Hybrid statistical-dynamical climate predictions

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Promoter: Prof S Piketh
Co-promoter: Dr GJ Holland

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Abstract

Global Circulation Models (GCMs) provide the basis of our capacity to simulate, understand and predict climate variability and change. These models are based on established physical laws and have proven fidelity for assessing changes to global quantities (Randall et al. 2007; Bengtsson et al. 2007; Gualdi et al. 2008; Oouchