017; Gouvras et al., 2017; Ismail et al., 2021; Hailegebriel et al., 2022). The mapped seasonal distribution within Mbombela local municipality show that post-rainy (autumn) followed the trend of the modelled historical distribution, along the Crocodile River and Komati River.

The model results also showed that one of most significant environmental variables for MaxEnt was the mean diurnal range, the difference between the minimum and maximum temperature in a month. This was also a significant factor in the GLM, and was likely because the life history of intermediate host snails and their interaction with the parasite are affected by changes in temperature, confirmed by Kalinda et al., (2017) in a study on the effect of temperature on *Schistosoma haematobium* system. Temperature changes can create favourable and unfavourable breeding conditions for both the schistosome and host snails and this affects the distribution and transmission rates (Adekiya et al., 2017).

The tolerance of the snail species *Bul. globosus* highly depends on the variations in climatic and environmental factors (Joubert et al., 1990, Manyandze et al., 2016, Kalinda et al*.,* 2017; Manyangadze et al*.,* 2021). The model results for MaxEnt and GLM showed that under historical conditions, suitability of *Bul. globosus* was concentrated mostly in the Mbombela area, around Matsulu. In Nkomazi the distribution was along the Malelane area and the southern parts of the municipality such as Thambokhulu. Similar findings were found in other studies looking at the distribution and habitats of schistosomiasis snails (Brown, 1966; Eeden & Combrinck,1966; De Kock & Wolmarans, 2005). These were suitable areas for the snail to reside due to the suitable conditions such as elevation, rainfall and higher temperatures found in these parts of the municipalities which represented the best conditions for the viability of the snail (Appleton & Miranda, 2015; Adekiya et al*.,* 2019). Another study by Kalinda et al., (2018) found that the habitat suitability for *Bul. globosus* was wider with the species being able to tolerate the cold/dry season for up to 50 days but can also survive the post-rainy and hot seasons, with the lowest values in the hot/dry season.

The model results for MaxEnt indicated some high distribution of both snail species on the northern areas of Mbombela local municipality, Hazyview area, with *Bul. globosus* extending to the far northern border of Mbombela. There was moderate distribution on the southern parts of Nkomazi with some areas showing high distribution in the south-west of the municipality. The models indicated a historical decrease in the distribution and suitable habitats of *Biom. pfeifferi* with the species limited close to water sources such as the Crocodile River. These findings conform to other studies on *Bul. globosus* and *Biom. pfeifferi* that have been conducted in southern Africa (Zimbabwe and Madagascar), showing a decrease in the geographic distribution of schistosomiasis host snails connected to changes in precipitation and temperature due to climate change (Pedersen et al., 2014; Kalinda et al., 2017; Kalinda et al., 2018; Adekiya et al., 2019). These studies found that areas that were considered suitable for intermediate host snails will either become too dry or too hot under future climate change scenarios to sustain schistosomiasis and its intermediate host snails (Pedersen et al., 2017). A study by Kalinda et al., (2018) used data from field experiments and laboratories to create a deterministic compartmental simulation model based on difference equations using a weekly time step that represented the life cycle of *Bul. globosus* to simulate snail population dynamics of the species. The study concluded that the increase in temperature due to climate change may alter the prevalence of *Bul. globosus* and lead to a decrease in the species population. This may be true as both models in the current study showed that the species are located close to water sources and in areas that are known to have moderate climate within the studied local municipalities. The seasonal results for *Bul. globosus* also showed that the species cannot survive too cold or too dry seasons, especially in the Mbombela local municipality. High temperatures are associated with ideal breeding conditions and high distribution for the snails, but these high temperatures can also reduce survival rates of the species by drying up the waterbodies in which they are found (McCreesh & Booth, 2014).

Understanding species historical distribution is one of the fundamental questions to determine vulnerability (Dai et al., 2022). Pedersen et al., (2014) modelled the impact of climate change on the spatial distribution of schistosomiasis host snails in Zimbabwe and concluded that climate change may cause a decrease in the spatial distribution of suitable habitats of host snails such as *Biom. pfeifferi.* This means that historical distribution patterns within Mbombela and Nkomazi local municipalities may have changed, and will possibly continue to change, due to shifts in the environmental variables. Climate change will more likely shift than expand the geographic ranges of the snail species within Mbombela and Nkomazi, which will likely create new vulnerability areas to schistosomiasis and this is something that has also been noted in other studies (McCreesh & Booth, 2013; Stensgraad et al*.,* 2013; Pederson et al., 2014; Stensgraad et al., 2019).

4.5 Conclusion

Species distribution modelling, such as the models used in this study, generates valuable information for the conservation management of species. The impact of different bioclimatic and climatic variables on the distribution of *Biomphalaria pfeifferi* and *Bulinus globosus* in Mbombela and Nkomazi local municipalities were evaluated with the use of the MaxEnt and GLM. Both the MaxEnt model and GLM results showed that within the two municipalities, Mbombela provided the most suitable distribution area with some parts of Nkomazi, which corresponded with studies conducted previously. It is therefore evident that these factors, such as temperature, precipitation and elevation, play an important role in the distribution dynamics of these intermediate host snails, and that climate change can alter the known distribution of schistosomiasis host snails. The prediction generated by MaxEnt were highly accurate compared to the model produced by GLM. However, MaxEnt was also shown that it could correctly operate with a higher similarity with models of presence/absence when the review coverage conducted was uniform and extensive. Unsuitable areas might become new risk areas for the distribution and transmission of schistosomiasis due to changes in the climatic and bioclimatic variables. It is vital to predict the distribution of the species using a sound ecological niche model so that we may understand which areas might be vulnerable to infection and transmission in case officials require information to implement schistosomiasis control and elimination measures currently and in the future. These historically suitable areas might have already shifted due to an increase in human population, increase in agricultural activities and land development. The findings of this study about the historical distribution of schistosomiasis host snails, can be used to identify additional localities where the intermediate host snails may already exist but have not been detected yet and where the disease is likely to spread, creating new vulnerable areas. Water (rainfall) was noted as one of the main factors that affect the distribution of schistosomiasis vectors, hence it was important to assess how changes in water quality may influence the distribution. The following chapter will therefore assess historic water quality in Mbombela local municipality and possible influence on the distribution of schistosomiasis vectors.

CHAPTER 5 ASSESSING THE HISTORIC WATER QUALITY OF RIVERS WITHIN MBOMBELA LOCAL MUNICIPALITY

5.1 Introduction

Variability of micro-climate parameters (rainfall and ambient temperatures) has drastically changed the dynamics of waterbodies such as flow, pH, salinity, conductivity, and the overall water quality (Merolla, 2011; Adekiya et al., 2019). Global changes such as climate change, population growth, urbanisation, industrial development and the expansion of agriculture have put huge pressure on natural resources, particularly water (Okello et al., 2015). In southern Africa where environmental sustainability issues are increasingly coming into conflict with human development objectives and where data is scarce, water is an important resource for social and economic wellbeing of the predominantly rural populations (Russell, 2013; Okello et al., 2015). Water quality is affected by both point and nonpoint sources of pollution in rural and urban areas (Glińska-Lewczuk et al., 2016). Some of these sources include sewage discharge, industrial discharge, and agricultural run-off (Khatri & Tyagi, 2015). Extreme weather events may alter chemical parameters of water by increasing variables such as nitrates, phosphates, and sodium chloride (Nicholls et al., 2012). Floods and droughts, as well as lack of awareness among end-users about hygiene, environment sanitation, storage and disposal need to be considered for the maintenance of water resources (Edokpayi et al., 2017; Manyangadze et al., 2021). These natural and human induced changes have led to decreased surface layer nutrient concentration and prolonged oxygen depletion in river systems (Parry, 1988).

Natural processes such as soil weathering and hydrological and biotic factors can cause fast-flowing water, leading to run-off that can degrade water quality by changing the physical and chemical composition of water (Barakat et al., 2016; Adekiya et al., 2019). Human contributions such as agriculture have both direct and indirect effects on surface water and groundwater quality (Shabalala et al., 2013). The agri-business is one of the principal causes of water quality degradation, particularly in rural areas, and this is as the result of excessive use of agrochemicals (Zia et al., 2013; Omer, 2019). Agro-pollutants associated with degrading water quality include nitrate- and phosphate-rich fertilisers, metals, pathogens, pesticides, irrigation, and the removal of natural habitats for farms and plantations (Shabalala et al., 2013). Modification of river systems has led to an increase in salts and organic and inorganic materials which degrade water quality (El Deeb et al., 2017). Consequently, both acute and long-term degradation lead to changes in water quality parameters such as pH, salinity and nutrients (Khatri & Tyagi, 2015).

Water from natural sources generally contains organisms that are a part of the biogeochemical cycles of aquatic systems (Walz et al., 2015; Koushali et al., 2021). Many ecosystems are sensitive to small changes in the physical and chemical composition of the water body, resulting in degradation of the ecosystem (Ghosh et al., 2020). Minerals and dissolved salts are necessary components of good quality water as they help maintain the health and vitality of organisms that rely on this ecosystem service (Khatri & Tyagi, 2015; Jones et al., 2021). Changes in water quality parameters, such as pH, salinity and nutrients have resulted in changes in productivity rate, species composition, distribution and organism abundance (Waide et al., 1999; Oehri et al., 2017). These changes may also influence disease patterns including population dynamics of vector and water-borne diseases such as schistosomiasis (de Necker, 2020).

Schistosomiasis is found in countries located in tropical and subtropical regions, primarily sub-Saharan Africa including South Africa (Olkeba et al., 2020). Schistosomiasis continues to be neglected as a health threat, especially in rural populations located within provinces in the north-eastern parts of the country (Paull & Johnson, 2011; Adekiya et al., 2019). The Mbombela local municipality in the Mpumalanga province falls under this endemic area. The municipality is located in the eastern parts of Mpumalanga, also known as the Lowveld, which are reported to have high prevalence of schistosomiasis (NICD, 2022). Mbombela is made popular by its moderate climate, making it agriculture friendly which, together with other natural factors, change the water quality. This places stress on freshwater ecosystems such as rivers and dams where various aquatic biota are found including molluscs that transmit schistosomiasis (Malan et al., 2009; Döll & Zhang, 2010). One of the major drivers of water quality deterioration within the Mbombela area (Nelspruit and Matsulu) is high pH and salinity levels which occur as a result of a combination of wastewater effluent and run-off from fertilisers used for intensively irrigated sugar cane and subtropical fruits (DWS, 2013; Khatri & Tyagi, 2015).

Human influenced ecological changes due to irrigation schemes and dam creation for agricultural purposes plus discharge of industrial, domestic wastewater and agricultural drainage have been reported to cause degradation of water quality (Stensgaard et al., 2013; Barakat et al., 2016). Agricultural activities in the Mbombela area occur predominantly in peri-urban areas, and many of these occur near rivers and dams (Shabalala et al., 2013; Khatri & Tyagi, 2015). Small- scale farming does not largely affect schistosomiasis distribution unlike large-scale farming where agrochemicals are widely used such as sugarcane plantations and the forestry industry found near river systems within Mbombela (Dallas & Day, 2004; DWS, 2013; Hoover et al., 2020). According to the National Freshwater Snail Collection (NFSC), 72% of *Biomphalaria pfeifferi* snails are found in perennial waterbodies within Mbombela, while *Bulinus globosus* snails were found to prefer permanently inundated aquatic habitats (Appleton et al., 1995; Malan et al., 2009). Any water quality changes due to environmental or human interference within this region can affect the snail species due to their prevalence which in turn influences the distribution of schistosomiasis (Merolla, 2011; McCreesh & Booth, 2014).

The variables mentioned above can change from one waterbody to another and from one ecological zone to another. Changes in water quality variables will differ between ecosystems and ecological regions and may have either a positive or negative effect on the presence and abundance of disease vectors (Lefcort et al., 2015; Yu et al., 2022). Research on how water quality changes over time is key to understanding how this may alter the abundance and distribution of intermediate host snails of schistosomiasis (Ndione et al., 2019). This will provide vital information for effective intervention strategies for such diseases in endemic areas. This study aimed to analyse changes in various water quality variables between 1977-2009 in the Mbombela river systems to understand how this may have influenced the distribution of schistosomiasis vectors in the region.

5.2 Data and Methods

5.2.1 Data collection

The historical water quality data for Sabie, Kaap, Komati and Crocodile rivers was obtained from the Department of Water and Sanitation (DWS) monitoring stations under the National Chemical Monitoring Programme for Surface Water. The historical data available was between 1977-2009 (Table 5-1). Seven monitoring stations located along the river systems under Mbombela local municipality were found to have enough data for this study. The Komati, Crocodile, Kaap and Sabie are located on the Incomati River basin and are main sub-catchments contributing approximately 94% of natural discharge with an area of 61% of the basin and are surrounded by small and large scale farmers with small communities (van der Zaag & Vaz, 2003; Okello et al., 2015) One site was located on the Komati River (X1H003), one site on the Kaap River (X2H022), two sites on the Crocodile River (X2H006 and X2H032) and three on the Sabie River (X3H001, X3H002 and X3H006; Table 5.1). The collection and analysis of the water quality data included sodium (Na mg.L^{-1}), conductivity (µS.cm^{-1}), calcium (Ca mg.L^{-1}), magnesium (Mg^{+} mg.L^{-1}), chloride (Cl^{-} mg.L^{-1}), sulfates (SO_4^{2-} mg.L $^{-1}$), nitrate nitrogen/nitrite nitrogen (NO_2/NO_3 mg.L -1), orthophosphate (PO_4^{3-} mg.L $^{-1}$), ammonium nitrogen (NH_4^{+} mg.L $^{-1}$), total dissolved solids (TDS mg.L $^{-1}$) and pH.

Table 5-1: Department of Water and Sanitation (DWS) monitoring stations used in this study including names, station numbers, years which the water quality data were available and site names as appearing in the results.

River Name	DWS Monitoring Station Number and Location	Years for which Historical Data is Available	Site Names
Komati River	X1H003 (Komati River at Tonga)	1977-2009	Komati
Kaap River	X2H022 (Kaap River at Dolton)	1977-2009	Kaap
Crocodile River	X2H006 (Crocodile River at Karino)	1977-2009	Crocodile 1
Crocodile River	X2H032 (Crocodile River at Weltevrede)	1977-2009	Crocodile 2
Sabie River	X3H001 (Sabie River at Sabie)	1977-2009	Sabie 1
Sabie River	X3H002 (Klein Sabie River at Sabie)	1977-2009	Sabie 2
Sabie River	X3H006 (Sabie River at Perry's Farm)	1977-2009	Sabie 3

5.2.2 Data analysis

The analysis was conducted using IBM SPSS Statistics 23 (IBM Corp. Released 2015. IBM Statistics for Windows, Version 23.0). Data analyses followed those reported by de Necker et al, (2019). The data was first separated into three decades, namely 1977-1987, 1988-1998 and 1999-2009 and analysed for spatio-temporal variability in water quality. For each site, the data is reported as an annual average per year. The data for each year was aggregated to represent annual records to make it easier to compare the sampling sites. The Physicochemical Driver Assessment Index (PAI) was used to determine the water quality within the local municipality for each decade. The PAI is used in South Africa as part of the eco-classification determination process; for a specific site the tool can determine the state of chemical and physical water quality (Rossouw, 2011; de Necker et al., 2019). Microsoft Excel-based weighting is used in the PAI, and this allows for the assessment of individual variables through rating and ranking. This is based on a multi-criteria decision analysis that considers several different water quality characteristics which include salts, pH and turbidity (Kleynhans et al., 2005; Divisi et al., 2017). The PAI was used to determine the water quality in the different time frames (1977-1987; 1988-1998 and 1999-2009) for each river system (Sabie, Crocodile, Komati and Kaap) and this is rated based on the degree to which water quality parameters have shifted from reference conditions, as well as the significance of each variable with the potential biotic responses it may cause. The program calculates a PAI score in % from 0 to 100 and an ecological category rating from A to F where A and 100% are the best or unmodified and F and 0% show the worst and most impacted ecosystem (see Table 5-2).

Descriptive statistics were done to test any significant differences in water quality parameters over the three decades for all the variables at each site. All the river sites were compared across the three decades (1977-1987; 1988-1998 and 1999-2009). Data normality was first tested using the D'Agostino-Pearson normality test to determine if the data was normally distributed (Ghasemi & Zahediasl, 2012). Following this, either a one-way ANOVAs or a Kruskal-Wallis H test was conducted to assess whether any significant differences were present between the three decades (de Necker et al, 2019). The data that met the assumptions of normality (parametric distribution) was tested for significance using the one-way ANOVA with Tukey's post-hoc test while data that did not meet this assumption (non-parametric distribution) was tested for significance using the Kruskal-Wallis H test with Dunn's multiple comparisons test (de Necker et al., 2019; IBM, 2021). The significance value was set at $p<0.05$.

To further compare the water quality within the four river systems, a principal component analysis (PCA) was used to compare changes of water quality variables to the three decades (1977-1987; 1988-1998 and 1999-2009). A PCA is based on a linear response model which relates a single variable, such as water quality data, to a site (Jolliffe & Cadima, 2016). A PCA is a method for lowering the dimensionality of such datasets, improving interpretability while reducing information loss (Solidoro et al., 2004). A diagram of the data for each site is visualised on a two-dimensional basis (de Necker et al., 2019). The placement of the sites on the diagram signifies either similarities or dissimilarities between the measured variable and sites based on the angle of the variables to one another. Variables at ≤90◦ are positively correlated while variables >90◦ are negatively correlated (Šmilauer & Lepš, 2014.). The PCA was completed using Canoco v5 for each of the different river systems (Sabie, Kaap, Komati and Crocodile) to determine possible changes in the water quality of each sampling site over the three decades.

Table 5-2: Ecological categories used for rating Physicochemical Driver Assessment Index (PAI) scores in percentages (%) (Adapted from de Necker et al., 2019).

Ecological Category	Description	Score
A	Unmodified, natural.	90–100
B	Largely natural with few modifications. A small change in natural habitats and biota may have taken place, but the ecosystem functions are essentially unchanged.	80–89
C	Moderately modified. Loss and change of natural habitat and biota have occurred, but the basic ecosystem functions are still predominantly unchanged.	60–79
D	Largely modified. A large loss of natural habitat, biota and basic ecosystem functions has occurred.	40–59
E	Seriously modified. Extensive loss of natural habitat, biota, and basic ecosystem functions.	20–39
F	Critically/Extremely modified. Modifications have reached a critical level and the system has been modified completely, with an almost complete loss of natural habitat and biota. In the worst instances the basic ecosystem functions have been destroyed and the changes are irreversible.	0–19

5.3 Results

The historic water quality of the Sabie River was in an unmodified state (A-rating) between 1977 and 1987 at two of the sites (Sabie 1 and 2) with one of the sites being in a largely natural state (B-rating; Figure 5-1a). For Sabie 1, the ecological category remained largely the same over all three decades (from 1977 to 2009) with the rating remaining between A and B, while the category for Sabie 2 and 3 declined to moderately modified state (C-rating) by 2009 with Sabie 2 having a lower overall score (75.92%) than Sabie 3 (79.13%). The decline in ecological category for all sites on the Sabie River, particularly Sabie 2 and Sabie 3 in 1988-1998 and 1999-2009 was driven by an increase in salinity (measured by conductivity, TDS, $Mg^{+;}$ Ca and Cl^{-}) as well as pH and organic nutrients (measured by NO_3^-/NO_2^- ; Appendix E and F). The PAI% for Crocodile 1 (84.86%) and Crocodile 2 (81.68%) indicated that the ecological category of the river was largely natural from 1977-1987 (Figure 5-1b). The ecological category declined to a moderately modified state between 1999-2009 for Crocodile 1 (72.06%). The PAI% for Crocodile 2 (66.54%) indicated a decline in ecological category from 1999-2009 which was driven by an increase in salts and pH. The ecological category for Kaap River and Komati River remained moderately modified (rating C) over the three decades (from 1977 to 2009; Figure 5-1c) with the PAI% of the Kaap River always lower; 1977-1987 (74.42%), 1988-1998 (67.12%), 1999-2009 (63.85%) compared to Komati River; 1977-1987 (78.5%), 1988-1998 (77.94%), 1999-2009 (71.59%).

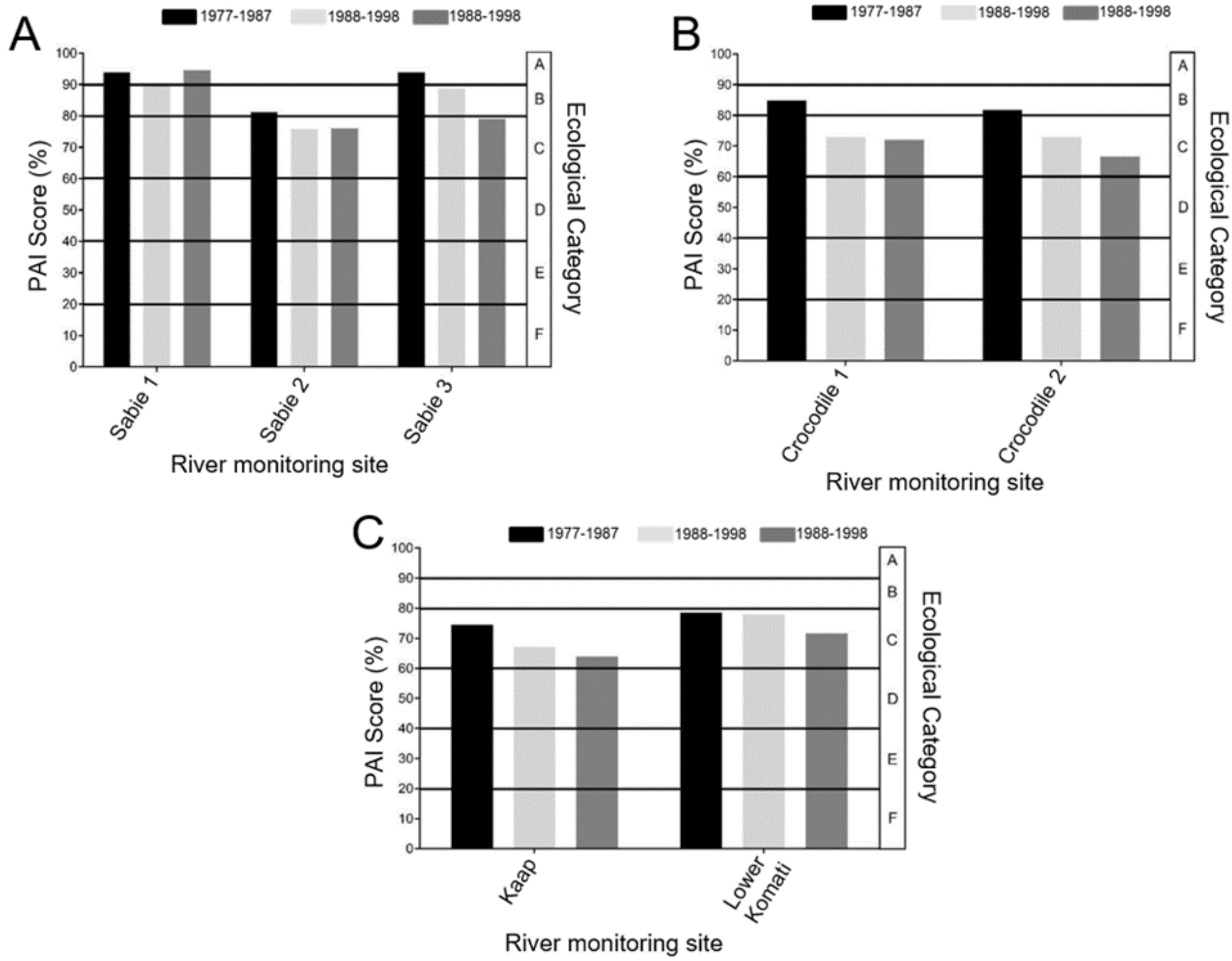

Figure 5-1: Physicochemical Driver Assessment Index (PAI) scores (%) and ecological categories calculated from monitoring stations located on the a) Sabie River, b) Crocodile River and c) Komati River catchment in Mbombela local municipality.

Significance tests were conducted to assess changes in water quality variables for the three decades within Mbombela local municipality. Fluctuations were evident in the water quality variables for all the sampling sites with a general increase occurring over all sites across all three decades (Appendix E to K). The significance tests determined several significant changes in the water quality variables at all the monitoring stations.

In the Sabie River there was a significant increase in pH and the measured salts, including conductivity, TDS, and Mg^+ from 1977 to 2009 at all three sampling locations ($p<0.05$; see Appendix E to G for specific p-values). In addition, Ca significantly increased at two of the sites along with NO_3^-/NO_2^- and NH_4^+ (Sabie 1 and Sabie 2) while SO_4^{2-} significantly decreased from 1977 to 2009 ($p<0.05$; Appendix E and G). There was also a significant increase in Cl^- and PO_4^{3-} at two of the Sabie River sites (Sabie 1 and Sabie 3; $p<0.05$; Appendix E and F). Salinity, including conductivity, Na, TDS, Ca, and Cl^- significantly increased for the Crocodile River system (1 & 2) between 1999-2009 along with pH ($p<0.05$). Other water variables such as NO_3^-/NO_2^-, SO_4^{2-}, PO_4^{3-} and NH_4^+ showed significant increases for the monitoring station within Crocodile River 1 (Appendix H and I). The Kaap and Komati Rivers both showed a similar trend regarding pH which increased significantly from 1977 to 2009 ($p<0.0001$; Appendix J and K). The results further indicated a significant increase in PO_4^{3-} in the Kaap River from 1977-2009 and significant increases in conductivity, TDS, Na, Mg^+, Ca, Cl^-, NO_3^-/NO_2^-, and SO_4^{2-} in the Komati River (Appendix K).

The PCA indicated a similar trend across all monitoring sites where there was a distinct separation between each of the three decades. The PCA of the first Sabie River site (Sabie 1) compared water quality variables over the three decades and explained 69.04% of data variation (Figure 5-2a). Separation on the first axis, which explains 52.53% of data variation, was the result of differences in water quality between the 1977-1987 decade and the other two decades (1988-1998 and 1999-2009). This was driven by salts (TDS, conductivity, Ca, Na and Mg^+) and pH that were generally much higher in the decades of 1988-1998 and 1999 to 2009 than in 1977-1987. Separation on the second axis explained 16.51% of data variation and this was driven largely by much higher values of nutrients (NO_3^-/NO_2^-; PO_4^{3-} and NH_4^+) in the 2000s compared to the other years.

The PCA for Sabie 2 (Figure 5-2b) explained 60.79% of data variation, with 35.94% explained on the first axis and 24.85% explained on the second axis. All three decades separated from one another as a result of significant changes in water quality (see Appendix E to G). The second decade, 1988-1998, was associated with conductivity, TDS, Mg^+ and Ca that were all significantly higher in this decade compared to the previous one. The third decade, 1999-2009, showed a positive association with most nutrients including NO_3^-/NO_2^-, PO_4^{3-} and NH_4^+ as well as pH while SO_4^{2-} was positively associated with 1977-1987 since it was also highest during this decade. The PCA for Sabie 3 (Figure 5-2c) explained a total of 66.40% of data variation, with 51.84% explained on the first axis and 14.56% explained on the second axis. The third decade, 1999-2009, was associated with significantly high conductivity, TDS, pH and Na. There were high levels of SO_4^{2-} over the decade of 1977-1987, and there was an association between pH and 1988-1998 due to the significant difference in water quality between this decade and 1977-1987 (see Appendix G).

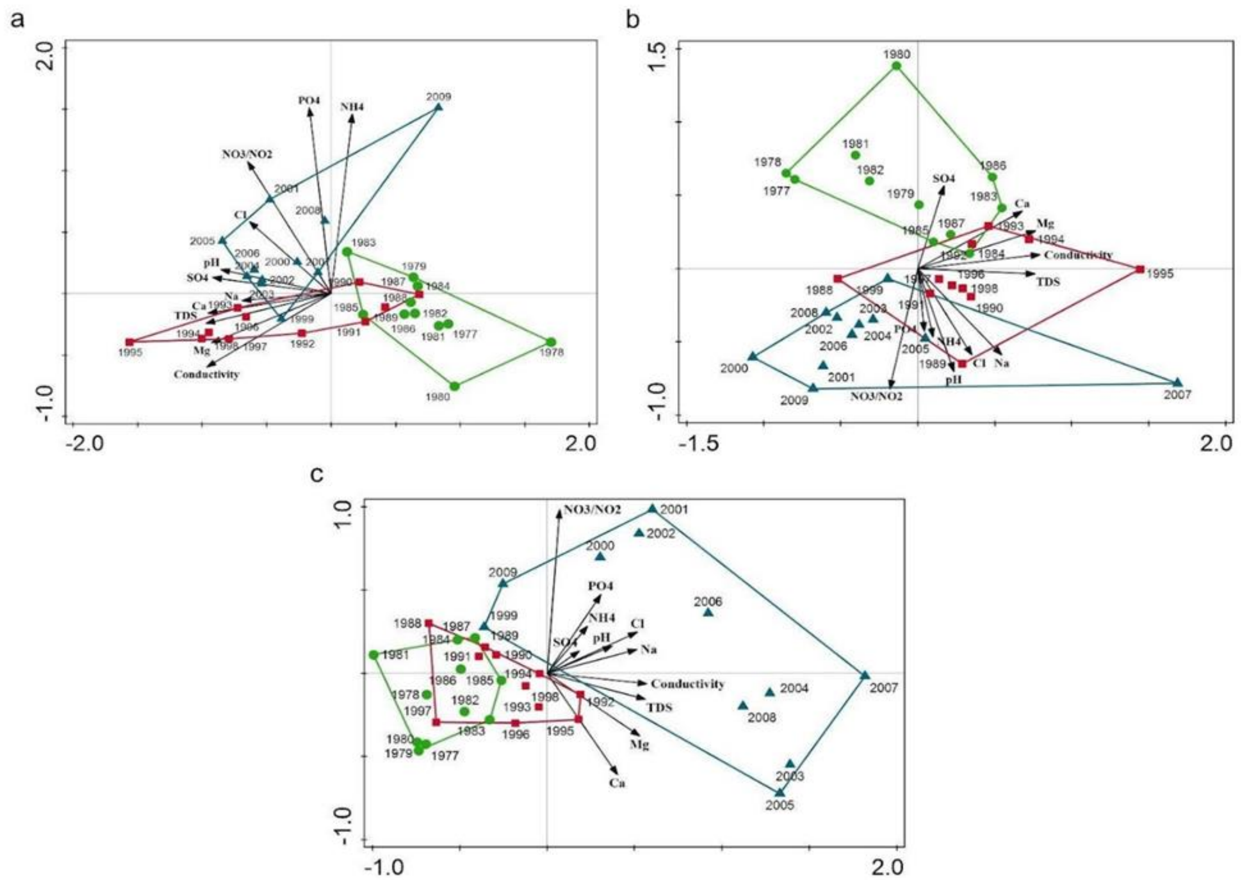

Figure 5-2: Principal Component Analysis (PCA) plot of chemical water variables measured from 1977-1987 (green circles and lines); 1988-1998 (red squares and lines) and 1999-2009 (blue triangles and lines) at the a) Sabie 1 (X3H001); b) Sabie 2 (X3H002) and c) Sabie 3 (X3H006) Department of Water and Sanitation (DWS) monitoring stations located on the Sabie River system.

The PCA of the first Crocodile River site (Crocodile 1) explained 78.95% of total data variation with 67.49% explained on the first axis and 11.46% on the second axis (Figure 5-3a). Separation on this graph was as a result of most water quality variables, that were significantly different between the three decades, particularly all salts, pH and nutrients, excluding NO_3^-/NO_2^- and NH_4^+, that were significantly higher in the 2000s compared to the other two decades (1977-1987 and 1988-1998). The PCA of the second Crocodile River site (Crocodile 2) accounted for 76.96% of data variation, with 64.56% explained on the first axis and 12.40% explained on the second axis (Figure 5-3b). Separation on this graph was similar to that of Crocodile 1, with separation largely as a result of significantly higher water quality variables, particularly salts and pH in the later decade (1999-2009) compared to earlier decades (1977-1987).

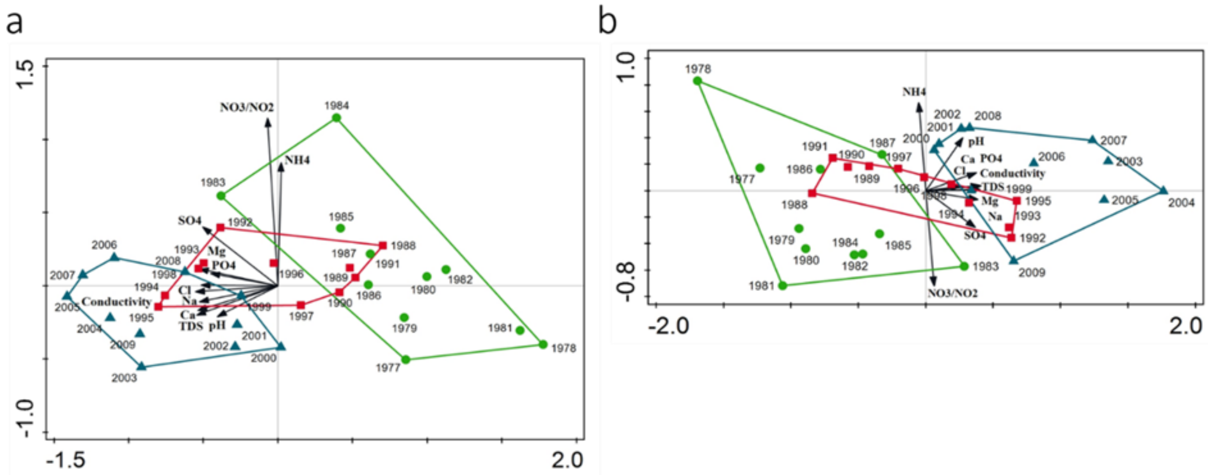

Figure 5-3: Principal Component Analysis (PCA) plot of chemical water variables measured from 1977-1987 (green circles and lines); 1988-1998 (red squares and lines) and 1999-2009 (blue triangles and lines) at the a) Crocodile 1 (X2H006) and b) Crocodile 2 (X2H032) Department of Water and Sanitation (DWS) monitoring stations located on the Crocodile River system.

The PCA for the Kaap River explained 70.98% of data variation, with 59.02% explained on the first axis and 11.96% on the second axis (Figure 5-4). Separation on this graph was as a result of most water quality variables, excluding PO_4^{3-}, NO_3^-/NO_2^-, SO_4^{2-} and conductivity, that were significantly higher in the later decades, particularly the 2000s, compared to the 1970s and 1980s (Appendix J). The PCA results for the Komati River were similar to that of the Kaap River, with a large difference in water quality in the 1970s and 1980s (1977-1987) compared to the later decades (Figure 5-5). The PCA for the Komati River explained 77.91% of data variation, with 67.93% explained on the first axis and 9.97% explained on the second axis. The water quality variables such as pH, Ca, TDS, Cl and conductivity, decreased in the Komati River during 1977-1987 and then increased over the other two decades. The water quality between 1988-1998 had moderately higher nutrients (PO_4^{3-}, NH_4^+), salt (Ca, TDS, Cl) and pH compared to the previous years.

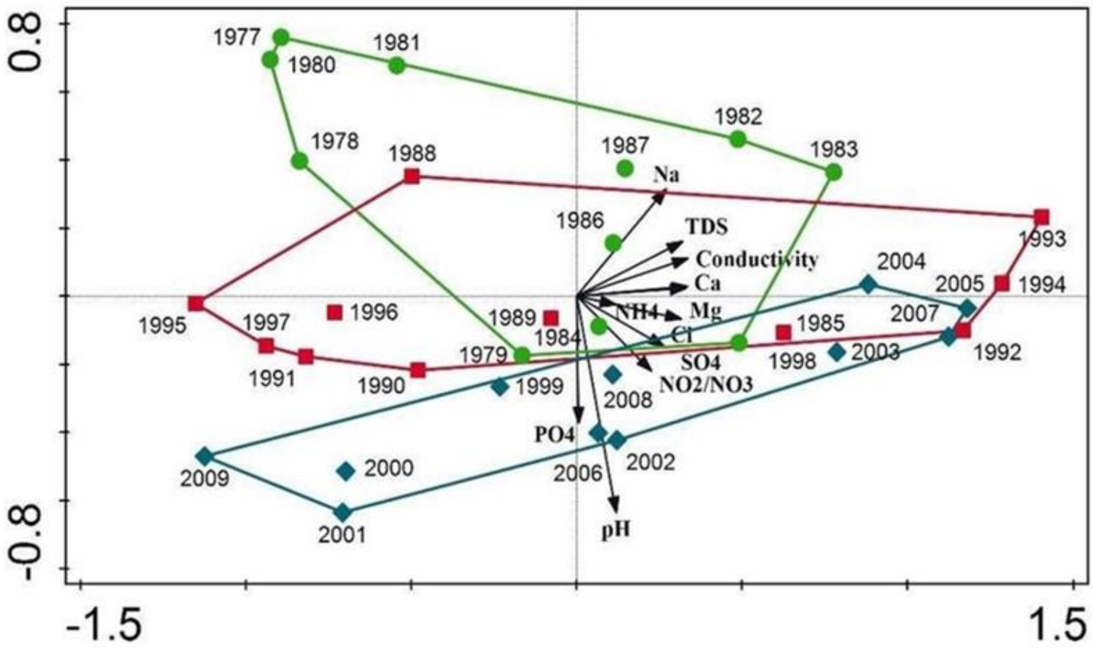

Figure 5-4: Principal Component Analysis (PCA) plot of chemical water variables measured from 1977-1987 (green circles and lines); 1988-1998 (red squares and lines) and 1999-2009 (blue triangles and lines) at the Kaap River, Dolton (X2H022) Department of Water and Sanitation (DWS) monitoring stations located on the Kaap River system.

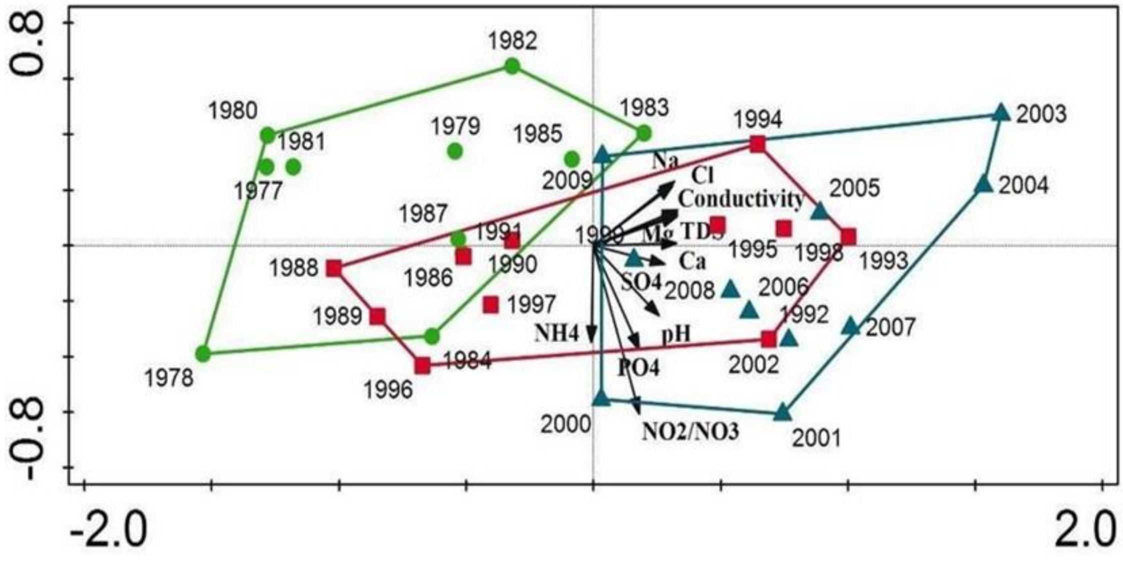

Figure 5-5: Principal Component Analysis (PCA) plot of chemical water variables measured from 1977-1987 (green circles and lines); 1988-1998 (red squares and lines) and 1999-2009 (blue triangles and lines) in Tonga (X2H022) Department of Water and Sanitation (DWS) monitoring stations located on the Komati River system.

5.4 Discussion

This study assessed how the changes in chemical water composition, including salts and nutrients, between 1977-2009 had an impact on water quality in the Mbombela river systems using a set of ecological factors and water parameters. The main findings of the study showed that the water quality in the Sabie, Crocodile, Kaap and Komati river systems changed significantly from 1977 to 2009. There was a noticeable change in nutrients and salts over the three decades with 1999-2009 showing the highest concentrations in most cases. There was a decrease in river ecological category for most of the river systems with one of the Sabie River sites (Sabie 1) having a high PAI% at monitoring points throughout the study. All other sites showed a decrease in their PAI% along with a steady increase in pH, conductivity and salinity, and changes in organic and inorganic nutrients with salinity levels significantly increasing for the four river systems.

5.4.1 Historic water quality patterns of Mbombela local municipality

Water quality in South Africa is considered a difficult issue, and the country has struggled to supply many rural and local municipalities (LeMarie et al., 2006). Rapid urbanisation and growing levels of pollution in our river systems are among the key reasons why South Africa is facing major challenges with its water quality (Nkomo & van der Zaag, 2004). However, some municipalities and districts have little funding for basic chemicals to clean wastewater, while others lack sound management and expertise, which has led to people using water from rivers and streams for basic needs. Water is critically important to the economies and social wellbeing of the predominantly rural populations of southern Africa, where environmental sustainability issues are increasingly coming into conflict with human development objectives, and where data is also scarce (Pollard et al., 2011; Riddell et al., 2013). The local economies and livelihoods of many southern African communities are strongly dependent on agriculture and fisheries, and water availability remains one of the main constraints to development in Africa (Pollard & du Toit, 2009).

The water quality variables alternated in concentration within the three studied decades, with overall water quality deteriorating from the 1970s to the 2000s. In general, even though there were significant increases in salinity and pH, sites on the Sabie River were the least impacted of all other river sites, with the PAI of this river decreasing the least of all the studied sites. In particular, the first site on the Sabie River (Sabie 1) remained between an Unmodified (Ecological Category A) and Largely Natural category (Ecological Category B). A significant proportion of the Sabie River catchment lies within Kruger National Park (KNP), hence the river is considered to be less modified compared to the other river systems in the region (Pollard et al., 2011; Gerber et al., 2015). Furthermore, KNP has had significant influence on water management outside of the park (Shikwambana et al., 2021), which has likely allowed for reduced negative impacts on the Sabie River. The increase in nutrients and salinity at the monitoring sites on this river was likely caused by impoundments and increased human activities located on the Sabie catchment outside the KNP. It is well-known that dams have the potential to cause negative impacts on downstream water quality, including nutrient loading into downstream ecosystems (Marcinkowski et al., 2017; de Necker et al., 2019). Other activities that contribute to increases in salinity and nutrients in riverine ecosystems include natural surface runoff and human activities such as farming and livestock (Carpenter et al., 1998; Dabrowski et al., 2014). Subsistence and commercial farming areas have increased in the past few decades around KNP along with increased population growth and urbanisation (Rivers-Moore et al., 2005). Run-off from these cultivated and urbanised areas, along with water abstraction, siltation and sediment erosion are likely to have reduced water flow and increased nutrient and salinity loading into this ecosystem. Similar findings were reported by Shikwambana et al. (2021) who made use of diatom communities to monitor water quality changes of KNP and also determined that water quality of the Sabie River has seen significant changes, with a definitive shift in the diatom communities as a result of much increased electrical conductivity and pH, particularly from 1983 to 2015.

There was a significant increase in nutrients and salinity in the water at both sites of the Crocodile River from 1977 to 2009 which resulted in a decline in the river's PAI scores from Largely natural (Ecological Category B) to Moderately modified (Ecological Category C). This was likely as a result of increased human development and activities surrounding the Crocodile River catchment that has occurred since the 1970s (Bunn & Arthington, 2002; Sauka, 2016). Indeed, the Crocodile River system is considered one of the most impacted and water-stressed ecosystems in South Africa as it is surrounded by intense agricultural activities, including 12 500 ha of sugarcane and several commercial crop farms for mangoes, citrus, avocadoes, and bananas (Bate et al., 1999; DWA, 2013 van der Laan et al. 2012). These are all known to use a great deal of nitrogen and phosphate rich fertilisers (Sahula, 2015). During periods of high rainfall, the fertilisers leach from the soils into nearby waterbodies such as rivers thus increasing the nutrient levels in these ecosystems (Shabalala et al., 2013). Large exotic pine and eucalyptus forests (approximately 1 775 km^2) and numerous rural and urban communities also surround the catchment of this river, further contributing toward greater water demand and increased salinity and eutrophication in this ecosystem (Bate et al., 1999; DWA, 2013; van der Laan et al., 2012).

The water quality of the Kaap River appears to have been negatively affected for several decades as the PAI scores for this river were already in a Largely modified state (Ecological Category C) in the 1970s with a further decline observed towards 2009. This resulted from significant increases in salinity, pH and nutrients over the three decades and was likely due to changes in land use patterns and continued misuse of this riverine ecosystem. Increases in conductivity as a result of high anthropogenic inputs such as agriculture and acid mine drainage (AMD) from old gold mines along the river course and river water evaporation, are the most likely causes of the observed high concentration of salts and nutrients in this river (van der Laan et al. 2012; Dlamini et al., 2021). The anthropogenic salinisation of inland waters is manifested by an increase in the total dissolved solids (TDS) which, among others, is caused by mining activity (Pond et al., 2008, Sowa et al., 2019). The Kaap River also flows past several pine tree forests which likely further contributed to increased levels of salts, nutrients and pH from 1999-2009, as forestry reduces the dilution capacity of effluents and contributes significantly to quantities of salt in river systems (van der Laan et al., 2012). Similarly, DWA (2013) reported that, based on several ecological indicators including fish and aquatic invertebrate presence, water quality, riparian vegetation and instream integrity, the present ecological state (PES) of the Kaap River was a C/D, making it a Moderate to Largely modified river ecosystem with several changes in not only ecosystem processes but a substantial loss of natural habitat and fauna.

There was a significant increase in nutrients and salts at the Komati River monitoring site from 1988-2009 and this was likely due to new developments and irrigation projects that started in the early 1990s including cattle and game farming near the river (Rahman et al., 2013). These, and irrigation activities from sugar mills, contribute significantly to nutrient inputs in this river while mines such as sand mining, also found in the river's catchment, likely contributed to the increased salinity, pH and other organic nutrients (Tapela, 2012; van der Laan et al., 2012). The water quality of this river is also severely impacted by water diversification at the Tonga Weir, located upstream of the monitoring point, which has led to substantial increases in salinity during low-flow periods as well as complete cessation of water flow on several occasions (AfriDev, 2005). These impacts resulted in the river PES being classified as E in 2005, which is a Seriously modified ecosystem with crucial changes in ecosystem function and loss of natural habitat and fauna (AfriDev, 2005).

5.4.2 Implications of water quality alterations on disease vectors in the Mbombela local municipality

Changes in water quality parameters of freshwater ecosystems have been known to have several negative impacts on the aquatic biota associated with these ecosystems (Dallas & Rivers-Moore, 2014). Anthropogenic and natural factors cause disturbances to the aquatic environment that contribute to the introduction of foreign objects that alter water quality which can cause freshwater species, including disease vectors, to experience stress when water quality parameters are altered (Sowa et al., 2019). These factors include, but are not limited to, wastewater pollution, changes in temperature, pH and salinity, increases in sedimentation and alterations to microhabitat structure (Edokpayi et al., 2017). Findings of the current study indicated that water quality of the river systems within Mbombela local municipality has degraded since the 1970s and this has likely impacted the distribution and abundance of aquatic biota of these ecosystems, including the freshwater snails that transmit schistosomiasis, which is prevalent in the Mbombela region (Malan et al., 2009; Riddell et al., 2019).

It has been reported that these snail vectors are sensitive to alterations in water pH and salinity, with research indicating a negative correlation between snail presence and pH levels <6 and >8.5 (Kazibwe et al., 2006). Further, the vector *Bul. globosus* reportedly prefers much lower salinity (100-300 ppm) than *Biom. pfeifferi* (601-1000 ppm) meaning that *Biom. pfeifferi*, would likely be able to survive higher levels of salinity reported from the studied river sites, while *Bul. globosus*, would not (Adekiya et al., 2019; Manyangadze et al., 2021). Increased nutrients observed within the four river systems most likely would not have any direct effects on the freshwater snails, although there would be indirect effects through alterations of the aquatic plants they feed and live on. Aquatic plant density and presence, food availability, and competition can affect freshwater snail distribution (McCreesh et al., 2015) and there exists a mutual relationship between submerged plant presence and snail presence (Tan et al., 2015). Increases in water nutrients stimulate plant growth, particularly submerged plants, and these plants provide a good habitat for snails that feed on periphyton, with both the density and biomass of snails being greater where plants are abundant (Wang et al., 2006; Mo et al., 2017). However, increased nutrient loading in an ecosystem, as was observed in the studied river systems over the three decades, may result in toxic algal blooms (van Ginkel, 2011), which will cause reduced oxygen in the water, leading to severely negative effects on not only aquatic vegetation, but the aquatic biota that rely on them (NRC, 2000; Frost & Sullivan, 2010), including freshwater snails. In this way the much-increased nutrients observed over the three decades could have severe consequences for the distribution and abundance of schistosomiasis vectors and, consequently, the disease as well.

5.5 Conclusion

This study successfully made use of multivariate statistical analyses and a water quality index in order to determine historical water quality trends and how these may have affected the distribution of schistosomiasis vectors. The changes in the water quality provide a clear indication of the historic influences on the habitats of these host snails. The study revealed that water quality has significantly changed and become much poorer since the 1970s up to 2009. Water pH, salinity and nutrient levels have increased in the four studied river systems over the three decades, with 1999-2000 having the highest of all the studied water quality parameters, and this may be causing alterations in the distribution patterns of schistosomiasis vectors in the Mbombela local municipality. Whilst there are unique circumstances in each river, there also appear to be diffuse impacts common to all the river systems, notably the effect of major salts, likely arising from upstream agriculture and large sediment delivery particularly during large peak flow events which are key characteristics of these large river systems. The results from this study further provide valuable insight into the long-term water quality trends and effect of degrading water quality within the main river systems in the Mbombela local municipality. The role of climate variability on the water quality within Mbombela cannot be over-emphasised as it indirectly impacts on the transmission of diseases such as schistosomiasis. It is therefore important to invest in research that will help to further determine how water quality impacts as this will help in predicting the population dynamics of the *Schistosoma* parasitic species and their snail hosts. Determining historical influences will enable researchers and management authorities to focus not only on current but also on potential future influences that need to be addressed in order to manage any changes that may take place within aquatic ecosystems and so potentially limit the distribution of schistosomiasis vectors among other disease vectors. There is an urgent need for control measures to be applied to the distribution of schistosomiasis host snails at local scales. These should include: an improvement and consistency in climate surveillance systems, sensitisation of the public about the disease and its impacts on public health and public health policies, as well as improvement in support towards water quality and schistosomiasis research in order to better understand the current and possible future distribution of the disease. Knowing the historical distribution patterns and the effect of water quality changes on the schistosomiasis vectors helps locating possible waterbodies the snails may be found in. People close to these waterbodies are vulnerable to schistosomiasis infection. The following chapter will use environmental and socio-economic factors to identify areas vulnerable to schistosomiasis in Mbombela and Nkomazi local municipalities.

CHAPTER 6 IDENTIFYING RURAL AREAS VULNERABLE TO SCHISTOSOMIASIS IN MBOMBELA AND NKOMAZI LOCAL MUNICIPALITIES

6.1 Introduction

Schistosomiasis transmission is a concern not only for vulnerable communities, but also for the public health sector due to the limited nature of available interventions (Richards, 2018). The transmission risk of schistosomiasis is higher in developing countries of which the majority are found in tropical and subtropical regions (Adekiya et al., 2019). Specifically, the transmission of schistosomiasis is higher in rural areas due to greater risk of exposure to waterbodies such as rivers and dams contaminated with the parasites and their snail vectors (Moodley, 2003, Gazzinelli et al., 2006). Most of the high transmission rate areas lack basic services such as piped water and proper sanitation (Moodley, 2003). Although all people living in these low-income areas may be exposed, certain factors such as age, gender and education are taken into consideration to determine those who are more vulnerable to schistosomiasis. Women and children are considered the most vulnerable to schistosomiasis as they tend to have more contact with water than other people (Aula et al., 2021). Poor environmental conditions are associated with the occurrence and spread of schistosomiasis, with people living in unfavourable conditions having a higher prevalence of the disease (Calasans et al., 2018; Gnazalé et al., 2021).

The spread of water-associated diseases such as schistosomiasis is intensified by several factors including inadequate infrastructures that do not support appropriate water and waste management; dense populations; uncontrolled rapid urbanisation; and environmental conditions related to climate and precipitation (Boischio et al., 2009; Fullerton et al., 2014). Abiotic factors such as rainfall and temperature also play a significant role in affecting the vulnerability to schistosomiasis. An early attempt at modelling the transmission of schistosomiasis in the African context used a deterministic model of the entire life cycle, suggesting that higher temperatures (> 30°C) could substantially reduce both the prevalence and intensity of transmission (Mangal et al., 2008; Monde et al., 2016). Therefore, abiotic factors are important to consider in potential vulnerability, since climate change is not the only factor that affects the distribution of this disease.

Most vulnerability measurement tools focus on when and where environmental conditions are optimal for an outbreak to occur, with little or no consideration of the role played by social determinants such as gender, age, and healthcare access, in shaping vulnerability (Fullerton et al., 2014). The Water-Associated Disease Index (WADI) was designed to measure and visualise the vulnerability of communities and regions to infectious water-related diseases in the face of global changes such as increasing urbanisation, land-use intensification, and climate change (WHO, 2004; Richards, 2018). The index assesses vulnerability by integrating disease-specific measures of environmental exposure such as temperature, precipitation, and land cover, with disease-specific measures of social susceptibility such as life expectancy, educational attainment, and access to healthcare, to provide a holistic picture of vulnerability to disease in the form of maps (Agapitova et al., 2017; Richards, 2018). This is a practical disease-specific tool for assessing vulnerability at a range of different spatial and temporal scales using publicly available data. It provides a new way of conceptualizing and communicating vulnerability to disease and demonstrates clear patterns of vulnerability and how these may change over time (Dickin et al., 2013).

The index examines links between humans, the disease vector, the virus (or parasite), the environment, and health by using indicators of susceptibility and exposure. Each of these components is identified using a combination of the social determinants of health with ecological/environmental determinants of health placed in a conceptual framework as an index model (Folke 2006; Fullerton et al., 2014). This presents public health officials with an integrated representation of vulnerabilities to schistosomiasis infection and provides information for public health promotion strategies that will aim to decrease the risk of transmission and thereby reduce the burden of the disease (Dickin et al., 2013; Dickin and Schuster 2014).

To achieve sustained control and elimination of schistosomiasis, it is important to identify communities that are most vulnerable and implement improvements in water, hygiene infrastructure, and sanitation, and modify risk behaviour (Steinmann et al., 2006; Echazú et al., 2015; WHO, 2021). Little research has been done on the impact of the provision of safe water on schistosomiasis infection, especially in South Africa. The focus has been on identifying the causes and remedial actions against the disease. The identification of vulnerable areas needs a multifaceted approach that includes all factors related to social, economic, environmental and ecological variables (Fine et al., 2011; Grimes et al., 2014; Tanser et al., 2018). Identifying these vulnerable areas will aid in moving beyond a simple household/individual level exposure approach and towards a sensitive community-level exposure estimate in the surrounding local community over an extended period preceding the measurement of the disease outcome (Useh & Ejezie, 1999; Tanser et al., 2018). Knowing which communities are vulnerable will also aid in creating mitigation strategies which will direct resources to specific areas to ease the disease burden of schistosomiasis (Wolmarans et al., 2001; Fullerton et al., 2014). The aim of this chapter was to develop a vulnerability index as an evidence-based approach to mapping historically vulnerable communities from 1955 to 2011 at micro-scale using favourable socio-environmental conditions for schistosomiasis host snails.

6.2 Data and Methodology

The study adapted the Water Associated Disease Index (WADI) method to create a vulnerability index for the communities of the Mbombela and Nkomazi local municipalities. To construct an index for the local municipalities, publicly available secondary datasets of known exposure (environmental /ecological) and susceptibility (social) components were used. The secondary datasets used as the source for creating a set of components that were combined to form a vulnerability criterion. Using Geographic Information System (GIS) software, ArcMap 10.8.1, index values were displayed on the map and coded according to colour for each municipality. The weighted overlay tool was used to combine indicators of susceptibility and exposure. These indicators were included in the results of the overall disease index map or risk analysis (Richards, 2018).

6.2.1 The Framework

The development of a framework is an important step in creating an index for vulnerability analysis. The conceptual framework, inspired by a study conducted by Dickin and Schuster-Wallace (2014), illustrated in Figure 6-1, shows important variables which were selected according to publicly available data sources for the Mbombela and Nkomazi local municipalities. This vulnerability framework was constructed based on the literature review on components that contribute to the increased risk of schistosomiasis infection. The conceptual framework includes vulnerability factors such as social, environmental, and ecological determinants of health. To demonstrate vulnerability, the framework gives a note to the social and natural interdependence between humans, schistosomiasis, the snail vector, and the environment (Richards, 2018). The framework helped to select data based on the ecological and social factors that mediate schistosomiasis transmission. The components included in the conceptual framework all play a role in increasing the risk of transmission of schistosomiasis. By highlighting explicit facets of the social and natural environment that are sensitive to an increased incidence of disease transmission, the framework provides a frame of reference for the implication of vulnerability to diseases such as schistosomiasis (Dickin et al., 2013).

These weak spots in the social, natural, and ecological environment have the potential to generate favourable conditions for the disease in the areas where humans live, work and play (Fullerton et al 2014). Highlighted in this conceptual framework are environmental conditions such as land-use, rainfall and temperature, and social conditions such as educational level, age and distance to open water sources (Dickin et al., 2013). First are the exposure components which include climate and environmental variables. The susceptibility components included age, number of females, level of education and distance to open water sources such as rivers. Combined, the exposure and susceptibility components make up the vulnerability index (Fullerton et al 2014). Low education levels, especially in females, are associated with an increase in susceptibility to infectious diseases by the Human Development Index (Richards, 2018).

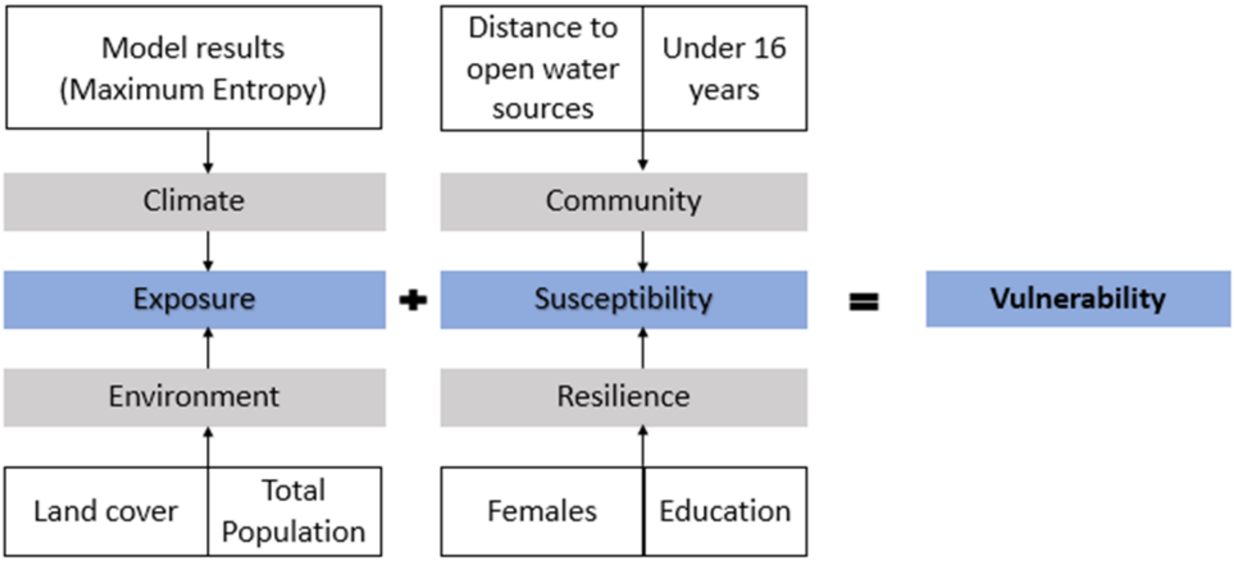

Figure 6-1: A conceptual framework developed to assess human vulnerability to schistosomiasis within Mbombela and Nkomazi local municipalities (Adapted from Dickin & Schuster-Wallace, 2014).

6.2.2 The vulnerability index components

The selection of data to measure the chosen indicators were based on the availability and quality of publicly accessible online datasets for the Mbombela and Nkomazi local municipalities. While most of the exposure datasets were readily available, indicators of susceptibility were challenging to find as most developing countries, such as South Africa, lack this information (Fullerton et al., 2014). However, proxies were used to describe indicators where exact measurements were unavailable. For instance, female education is an important indicator of susceptibility and was measured using the number of people that do not have education and those who have matric (progression to secondary school).

- **Exposure components**

Exposure represents conditions conducive to the presence and transmission of the pathogen within the environment (Dickin et al., 2013). For the climate variables, this study made use of the historical distribution results produced by maximum entropy in Chapter 4 because the model produced high AUC scores for both vector snails *Biomphalaria pfeifferi* (0.93) and *Bulinus* *globosus* (0.94). The model outcome consisted not only of climate factors such as temperature and precipitation but additional information from the snail data points. The land cover data, which contained different types of land uses within the Mbombela and Nkomazi local municipalities, were obtained from the Department of Forestry, Fisheries and the Environment of South Africa (2020). The Stats SA 2011 Census was used to obtain the total population within the local municipalities. This data was used to assess how exposure contributed to people's vulnerability to schistosomiasis by using conditions that are favourable to the host snails - summarised in Table 6-1, including motivation for each indicator.

Table 6-1: Exposure indicators, dimensions, motivations and data sources used according to the availability of data within Mbombela and Nkomazi local municipalities.

Category	Indicator	Motivation	Data Source
Model results	Bioclimatic and climatic variables from MaxEnt	Warm temperatures are necessary for the schistosomiasis life cycle and rainfall is important for the transmission of the disease. Excess of these can also limit the distribution of freshwater snails. MaxEnt had the highest AUC values.	Copernicus climate data store. Objective 1 source.
Land cover Total population	1. Land cover and land use activities within the communities 2. Number of people residing in the community	The type of land use contributes to how vulnerable a person can be and the rate of transmission increases in a densely populated area.	Department of Forestry, Fisheries and the Environment SA (2020) & South African Census (2011)

- **Susceptibility components**

Susceptibility represents the existing social determinants of health and economic or cultural conditions that make a population sensitive to water-associated diseases (Fullerton et al., 2014). The data for this study was chosen to include only the relevant factors that cause people to be susceptible to the disease such as age, distance to open water sources, females, and education. The factors and their dimensions that were considered when creating the vulnerability map are summarised in Table 6-2. It was necessary to set indicator selection criteria to guide the assessment and selection process. Indicator selection criteria ensure measures are selected systematically based on the quality and appropriateness of the data (Cole et al., 1998). Indicators of susceptibility were selected for their ability to meet indicator criteria as outlined by Garriga and Foguet (2010), their ability to closely describe the susceptibility indicator they are chosen to represent, and publicly accessible data.

Table 6-2: Susceptibility indicators, dimensions, motivations and data sources used according to the availability of data within the Mbombela and Nkomazi local municipalities.

Category	Indicator	Dimension	Motivation	Data sources
Community	Age	population <15 years (number of children below age 15)	Children in this age group are more susceptible to schistosomiasis infection.	South African Census (2011)
	Distance to rivers and water areas	People living within a 5 km radius of open water sources	Schistosomiasis vulnerability is low within communities that have less contact with open water sources that may be infested.	Department of Water and Sanitation (DWS, 2020)
	Females	Number of females within the communities	Women most frequently take care of households and fetch water. Risk is associated with the level of knowledge women have.	South African Census (2011) and General house survey of South Africa (2018)
	No education & secondary education (matric)	The number of people that do not have an education and the number of people with a matric certificate.	No education is associated with high-risk levels and the uptake of public health is associated with education levels.	General house survey of South Africa (2018)

6.2.3 Index construction

Different weights were assigned to exposure indicators to create the exposure component, as were the indicators comprising the susceptibility component. The tool creates an integrated analysis by applying a common measurement scale of values to diverse data (Riad et al., 2011). The weighting of each indicator towards the overall vulnerability index was based on those identified in the WADI proof of concept study by Dickin et al., (2013) as well as on the historical and current understanding of the contribution of environmental and social factors to schistosomiasis transmission identified from literature. Based on the literature describing the relative contributions of social and environmental factors to schistosomiasis transmission, a larger weighting towards the overall vulnerability index was attached to the exposure component. The threshold created for each vulnerability indicator was used to create raster datasets in ArcMap 10.8.1.

A separate vulnerability index was created for each snail species, *Biomphalaria pfeifferi* and *Bulinus globosus*, due to the difference in socio-environmental preferences and thresholds. To prepare the datasets for index construction, each component value was given a score between 1 and 5, and the values for each variable was weighted so that the resulting index value ranged between 1 and 5 (Richards, 2018). Very high risk is represented by 5, and the lowest risk by 1. Exposure and susceptibility scores were assigned based on general schistosomiasis thresholds identified in the literature and their contribution to the overall vulnerability of people to schistosomiasis (Dickin et al., 2013; Table 6-3, Table 6-4 and Table 6-5). For the susceptibility components the number of people for each indicator were used, for example, the number of people with secondary education were assigned between 1 to 5. For the water sources, the values were assigned looking at the distance from the water sources, with 1 km assigned a value of 5 since the risk of vulnerability increases the closer people are to open water sources, and 5 km was assigned a value of 1 due to lower risk (Table 6-4). It is important to use criteria to separate low-risk, medium-risk and high-risk areas within the municipalities as this aid in mapping vulnerable areas.

Table 6-3: Criteria used to classify the exposure components for host snails *Bulinus globosus* and *Biomphalaria pfeifferi* using ArcGIS 10.8 (adapted from Dickin et al., 2013).

Exposure Indicator	**Dimension**	***Bulinus globosus* exposure scores**	***Biomphalaria pfeifferi* exposure scores**	**Studies**
Total population	673 – 10064	1	1	
	10064 – 39651	2	2	Wanner (1999)
	39651 – 60092	3	3	Moodley (2003)
	60092 – 150357	4	4	WHO (2021)
	150357 – 348626	5	5	
Land cover	Villages/rivers/wetlands	5	5	
	Mines/ sewage ponds/dry pans	1	1	Appleton (1997)
	Rain-fed crops/subsistence farming	4	3	Hu et al., (2017)
	Dense forests and woodlands/shrublands	2	2	Oso & Odaibo (2021)
	Smallholding/commercial cultivated fields	4	2	
	Mixed vegetated/indigenous forests/cultivated land	3	4	

Table 6-4: Criteria used to classify Maximum Entropy results (climate variable exposure component) for host snails *Bulinus globosus* and *Biomphalaria pfeifferi* using ArcGIS 10.8 (adapted from Dickin et al., 2013).

Maximum Entropy – *Bulinus globosus*		**Maximum Entropy – *Biomphalaria pfeifferi***	
Dimension	**Exposure scores**	**Dimension**	**Exposure scores**
0.00006 - 0.039497	1	0.000008 - 0.035492	1
0.039497 – 0.104024	1	0.035492 – 0.093089	1
0.104024 – 0.187737	2	0.093089 – 0.169782	1
0.187737 – 0.288759	2	0.169782 – 0.261528	2
0.288759 – 0.399503	3	0.261528 – 0.364235	2
0.399503 – 0.519322	3	0.364235 – 0.492657	3
0.519322 – 0.654942	4	0.492657 – 0.64608	3
0. 654942 – 0.807485	5	0.64608 – 0.803868	4
0. 807485 – 0.990879	5	0.803868 – 0.99749	5

Table 6-5: Criteria used to classify susceptibility components for host snails Bulinus globosus and Biomphalaria pfeifferi using ArcGIS 10.8 (adapted from Dickin et al., 2013).

Susceptibility Indicator	Dimension	*Bulinus globosus* susceptibility scores	*Biomphalaria pfeifferi* susceptibility *scores*	Studies
Distance to rivers and water areas	1 km	5	5	
	2 km	4	4	Saathof et al., (2004)
	3 km	3	3	Appleton & Madsen (2013)
	4 km	2	2	Adoka et al., (2014)
	5 km	1	1	
Females (total number of females)	0 - 4150	5	5	
	4150 - 8300	4	4	Lesshafft et al., (2012)
	8300 - 12450	3	3	Salawu & Odaibo (2014)
	12450 - 16601	2	2	WHO (2021)
	16601 - 20752	1	1	
No education **(**total number of persons with no education)	111 - 256	1	1	
	256 - 5642	2	2	
	5642 - 10531	3	3	Grimes et al (2015)
	10531 - 45929	4	4	Salawu & Odaibo (2014)
	45929 - 89574	5	5	Agapitova et al (2017)

Table 6-5 continued: Criteria used to classify the susceptibility components for host snails Bulinus globosus and Biomphalaria pfeifferi using ArcGIS 10.8.

Susceptibility Indicator	**Dimension**	***Bulinus globosus* susceptibility scores**	***Biomphalaria pfeifferi* susceptibility *scores***	**Studies**
Secondary education (total number of persons with matric)	133 – 176	5	5	
	176 - 1282	4	4	Grimes et al., (2015)
	1282 – 2970	3	3	Salawu & Odaibo (2014)
	2970 – 10951	2	2	Agapitova et al (2017)
	10951 – 26082	1	1	
Total number of children between 0 – 4 years	0 – 929	1	1	
	929 – 1859	2	2	Schutte et al (1995)
	1859 – 2789	3	3	Moodley (2003)
	2789 – 3719	4	4	
	3719 – 4649	5	5	
Total number of children between 5 – 9 years	0 – 785	1	1	Moodley (2003)
	785 – 1571	2	2	De Kock (2004)
	1571 – 2358	3	3	Kibira et al (2019)
	2358 - 3144	4	4	
	3144 - 3930	5	5	
Total number of children between 10 – 14 years	0 - 839	1	1	
	839 - 1679	2	2	Moodley (2003)
	1679 - 2518	3	3	Kibira et al (2019)
	2518 - 3358	4	4	
	3358 - 4198	5	5	

After gathering all the necessary datasets, ArcMap 10.8 was used to define the dimension for each dataset. Using the reclassification tool, the datasets in raster format were reclassified into five vulnerability categories for each species. Depending on the transmission pathways associated with a water-associated disease, such as schistosomiasis, the weightings of the exposure and susceptibility components used for vulnerability analysis may change (Fullerton et al., 2014). After all the datasets were assigned vulnerability values, 1 to 5, the weighted overlay tool was used to weigh exposure and susceptibility indicators to construct the final map or index based on the contribution of each indicator to overall vulnerability (Richards, 2018). To produce vulnerability maps, the resulting exposure and susceptibility raster layers were combined for the final weight using a weighted overlay with an evaluation scale of 1 to 5 by 1 (1 being very low and 5 very high vulnerability, increasing by increments of 1). The percentage (%) of influence (weight) was assigned for each exposure and susceptibility component according to the contribution to vulnerability in the local municipalities. All exposure indicators were assigned a weight of 12% including susceptibility indicators, rivers and water areas. The rest of the susceptibility indicators were assigned a weight of 7% except for children between 0-4 years and no education which were assigned a weight of 6%. The exposure components assigned a higher weight because a person can be susceptible but if there is no exposure, the risk is low. Due to data limitations, it was not possible to have a detailed investigation of the relative contribution of each component of exposure and susceptibility indicators. After the creation of the vulnerability index, the created vulnerability zones were used to calculate the area and percentage of communities in each zone.

6.3 Results

Map outputs of the vulnerability index for schistosomiasis indicated different vulnerability zones within Mbombela and Nkomazi local municipalities. The Mbombela area was found to be surrounded by highly populated communities where one or more exposure and susceptibility variables are found, especially in the eastern parts with an average number of 110 persons/ km^2. Nkomazi had 82 persons/km^2 and high vulnerability was found in areas that had high population, lacked piped water or sanitation facilities and water induced activities such as small-scale farming taking place. The people with no access to proper sanitation were found to make up the communities that are most vulnerable within the local municipalities for both *Biomphalaria* and *Bulinus* snail species. Although the difference observed on the final maps was not significant for the vulnerability zones for each snail species, it is important to note that the vulnerability index, using the same exposure and susceptibility components, was different for each snail species depending on habitat suitability (Figures 6.2 and 6.3). The overall vulnerability was observed along the areas where models had shown the host snails to be abundant, especially the high and very high vulnerability areas.

6.3.1 Vulnerability index zones for *Biomphalaria pfeifferi*

The northern parts of the local municipalities, Skukuza were found to be mainly very low and low vulnerability zones, including some parts on the southern areas of Mbombela which were found to be low risk (Figure 6-2). The area calculated from the index results indicated that communities of very low vulnerability were about 1432 km^2 (12.04%) and low vulnerability areas made up about 3943 km^2 (33.18%) of the local municipalities. The town of Barberton fell under the low vulnerability zone due to a high altitude. Areas of very low and low vulnerability were also found in areas that had low temperatures of about 13.78°C to 16.38°C for *Biom. pfeifferi*. For both local municipalities about 5926 km^2 (49.84%) of communities were moderately vulnerable to schistosomiasis transmitted by *Biom. pfeifferi* snails. The moderately vulnerable communities included Hectorspruit, Numbi gate, Hazyview and Witrivier. The Ngodwana area within Mbombela also showed to be moderately vulnerable and it was found that the low number of children between the ages of 0 and 14 years (643) and general low population (3483) contributed to the vulnerability level. Towns such as Malelane and Komatipoort, found in the Nkomazi municipality, were found close to agricultural activities which contributed to the towns to be moderately vulnerable to schistosomiasis.

The results also showed that the Nelspurit area, although the majority was moderately vulnerable, was surrounded by rural communities with poor access to sanitation facilities that had high vulnerability. High vulnerability areas were found in areas with high population such as the community of Ngodini, Kwamandulu and Sibayeni. The communities of Matsulu in Mbombela and Kaapmuiden were found to be closely situated to open water sources such as the Crocodile River and the index results showed these communities having high vulnerability. The index showed that a few communities, 318 km^2 (2.67%), were highly vulnerable to *Biom. pfeifferi*. The Nyamzaneni area was found to have a high population (2,792.20 per km^2), had about 4800 children between the ages 0-14 years and several open water points. The small communities, 3 km^2 (0.02%) in Nyamazaneni had very high vulnerability to *Biom pfeifferi.*

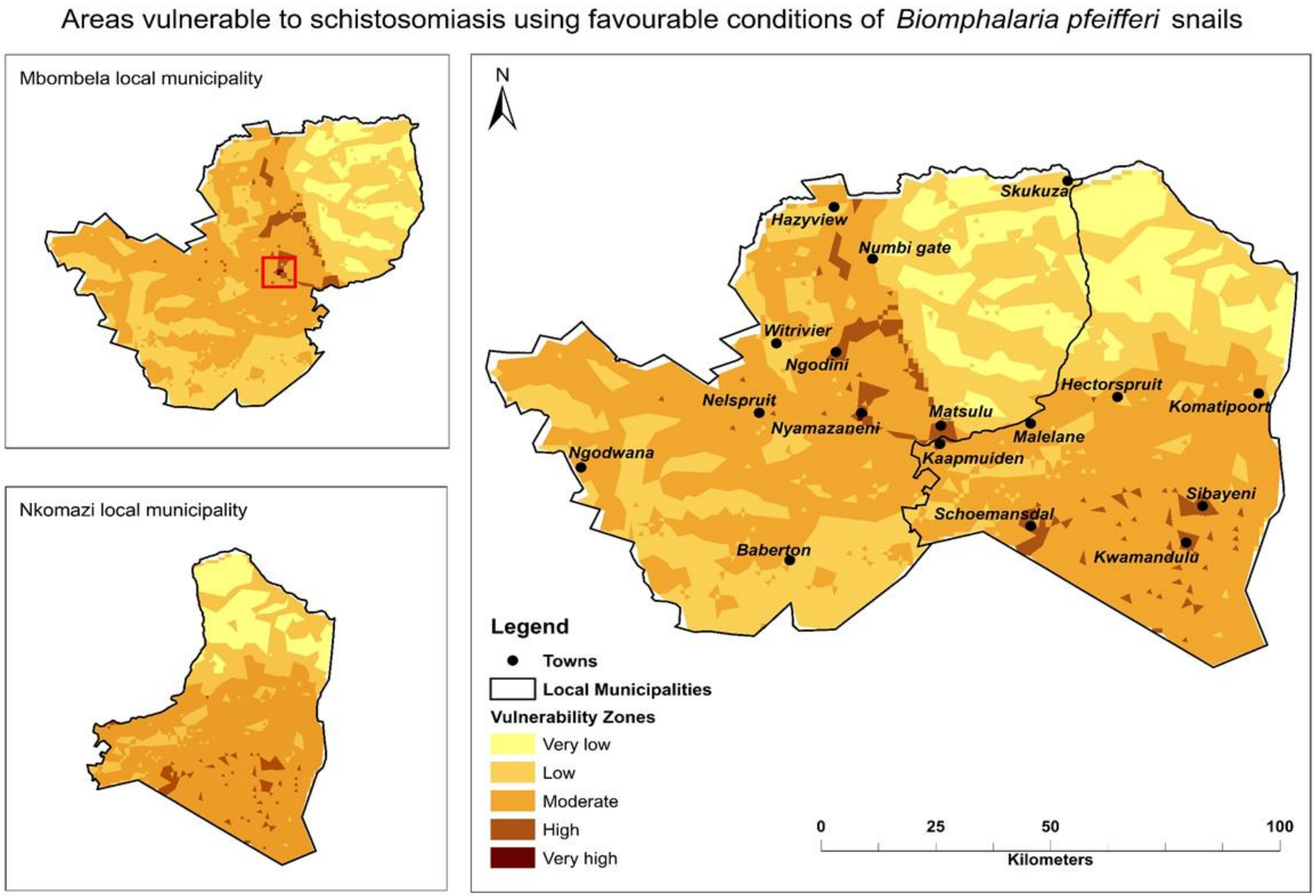

Figure 6-2: Vulnerability index created for Mbombela and Nkomazi local municipalities' communities using social and climate variables. The red square in Mbombela local municipality indicates areas that were found to have very high vulnerability to schistosomiasis transmitted by *Biomphalaria pfeifferi* snails.

6.3.2 Vulnerability Index zones for *Bulinus globosus*

The vulnerability index trend for *Bulinus globosus* was almost similar to that of *Biom. pfeifferi*. Areas of low vulnerability were observed in areas with low temperatures, between 13.78°C to 17.57°C for *Bul. globosus*. An area of 1433 km² (12.05%) was found to be very low risk, the index showed this area was mainly on the northern parts of the local municipalities within the Kruger National Park (KNP). The vulnerability index indicated Witrivier had low vulnerability along with some parts of the Barberton area, these communities were found to take up 3683 km² (30.98%) of the vulnerability zones. Witrivier was also found to be surrounded by moderate to highly vulnerable communities with practices of farming such as tropical fruits. Moderate vulnerability was observed in communities such as Ngodwana, Malelane and Komatipoort. The areas of moderate vulnerability for both local municipalities, were about 6107 km² (51.36%) with rural communities in this zone found next to semi-permanent and temporary water sources.

Observable in the vulnerability index results were more high vulnerability communities for *Bul. globosus* within Nkomazi in comparison to *Biom. pfeifferi* (Figure 6-3). Vulnerability to schistosomiasis was found to be high in Nkomazi local municipality communities such as Schoemansdal, Sibayeni and Kwamandulu. These communities were found located close to open water sources such as ponds and pools and driven by intensive sugarcane farming. High vulnerability was found within Mbombela local municipality in Matsulu, Ngodini and towards the northern parts of the municipality including Numbi gate close to Hazyview. Communities with high vulnerability were found in areas lacking proper sanitation, close to open water sources and populated with an area of about 406 km² (3.42%). Very high vulnerability zones had an area of 4 km² (0.03%), between Mbombela and Nkomazi local municipalities. Very high vulnerability was also observed in the Nyamazaneni communities situated in the middle of areas where snails were historically distributed as shown by the modelling results (see Chapter 4).

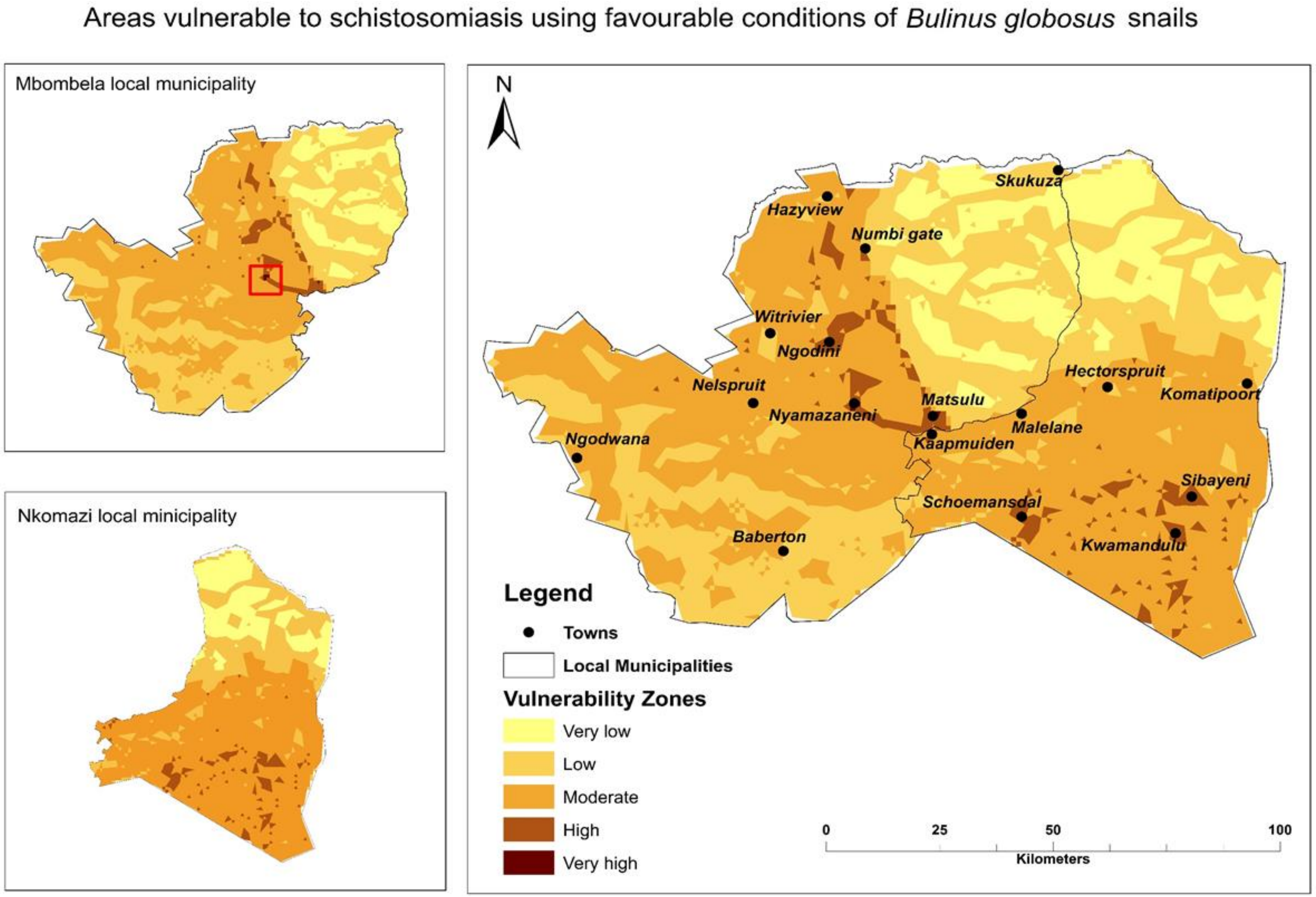

Figure 6-3: Vulnerability index created for Mbombela and Nkomazi local municipalities' communities using social and climate variables. The red square in Mbombela municipality indicates areas that were found to have very high vulnerability to schistosomiasis transmitted by Bulinus globosus snails.

6.4 Discussion

The focus of this chapter was to develop an index as an evidence-based approach to mapping historically vulnerable areas to schistosomiasis at micro-scale using favourable socio-environmental conditions for schistosomiasis host snails. The vulnerability index was applied at a local level in the Mbombela and Nkomazi municipalities in South Africa, illustrating differential patterns of vulnerability based on social determinants and climate trends at a micro-scale. There was a generalized vulnerability throughout the local municipalities except for small areas in the northern parts that had very low vulnerability.

There was some consistency in the susceptibility components within the local municipalities. Communities such as Ngodini, that had a high number of children within the vulnerable age group, also had a high number of females present. The index results showed that these areas had high vulnerability when combined with other factors such as population and education levels. A large percentage of households are headed by females in Nkomazi and in Mbombela local municipalities. Women take care of children in the household and are therefore the first to realise when children are ill (Schuster et al., 2022), thus educating the females of the community will be beneficial. A study conducted by Lesshafft et al., (2012) in Brazil found that mothers, although not able to translate their knowledge of schistosomiasis into prevention strategies, were aware of the risk factors and transmission of the disease, further supporting the importance of females and educating them within these endemic communities. Therefore, to improve social circumstances to limit schistosomiasis prevalence, females must have some form of education and the whole community must be knowledgeable of schistosomiasis.

The index results indicated that towns which presented a high number of children within this age group have high risk of infection including Ngodini, and Matsulu in the Mbombela area (32% of the population between the vulnerable ages). In the Nkomazi area, a large proportion of the population are children and hosted in communities such as Sibayeni and KwaMandulu. Studies conducted in the South African context such as De Boni et al., (2021) showed that prevalence is highest within the age 10-14 (percentage of risk 52.0%), with ages between 0-9 years following right behind in terms of vulnerability. In Mbombela and Nkomazi, these areas presented moderate to high vulnerability.

The Ngodwana community in Mbombela and KwaMandulu in Nkomazi communities were moderately and highly vulnerable to infection with schistosomiasis due to the distance of these communities to the main rivers in the area, namely the Crocodile, Kaap, Komati and Sabie rivers.

The water sources available to a community determines the frequency and type of water contact people will have (Hutton & Chase. 2017; Manz et al., 2020) and thus alters their risk of infection. People that live far away from the main water sources within Mbombela and Nkomazi are likely to use ponds and pools for their daily water activities and this increases their risk of infection since the snail vectors transmitting schistosomiasis are more commonly found in slow-flowing habitats such as pools and ponds (Quayle et al., 2010; Grimes et al., 2015). The main river systems that flow through Mbombela's local municipality further influences the vulnerability of communities around them. The Crocodile River has had increased human activities along it since the 1970s (see Chapter 5) and there has also been an increase in the creation of dams, streams and pools using water from this river (Bunn & Arthington, 2002). Changes in the socio-economic cycles and the environment along this river system created ideal conditions for schistosomiasis transmission as the clustered communities have high infection rates. According to a study by Bosco et al., (2022), the distribution of schistosomiasis is concentrated in areas near open water sources.

6.4.1 Vulnerability trends within Mbombela and Nkomazi local municipalities

Due to anthropogenic changes within the two studied local municipalities, including increased urbanization, land-use shifts, and development of services, the vulnerability dynamic has also shifted (Sietz, 2014). Therefore, some areas are highly exposed but have low susceptibility. The farming areas have high exposure since most farms are usually far from basic services and people use the nearest open water source (Boelee & Madsen 2006; Dickin et al., 2013). Dependence on surface water ensures some baseline level of exposure and vulnerability through household activities that require regular water contact, especially in over-populated communities. A study conducted by Bavia et al., (1999) showed that some of the most significant variables in the distribution of schistosomiasis were the annual duration of the dry season and densely populated areas.

Schistosomiasis spreads faster in densely populated areas (Nagi et al., 2014) and Mbombela being an economic hub draws people from all places looking for a better life. A high population contributes significantly to the vulnerability of communities as it leads to increased transmission. The highly populated towns of Mbombela local municipality such as Matsulu, Nelspruit and Nyamazaneni are infection grounds for schistosomiasis due to the clustered conditions. The Nkomazi municipality is smaller than Mbombela and so is the population, this makes a small number of areas to be clustered such as Sibayeni, Malelane and Komatipoort. In Skukuza, although having the right conditions for schistosomiasis transmissions such as open water sources (Sabie River, pools and ponds) and vegetation, has a low vulnerability because the permanent population is small (mostly visitors) and scattered within the Kruger National Park. The rural villages of Mbombela are high in poverty, with limited infrastructure and economic growth with employment rates between 25% to 41% (Mbombela Annual Report 2011-2012). The villages, located on steep slopes, have limited water areas with a few streams passing through the town. They also have a good number of municipal clinics for people to receive help and are home to a referral healthcare facility, Rob Ferreira Hospital (Adams & Moila, 2004)

Places such as Barberton, located in the Mbombela municipality, have the right conditions to promote vulnerability in communities but due to important factors such as land cover, which limit the snails, mountains and rock, the index results showed the town had a low to moderate vulnerability. There are a few studies that have reasoned that a high altitude is associated with steeper slopes, and this makes the habitat less suitable for schistosomiasis snails due to less temporary and standing waterbodies (Brooker & Michael, 2000; Koukounari et al., 2011; Schur et al., 2013). *Biomphalaria pfeifferi* species are sensitive to changes in the environment and this could be seen in the results of the index where areas vulnerable to the snail species were distributed along more permanent water systems. *Bulinus globosus* vulnerability zones were more scattered within the local municipalities, especially in the Nkomazi municipality. This may be due to increases in agricultural activities which have led to the creation of pools and small dams within the municipality (Bunn & Arthington, 2002; Sauka, 2016). Agricultural activities lead to the creation of pools and dams and these are the favourite waterbodies for the *Bulinus* species. In Nkomazi, land use activities such as urban agriculture are practised in the shallows and around the water supply dam. To facilitate the watering of crops, farmers often make wells around these water points. Furthermore, the children of farmers are often engaged in watering. This potentially puts the children in constant direct contact with unhygienic water and increases the risk of infection. Land cover, such as vegetation, is also a significant variable in predicting schistosomiasis vulnerability as noted by Ajakaye et al., (2017) in a study of modelling risk of transmission of schistosomiasis in a local government area, Nigeria.

Seasonal distribution of *Bul. globosus* within Mbombela and Nkomazi local municipalities showed that the snails prefer warmer seasons than the cold and dry seasons. A study done in southern Rhodesia, Zimbabwe by Shiff (1964) demonstrated how the drying of habitats and low winter temperatures can reduce or stop the reproduction of *Bul. globosus* snails, especially in seasonal pools. Nkomazi local municipality has plenty of seasonal pools due to activities such as sugarcane farming and these depend on rainfall to not dry out. This makes some communities such as Thambokhulu have moderate vulnerability. Schistosomiasis transmission is also positively correlated to rainfall. A study conducted by Brooker et al., (2002) in Chad found that *Bul. globosus* distribution is highly associated with monthly mean temperatures and rainfall. This is different for *Biom. pfeifferi* where the dry season is associated with determining the prevalence of infection. A consistent quantity of rainfall over a given period would ensure *Biom. pfeifferi* survives better than the cumulative effect of rainfall as the snail occurs in stable, slow-flowing and permanent waters (Brown, 1994). Hence, *Biomphalaria* snails are mostly found in communities closer to more permanent water sources, such as Matsulu and Hazyview. The areas around Malelane do not receive much rain and have on average about 121 rainy days annually. The town is in proximity to the Crocodile River which flows all year long, but some of the residents who stay in traditional houses struggle with a water supply and proper sanitation (van der Werf et al., 2003).

A model-based study by Schur et al., (2011) indicated the importance of climatic factors such as precipitation and rainfall on the prevalence of schistosomiasis in children. In the Koppen climate types of South Africa, Mbombela and Nkomazi municipalities fall under the humid subtropical, and the northern parts of the municipalities, including Kruger National Park, are hot semi-arid. The low vulnerability in the western region of the local municipalities may be due to the lower and unfavourable temperatures for schistosomiasis snails in the southwest. Lower temperatures are part of the limiting conditions for the distribution of snails and the maturation of cercariae (Lai et al., 2015). During spring (September to November) and summer (December to March), water pools tend to get warmer than the main streams or rivers and *Bul. globosus* can handle these high temperatures better than *Biom. pfeifferi*. Nkomazi communities provide suitable temperatures for the *Bul. globosus* snails. The vulnerability zones for *Biomphalaria* were more scattered within the Mbombela areas as it provides deep waters for the snail to shelter from high temperatures. Moodley (2003) found that suitable conditions for schistosomiasis transmission are moderate temperatures in winter or summer compared to extremely low and high temperatures. Since air temperature influences water temperature, *Biom. pfeifferi* snails prefer warm temperatures and do not prefer shallow waters (Moodley, 2003).

6.5 Conclusion

The study aimed to develop an index as an evidence-based approach to mapping historically vulnerable areas at micro-scale using favourable socio-environmental conditions for schistosomiasis host snails. To achieve this aim, the Water Associated Disease Index (WADI) methodology was adapted along with the publicly accessible data for these local municipalities to create a vulnerability index. Results of this study found there was a generalized vulnerability throughout the local municipalities except for the northern parts that had very low vulnerability.

The index maps provided a clear indication of how vulnerability is distributed for each snail species by creating vulnerability zones within Mbombela and Nkomazi local communities. Although there are a few communities within the local municipalities that showed high and very high vulnerability, the results showed that most communities are still vulnerable, and this may be due to the difference in exposure and susceptibility preference. These areas, although susceptible, may have limited exposure due to the environment.

Climate change, along with widespread urbanization and increasing human movements, will increasingly influence water-associated disease and the well-being of human communities. Assessing vulnerability to water-associated disease will contribute to the identification of ways to sustainably improve health while offsetting drivers of environmental change. This study demonstrated that these dynamic changes can contribute to increased vulnerability to schistosomiasis at a local level. Moreover, the possible impacts of climate change are poorly understood in the context of schistosomiasis at a local scale and this could be further investigated using the WADI approach. As a global environmental change, including climate change, is expected to increase pressure on disease transmission processes, integrated tools such as the vulnerability index will become even more important. The methodology used in this study can be extended with the use of scenarios or projected data (e.g. climate change, land-use change, or population projections) to better understand the dynamic nature of vulnerability to water-associated disease. The approach also has the potential to be incorporated with other types of vulnerability assessment, such as for floods or droughts, and forms part of an emerging suite of tools available for vulnerability assessment. A tool such as this could be useful in early-warning disease, such as schistosomiasis, and surveillance systems. The next chapter will tie all the objectives together and and draw main conclusions.

CHAPTER 7 SUMMARY, CONCLUSION AND RECOMMENDATIONS

7.1 Summary and Conclusion

Schistosomiasis is one of the neglected tropical diseases caused by parasitic flatworms (schistosomes) carried by intermediate host snails (vectors) and is second to Malaria in morbidity. Sub-Saharan African countries make up about 85% of the infections, this is because most of these countries are still developing consisting mainly of low-income communities. These communities have poor sanitation and health systems and lack awareness of the disease. There are many factors that have been found to contribute to the spread of schistosomiasis; population growth, irrigation systems and most open water sources such as rivers and ponds. The aim of this study was to understand the spatial and seasonal distribution of schistosomiasis vectors *Biomphalaria pfeifferi* and *Bulinus globosus* in the Mpumalanga province from 1955 to 1995.

- **Determining the historical distribution of schistosomiasis transmitting vectors**

The first objective was to determine the historical distribution of schistosomiasis transmitting vectors (snails) in Mbombela and Nkomazi local municipalities. This was achieved by using digitized snail points, *Biom. pfeifferi* and *Bul. globosus*, and environmental variables which were found suitable for the distribution of schistosomiasis. To contribute to the model results, historical seasonal distribution maps were created using kriging interpolation in ArcGIS. The historical distribution for *Biom. pfeifferi* and *Bul. globosus* indicated that each snail species prefers different environmental conditions. The distribution patterns for the two models were almost similar for each snail species. The Mbombela local municipality was found to be favourable for the historical distribution of the snails. The models indicated *Biomphalaria* snail was found along main water sources such as Crocodile River and Kaap River, Komati River. *Bulinus globosus* was more widely distributed according to the models compared to *Biom. pfeifferi.* This is why it was important to look at changes in water quality parameters in these rivers and how they historically affected schistosomiasis vector distribution.

- **Assessing historical water quality of rivers**

The second objective was to assess the historic water quality of rivers using water parameters such as pH and salinity, within the Mbombela local municipality from 1977 to 2009 to understand how changes in water parameters may have influenced the distribution of schistosomiasis vectors within the municipality. There were visible fluctuations in the water quality variables across the monitoring stations in Mbombela for all three decades. Sabie River remained in an unmodified state between 1977 and 1987. Ecological category for Crocodile River declined to moderately modified between 1999 – 2009. The decline was driven by increases in salts and pH. The Komati and Kaap rivers were historically negatively impacted and remained in a moderately modified condition through the three decades. These decreases in water quality may have already impacted the distribution of the schistosomiasis snail vectors and may continue to do so in the future. It is important to understanding the historical distribution patterns and the effect of water quality changes on the schistosomiasis vectors. This can help in locating communities vulnerable to schistosomiasis infection by looking at modelled patterns.

- **Identifying rural areas vulnerable to schistosomiasis**

The third objective was to identify rural areas that are vulnerable to schistosomiasis in Mbombela and Nkomazi local municipalities by creating a Vulnerability Index. This was done by making use of exposure variables such as land cover and total population, and susceptibility variables such as education, distance to open water sources and females. This was done for each species as they prefer different socio-environmental conditions. The vulnerability index results showed that the overall vulnerability was observed in areas that were modelled (historical distribution) to have high distribution of the host snails. Although the observed difference in the vulnerability maps was small, there were differences in the vulnerability zones for each snail species in each local municipality depending on the favourable exposure and susceptibility conditions. The approach also has the potential to be incorporated with other types of vulnerability assessment, such as for floods or droughts, and forms part of an emerging suite of tools available for vulnerability assessment. A tool such as this could be useful in early-warning disease, such as schistosomiasis, and surveillance systems. The next chapter will tie all the objectives together and and draw main conclusions.

- **Final thoughts**

It is important to predict the historical, current and future distribution of the intermediate host snails using sound species distribution models so that we can know which areas might be vulnerable to infection and transmission. This will also aid disease control managers with required information to implement schistosomiasis control and elimination measures. The findings of this study regarding the historical distribution of schistosomiasis host snails, can be used to identify other local communities where the intermediate host snails may already exist but have not been detected yet and where the disease is likely to spread, creating new vulnerable areas. There is a poor understanding on the impact of climate change in the schistosomiasis context, especially at local level but a vulnerability index can make way for new research to further investigate this relationship. Vulnerability index can be used in early warning disease systems, especially for the small communities. Some important measures that can be implemented for schistosomiasis control in local communities include: (i) teaching the endemic communities about the dangers of having contact with infested waters, (ii) Support towards the improvement of the water quality people have access to, (iii) climate surveillance systems on schistosomiasis and lastly, (iv) teaching the public and engaging health officials to better understand the disease.

7.2 Future recommendations

Current and future studies should make use of more modelling techniques to track the progression of schistosomiasis in endemic communities. The focus should not only be to map but find ways to reduce uncertainty in the data by using collection methods that preserve the spatial resolution and information of the data. Different modelling techniques can be utilised to produce better and clear results for the distribution of schistosomiasis. Current and future studies are encouraged to explore other techniques to assess and predict schistosomiasis transmissions by maximising available datasets use. Looking for alternative sources of data, especially for local communities that are vulnerable may strengthen on-going studies. Knowing the historical distribution of schistosomiasis and historically vulnerable areas will aid in predicting areas that may be vulnerable to exposure currently and in the future as it provides a guide for health officials on which areas need fast interventions. This will have vital implications for the feasibility of schistosomiasis control endeavours. The study recommends for the installation of water quality monitoring stations in communities such as Nkomazi or repairing those that may already be present, not only to monitor the influence on the disease but can be useful to the communities especially those surrounded by agricultural activities that have systems that may change water parameters. The changes in the climate may result in snails being distributed to other areas previously not vulnerable, so continuous monitoring into the future is recommended. Community engagement to teach the susceptible and exposed about the disease, how to protect themselves and where help can be obtained is also key to reduce and eliminate schistosomiasis as a public health problem in these endemic areas.

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APPENDICES

The section is supplementary materials that are referred to in the study where applicable.

Appendix A

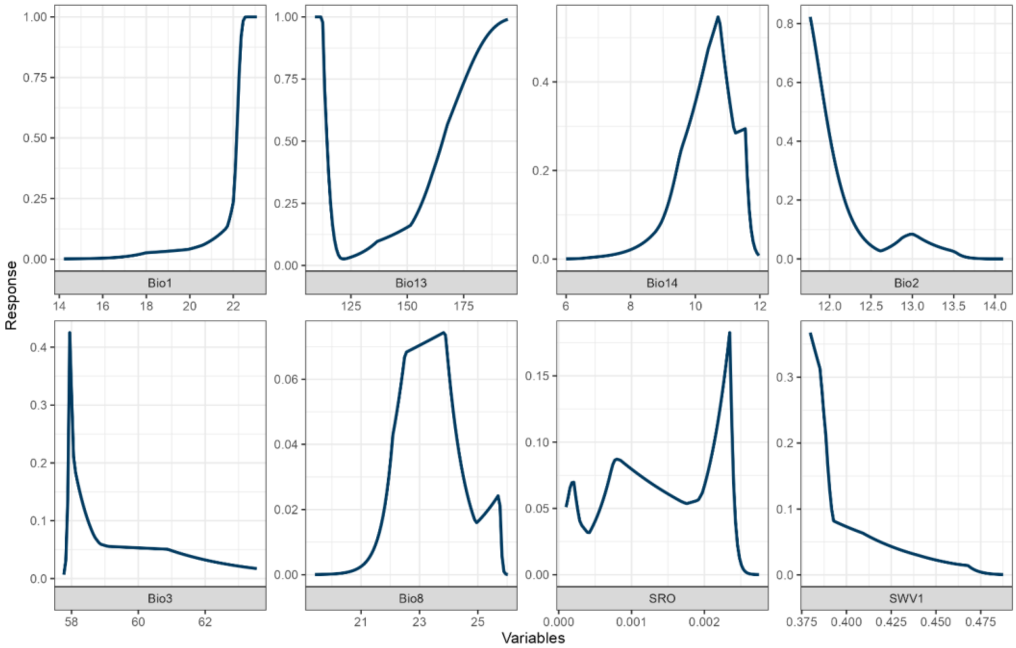

Figure A1: Response curves showing how environmental variables affected the Maximum Entropy predicted distribution for Biomphalaria pfeifferi.

Appendix B

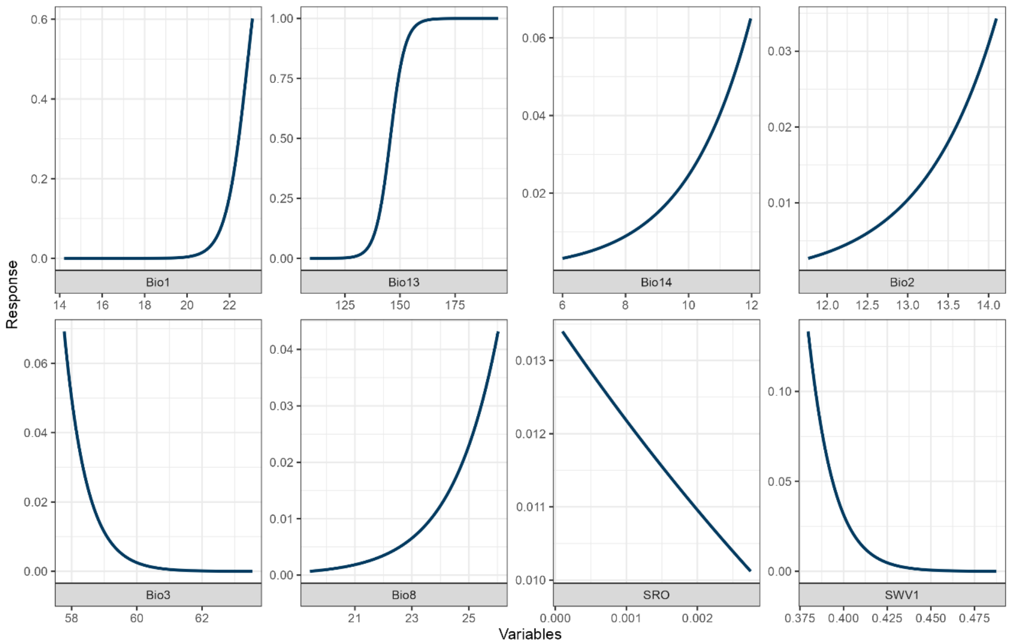

Figure B1: Response curves showing how environmental variables affected the Generalized Linear Model predicted distribution for *Biomphalaria pfeifferi.*

Appendix C

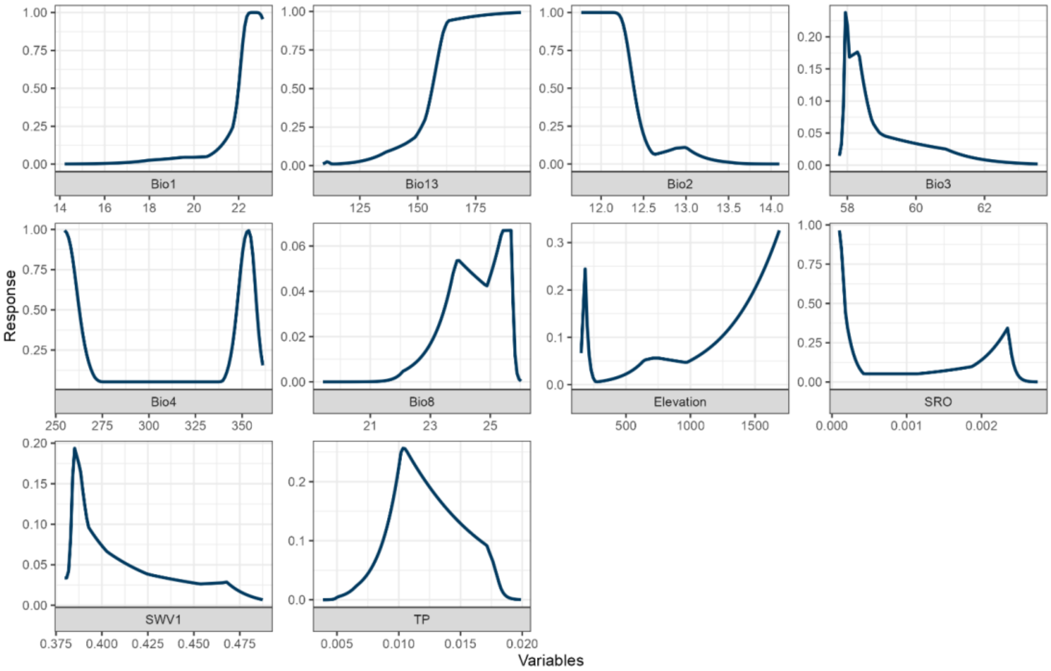

Figure C1: Response curves showing how environmental variables affected the Maximum Entropy predicted distribution for *Bulinus globosus.*

Appendix D

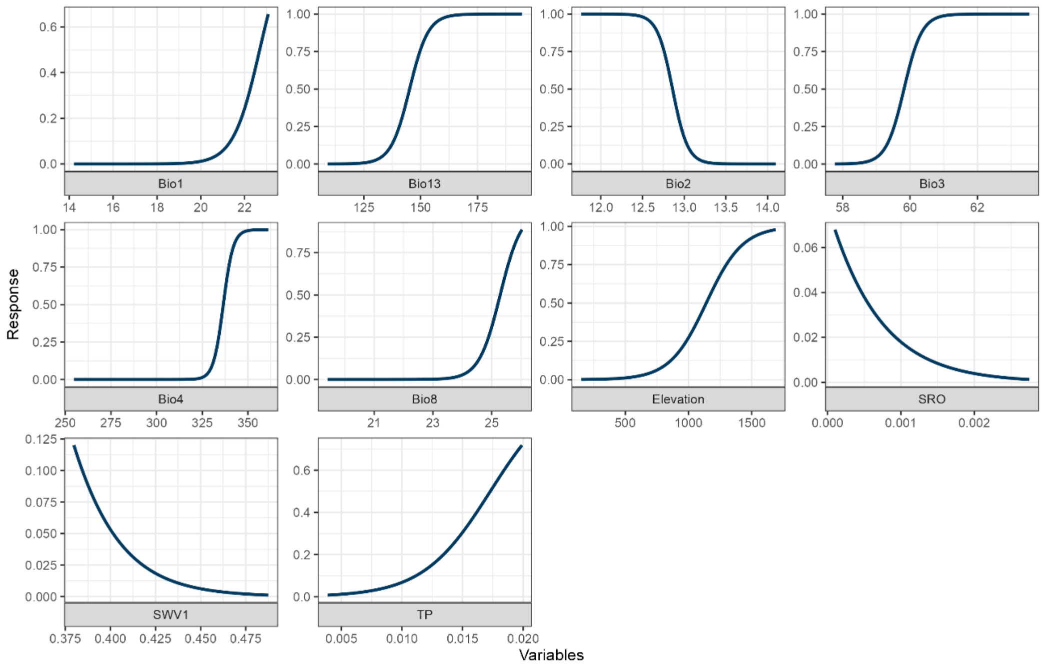

Figure D1: Response curves showing how environmental variables affected the Generalized Linear Model predicted distribution for *Bulinus globosus.*

Appendix E

Table E1: Parametric ANOVA and non-parametric Kruskal-Wallis H test results comparing chemical nutrient variables measured over three decades (1977-1987; 1988-1998 and 1999-2009) at Klein Sabie River, Sabie 2 (X3H002) Department of Water and Sanitation (DWS) monitoring station located on the Sabie River system. Data are presented as mean±SD and range in parentheses. Common superscripts within rows indicate significant differences (p<0.05).

Variable	**1977-1987 (n=11)**	**1988-1998 (n=11)**	**1999-2009 (n=11)**	**Significance**
Conductivity ($\mu S.cm^{-1}$)	137.6±14.39 (115.9-162.5)	146.6 ± 11.06^{a} (129.7-174.6)	130.4 ± 18.97^{a} (110.5-180.9)	p=0.0112 ; χ^2=8.992
pH	7.03 ± 0.30^{ab} (6.47-7.43)	7.79 ± 0.36^{a} (6.78-8.05)	7.70 ± 0.12^{b} (7.53-7.88)	p<0.0001 ; $F_{(2,30)}$ =25.06
TDS ($mg.L^{-1}$)	90.47 ± 6.46^{a} (79.63-103.3)	101.8 ± 10.67^{ab} (82.73-125)	89.08 ± 14.33^{ab} (67.67-126.1)	p=0.0208 ; $F_{(2,30)}$ =4.419
Na ($mg.L^{-1}$)	2.33±0.72 (1.54-3.63)	2.92±0.73 (2.09-4.74)	3.21±1.28 (2.36-6.94)	p=0.0691 ; χ^2=5.346
Mg^+ ($mg.L^{-1}$)	6.9 ± 0.78^{a} (5.31-7.71)	7.23 ± 0.51^{b} (6.19-8.10)	6.03 ± 0.97^{ab} (4.87-8.62)	p=0.003 ; $F_{(2,30)}$ =7.076
Ca ($mg.L^{-1}$)	11.72±0.45 (11.10-12.36)	11.91 ± 1.14^{a} (10.17-14.52)	10.82 ± 1.0^{a} (9.54-13.06)	p= 0.0195; $F_{(2,30)}$ =4.501
Cl^- ($mg.L^{-1}$)	4.03±1.94 (1.94-7.25)	5.18±1.20 (3.28-7.72)	5.02±1.04 (3.68-7.59)	p=0.1509 ; $F_{(2,30)}$ =2.015
NO_3^-/NO_2^- ($mg.L^{-1}$)	0.24 ± 0.08^{ab} (0.06-0.37)	0.30 ± 0.05^{ac} (0.21-0.39)	0.38 ± 0.07^{bc} (0.27-0.48)	p=0.0001 ; $F_{(2,30)}$ =12.22
SO_4^{2-} ($mg.L^{-1}$)	13.98 ± 4.22^{ab} (6.40-21.85)	8.94 ± 2.86^{a} (6.2-16.66)	9.47 ± 2.12^{b} (6.6-12.21)	p=0.0013 ; $F_{(2,30)}$ =8.310
PO_4^{3-} ($mg.L^{-1}$)	0.007±0.004 (0.003-0.015)	0.01±0.005 (0.008-0.022)	0.03±0.04 (0.009-0.15)	p=0.0495; $F_{(2,30)}$ =3.327
NH_4^+ ($mg.L^{-1}$)	0.06 ± 0.05^{a} (0.02-0.20)	0.05 ± 0.04^{b} (0.02-0.16)	0.12 ± 0.08^{ab} (0.04-0.29)	p=0.0132; χ^2=8.653

Appendix F

Table F1: Parametric ANOVA and non-parametric Kruskal-Wallis H test results comparing chemical nutrient variables measured over three decades (1977-1987; 1988-1998 and 1999-2009) at Perry's Farm, Sabie 3 (X3H006) Department of Water and Sanitation (DWS) monitoring station located on the Sabie River system. Data are presented as mean±SD and range in parentheses. Common superscripts within rows indicate significant differences (p<0.05).

Variable	1977-1987 (n=11)	1988-1998 (n=11)	1999-2009 (n=11)	Significance
Conductivity ($\mu S.cm^{-1}$)	102.4 ± 7.99^{a} (85.18-115)	112.2 ± 11.62^{b} (92.4-133.6)	180 ± 50.05^{ab} (100.6-241.1)	$p<0.0001$; $F_{(2,30)}=21.83$
pH	6.97 ± 0.31^{ab} (6.37-7.35)	7.67 ± 0.37^{a} (6.72-8.03)	7.79 ± 0.07^{b} (7.70-7.91)	$p<0.0001$; $F_{(2,30)}=27.92$
TDS ($mg.L^{-1}$)	70.21 ± 4.92^{a} (62.53-79.67)	80.81 ± 10.20^{b} (64.92-96.70)	113.4 ± 27.52^{ab} (72.57-151.2)	$p<0.0001$; $F_{(2,30)}=18.88$
Na ($mg.L^{-1}$)	3.59 ± 0.43^{a} (3.09-4.51)	3.63 ± 0.7^{b} (2.13-4.71)	11.22 ± 3.58^{ab} (4.21-16.32)	$p<0.0001$; $F_{(2,30)}=47.24$
Mg^{+} ($mg.L^{-1}$)	4.84 ± 0.50^{a} (3.87-5.41)	5.27 ± 0.65^{b} (4.28-6.36)	7.02 ± 2.31^{ab} (3.77-9.81)	$p=0.0026$; $F_{(2,30)}=7.326$
Ca ($mg.L^{-1}$)	7.92±0.61 (6.38-8.69)	8.33±0.9 (7.03-9.72)	8.97±2.21 (4.77-11.67)	$p=0.2368$; $F_{(2,30)}=1.512$
Cl^{-} ($mg.L^{-1}$)	4.41 ± 1.74^{a} (2.38-6.95)	5.29 ± 0.86^{b} (4.08-6.43)	18.03 ± 6.79^{ab} (5.55-26.32)	$p<0.0001$; $F_{(2,30)}=38.41$
NO_3^-/NO_2^- ($mg.L^{-1}$)	0.18±0.08 (0.09-0.32)	0.20±0.06 (0.09-0.32)	0.28±0.15 (0.07-0.53)	$p=0.0824$; $F_{(2,30)}=2.716$
SO_4^{2-} ($mg.L^{-1}$)	5.11±2.08 (2.75-9.44)	5.52±1.84 (2.18-8.29)	5.62±1.31 (3.17-7.5)	$p=0.7725$; $F_{(2,30)}=0.2603$
PO_4^{3-} ($mg.L^{-1}$)	0.007 ± 0.003^{a} (0.003-0.01)	0.02±0.01 (0.007-0.04)	0.03 ± 0.03^{a} (0.008-0.12)	$p=0.0002$; $\chi^2=17.48$
NH_4^{+} ($mg.L^{-1}$)	0.04±0.02 (0.02-0.09)	0.04±0.02 (0.01-0.07)	0.05±0.02 (0.03-0.09)	$p=0.3043$; $F_{(2,30)}=1.238$

Appendix G

Table G1: Parametric ANOVA and non-parametric Kruskal-Wallis H test results comparing chemical nutrient variables measured over three decades (1977-1987; 1988-1998 and 1999-2009) at Sabie, Sabie 1 (X3H001) Department of Water and Sanitation (DWS) monitoring station located on the Sabie River system. Data are presented as mean±SD and range in parentheses. Common superscripts within rows indicate significant differences (p<0.05).

Variable	1977-1987 (n=11)	1988-1998 (n=11)	1999-2009 (n=11)	Significance
Conductivity ($\mu S.cm^{-1}$)	137.6±14.39 (115.9-162.5)	146.6 ± 11.06^{a} (129.7-174.6)	130.4 ± 18.97^{a} (110.5-180.9)	p=0.0112 ; χ^2=8.992
pH	7.03 ± 0.30^{ab} (6.47-7.43)	7.79 ± 0.36^{a} (6.78-8.05)	7.70 ± 0.12^{b} (7.53-7.88)	p<0.0001 ; $F_{(2,30)}$ =25.06
TDS ($mg.L^{-1}$)	90.47 ± 6.46^{a} (79.63-103.3)	101.8 ± 10.67^{ab} (82.73-125)	89.08 ± 14.33^{ab} (67.67-126.1)	p=0.0208 ; $F_{(2,30)}$ =4.419
Na ($mg.L^{-1}$)	2.33±0.72 (1.54-3.63)	2.92±0.73 (2.09-4.74)	3.21±1.28 (2.36-6.94)	p=0.0691 ; χ^2=5.346
Mg^{+} ($mg.L^{-1}$)	6.9 ± 0.78^{a} (5.31-7.71)	7.23 ± 0.51^{b} (6.19-8.10)	6.03 ± 0.97^{ab} (4.87-8.62)	p=0.003 ; $F_{(2,30)}$ =7.076
Ca ($mg.L^{-1}$)	11.72±0.45 (11.10-12.36)	11.91 ± 1.14^{a} (10.17-14.52)	10.82 ± 1.0^{a} (9.54-13.06)	p= 0.0195; $F_{(2,30)}$ =4.501
Cl^{-} ($mg.L^{-1}$)	4.03±1.94 (1.94-7.25)	5.18±1.20 (3.28-7.72)	5.02±1.04 (3.68-7.59)	p=0.1509 ; $F_{(2,30)}$ =2.015
NO_3^{-}/NO_2^{-} ($mg.L^{-1}$)	0.24 ± 0.08^{ab} (0.06-0.37)	0.30 ± 0.05^{ac} (0.21-0.39)	0.38 ± 0.07^{bc} (0.27-0.48)	p=0.0001 ; $F_{(2,30)}$ =12.22
SO_4^{2-} ($mg.L^{-1}$)	13.98 ± 4.22^{ab} (6.40-21.85)	8.94 ± 2.86^{a} (6.2-16.66)	9.47 ± 2.12^{b} (6.6-12.21)	p=0.0013 ; $F_{(2,30)}$ =8.310
PO_4^{3-} ($mg.L^{-1}$)	0.007±0.004 (0.003-0.015)	0.01±0.005 (0.008-0.022)	0.03±0.04 (0.009-0.15)	p=0.0495; $F_{(2,30)}$ =3.327
NH_4^{+} ($mg.L^{-1}$)	0.06 ± 0.05^{a} (0.02-0.20)	0.05 ± 0.04^{b} (0.02-0.16)	0.12 ± 0.08^{ab} (0.04-0.29)	p=0.0132; χ^2=8.653

Appendix H

Table H1: Parametric ANOVA and non-parametric Kruskal-Wallis H test results comparing chemical nutrient variables measured over three decades (1977-1987; 1988-1998 and 1999-2009) at Karino, Crocodile 1 (X2H006) Department of Water and Sanitation (DWS) monitoring station located on the Crocodile River system. Data are presented as mean±SD and range in parentheses. Common superscripts within rows indicate significant differences (p<0.05).

Variable	**1977-1987 (n=11)**	**1988-1998 (n=10)**	**1999-2009 (n=12)**	**Significance**
Conductivity ($\mu S.cm^{-1}$)	142.4 ± 23.78^{ab} (111.2-188.3)	181.1 ± 31.25^{ac} (147.3-225)	227 ± 29.83^{bc} (185.1-275.6)	$p<0.0001$; $F_{(2,30)}=25.54$
pH	6.91 ± 0.33^{ab} (6.15-7.3)	7.76 ± 0.33^{a} (6.86-8)	7.77 ± 0.12^{b} (7.59-7.93)	$p<0.0001$; $F_{(2,30)}=35.85$
TDS ($mg.L^{-1}$)	93.71 ± 13.20^{ab} (72.92-121.7)	119.2 ± 20.18^{ac} (95.92-148.6)	43.4 ± 21.10^{bc} (114-173.1)	$p<0.0001$; $F_{(2,30)}=20.60$
Na ($mg.L^{-1}$)	5.63 ± 1.20^{a} (4.23-8.6)	6.88 ± 1.42^{b} (4.64-9.45)	10.34 ± 2.22^{ab} (7.33-13.21)	$p<0.0001$; $\chi^2=20.27$
Mg^+ ($mg.L^{-1}$)	7.04 ± 1.02^{ab} (5.39-9.27)	8.57 ± 1.4^{a} (7.13-10.75)	9.30 ± 1.31^{b} (6.83-11.16)	$p=0.0006$; $F_{(2,30)}=9.697$
Ca ($mg.L^{-1}$)	9.76 ± 1.63^{ab} (7.19-12.80)	12.03 ± 2.53^{ac} (9.27-15.40)	14.44 ± 1.97^{bc} (11.61-17.83)	$p<0.0001$; $F_{(2,30)}=14.92$
Cl^- ($mg.L^{-1}$)	5.84 ± 2.35^{ab} (2.95-9.72)	9.61 ± 1.38^{ac} (7.69-11.90)	15.83 ± 3.81^{bc} (10.25-20.62)	$p<0.0001$; $F_{(2,30)}=37.96$
NO_3^-/NO_2^- ($mg.L^{-1}$)	0.87 ± 0.51 (0.20-1.95)	0.87 ± 0.28 (0.57-1.50)	0.57 ± 0.18 (0.31-0.82)	$p=0.0816$; $F_{(2,30)}=2.727$
SO_4^{2-} ($mg.L^{-1}$)	10.59 ± 5.70^{a} (3.20-22.30)	12.96 ± 4.46^{b} (7.63-19.33)	19.25 ± 5.00^{ab} (11.71-26.25)	$p=0.0009$; $F_{(2,30)}=8.92$
PO_4^{3-} ($mg.L^{-1}$)	0.02 ± 0.02^{a} (0.005-0.08)	0.03 ± 0.02 (0.02-0.08)	0.05 ± 0.02^{a} (0.03-0.10)	$p=0.0009$; $\chi^2=13.95$
NH_4^+ ($mg.L^{-1}$)	0.09 ± 0.09 (0.01-0.33)	0.10 ± 0.05 (0.03-0.16)	0.09 ± 0.05 (0.04-0.19)	$p=0.8967$; $F_{(2,30)}=0.1094$

Appendix I

Table I1: Parametric ANOVA and non-parametric Kruskal-Wallis H test results comparing chemical nutrient variables measured over three decades (1977-1987; 1988-1998 and 1999-2009) at Weltevrede, Crocodile 2 (X2H032) Department of Water and Sanitation (DWS) monitoring station located on the Crocodile River system. Data are presented as mean±SD and range in parentheses. Common superscripts within rows indicate significant differences ($p<0.05$).

Variable	**1977-1987 (n=11)**	**1988-1998 (n=10)**	**1999-2009 (n=12)**	**Significance**
Conductivity ($\mu S.cm^{-1}$)	154.8 ± 22.83^{ab} (120.4-203.1)	188.3 ± 30.64^{ac} (155.2-230.8)	238.3 ± 45.68^{bc} (189.5-331.2)	$p<0.0001$; $F_{(2,30)}=16.66$
pH	7.02 ± 0.08^{ab} (6.40-7.40)	7.62 ± 0.29^{a} (6.93-7.97)	7.81 ± 0.09^{b} (7.67-7.96)	$p<0.0001$; $F_{(2,30)}=34.98$
TDS ($mg.L^{-1}$)	102 ± 12.55^{ab} (83.95-134)	97.92 ± 156.6^{ac} (126.6-22.65)	155.7 ± 30.03^{bc} (126.5-220)	$p<0.0001$; $F_{(2,30)}=15.48$
Na ($mg.L^{-1}$)	6.84 ± 1.37^{a} (5-10.27)	8.02 ± 1.70^{b} (5.09-10.98)	12.21 ± 3.76^{ab} (8.69-21.45)	$p<0.0001$; $\chi^2=18.71$
Mg^{+} ($mg.L^{-1}$)	7.43 ± 0.95^{a} (5.71-9.49)	8.63 ± 1.31 (7.13-10.94)	9.79 ± 2.08^{a} (7.54-14.01)	$p=0.004$; $F_{(2,30)}=6.691$
Ca ($mg.L^{-1}$)	10.47 ± 1.16^{ab} (8.85-13.47)	12.68 ± 2.45^{ac} (9.74-15.79)	15.06 ± 2.27^{bc} (12.73-19.09)	$p<0.0001$; $F_{(2,30)}=14.65$
Cl^{-} ($mg.L^{-1}$)	6.65 ± 2.17^{ab} (3.70-10.45)	9.71 ± 1.45^{ac} (7.83-13.02)	16.35 ± 4.16^{bc} (10.51-24.87)	$p<0.0001$; $F_{(2,30)}=33.27$
NO_3^-/NO_2^- ($mg.L^{-1}$)	0.88 ± 0.39 (0.22-1.35)	0.78 ± 0.25 (0.40-1.24)	0.74 ± 0.35 (0.42-1.76)	$p=0.6144$; $F_{(2,30)}=0.4948$
SO_4^{2-} ($mg.L^{-1}$)	11.89 ± 7.21^{a} (3.78-29.91)	13.75 ± 5.72 (7.01-20.93)	19.32 ± 4.61^{a} (12.69-26.30)	$p=0.014$; $F_{(2,30)}=4.937$
PO_4^{3-} ($mg.L^{-1}$)	0.05 ± 0.04 (0.01-0.17)	0.06 ± 0.04 (0.02-0.11)	0.07 ± 0.03 (0.04-0.13)	$p=0.3855$; $F_{(2,30)}=0.9842$
NH_4^+ ($mg.L^{-1}$)	0.05 ± 0.03 (0.02-0.10)	0.04 ± 0.01 (0.02-0.07)	0.05 ± 0.02 (0.03-0.09)	$p=0.6742$; $F_{(2,30)}=0.3995$

Appendix J

Table J1: Parametric ANOVA and non-parametric Kruskal-Wallis H test results comparing chemical nutrient variables measured over three decades (1977-1987; 1988-1998 and 1999-2009) at Dolton, Kaap (X2H022) Department of Water and Sanitation (DWS) monitoring station located on the Kaap River system. Data are presented as mean±SD and range in parentheses. Common superscripts within rows indicate significant differences ($p<0.05$).

Variable	1977-1987 (n=11)	1988-1998 (n=10)	1999-2009 (n=12)	Significance
Conductivity ($\mu S.cm^{-1}$)	540.7±88.08 (439.8-701.8)	528.8±154.7 (376-771.4)	559.8±122.8 (375.4-743.3)	$p= 0.8386$; $F_{(2,30)} = 0.1771$
pH	$7.85±0.31^{ab}$ (7.45-8.53)	$8.10±0.17^{a}$ (7.68-8.29)	$8.30±0.06^{b}$ (8.20-8.39)	$p<0.0001$; $F_{(2,30)} =14.12$
TDS ($mg.L^{-1}$)	421.2±76.92 (329.3-547.4)	417.5±135.7 (273-636.8)	419.4±119.2 (224.7-590.5)	$p=0.9972$; $F_{(2,30)} =0.0028$
Na ($mg.L^{-1}$)	47.51±10.14 (35.90-68.91)	38.08±13.81 (21.50-69.33)	41±14.55 (22.98-62.74)	$p=0.2459$; $F_{(2,30)} =1.47$
Mg^+ ($mg.L^{-1}$)	29.59±7.02 (22.62-46.74)	31.05±12.08 (18.20-51.70)	32.68±7.69 (20.89-44.20)	$p=0.7184$; $F_{(2,30)} =0.3344$
Ca ($mg.L^{-1}$)	27.47±3.82 (22.75-36.23)	29.81±8.90 (22.60-43.79)	29.41±4.81 (21.35-36.46)	$p=0.6365$; $F_{(2,30)} =0.4586$
Cl^- ($mg.L^{-1}$)	20.43±4.62 (13.97-27.68)	21.49±6.25 (12.81-31.90)	24.66±6.55 (16.83-34.07)	$p=0.2147$; $F_{(2,30)} =1.620$
NO_3^-/NO_2^- ($mg.L^{-1}$)	0.53±0.30 (0.18-1.29)	0.51±0.31 (0.002-1.16)	0.63±0.13 (0.35-0.82)	$p=0.5065$; $F_{(2,30)} =0.6945$
SO_4^{2-} ($mg.L^{-1}$)	39.15±12.89 (24.06-71.80)	56.09±26.33 (32.06-109.4)	55.53±14.87 (35.84-76.62)	$p=0.0678$; $F_{(2,30)} =2.948$
PO_4^{3--} ($mg.L^{-1}$)	$0.02±0.02^{a}$ (0.004-0.08)	0.02±0.007 (0.01-0.03)	$0.03±0.007^{a}$ (0.02-0.05)	$p=0.0104$; $\chi^2=9.125$
NH_4^+ ($mg.L^{-1}$)	0.05±0.03 (0.01-0.12)	0.05±0.03 (0-0.09)	0.06±0.03 (0.02-0.12)	$p=0.7632$; $F_{(2,30)} =0.2727$

Appendix K

Table K1: Parametric ANOVA and non-parametric Kruskal-Wallis H test results comparing chemical nutrient variables measured over three decades (1977-1987; 1988-1998 and 1999-2009) at Tonga, Komati (X1H003) Department of Water and Sanitation (DWS) monitoring station located on the Komati River system. Data are presented as mean±SD and range in parentheses. Common superscripts within rows indicate significant differences (p<0.05).

Variable	**1977-1987 (n=11)**	**1988-1998 (n=11)**	**1999-2009 (n=11)**	**Significance**
Conductivity ($\mu S.cm^{-1}$)	220.9 ± 58.45^{a} (142.5-328.9)	280.6 ± 95.35^{b} (180.4-429.6)	394 ± 111.1^{ab} (249.5-591.9)	$p=0.0004$; $F_{(2,30)}=10.27$
pH	7.21 ± 0.38^{ab} (6.36-7.69)	7.99 ± 0.33^{a} (7.09-8.25)	8.09 ± 0.08^{b} (7.97-8.23)	$p<0.0001$; $F_{(2,30)}=29.09$
TDS ($mg.L^{-1}$)	146.1 ± 38.90^{a} (97.71-221.3)	192.1 ± 65.25^{b} (116.1-288.5)	258.3 ± 78.72^{ab} (169.2-410.7)	$p=0.001$; $F_{(2,30)}=8.777$
Na ($mg.L^{-1}$)	21.24 ± 8.14^{a} (10.71-37.31)	28.52 ± 13.84 (12.54-50.06)	39.65 ± 14.52^{a} (19.54-67.19)	$p=0.0062$; $F_{(2,30)}=6.051$
Mg^{+} ($mg.L^{-1}$)	8.19 ± 1.84^{a} (5.37-10.79)	10.13 ± 2.50^{b} (7.31-14.10)	14.07 ± 4.13^{ab} (9.48-22.94)	$p=0.0002$; $F_{(2,30)}=11.09$
Ca ($mg.L^{-1}$)	9.01 ± 1.48^{a} (7.16-11.75)	11.17 ± 2.74^{b} (7.61-15.33)	15.05 ± 3.85^{ab} (10.73-23.47)	$p=0.0001$; $F_{(2,30)}=12.59$
Cl^{-} ($mg.L^{-1}$)	24.31 ± 10.77^{a} (9.01-42.95)	32.78 ± 17.01^{b} (10.91-60.99)	49.59 ± 19.18^{ab} (21.09-90.30)	$p=0.0031$; $F_{(2,30)}=7.064$
NO_3^{-}/NO_2^{-} ($mg.L^{-1}$)	0.08 ± 0.05^{ab} (0.03-0.17)	0.15 ± 0.06^{a} (0.10-0.30)	0.20 ± 0.08^{b} (0.09-0.33)	$p=0.0004$; $F_{(2,30)}=10.26$
SO_4^{2-} ($mg.L^{-1}$)	5.72 ± 3.01^{a} (2.08-11.73)	8.53 ± 3.86 (3.33-15.78)	11.75 ± 4.12^{a} (8.10-22.91)	$p=0.0025$; $F_{(2,30)}=7.348$
PO_4^{3-} ($mg.L^{-1}$)	0.01 ± 0.006^{a} (0.003-0.03)	0.02 ± 0.007 (0.009-0.03)	0.02 ± 0.006^{a} (0.008-0.03)	$p=0.0214$; $F_{(2,30)}=4.383$
NH_4^{+} ($mg.L^{-1}$)	0.05 ± 0.03 (0.02-0.11)	0.04 ± 0.01 (0.02-0.06)	0.05 ± 0.02 (0.03-0.09)	$p=0.4203$; $F_{(2,30)}=0.2321$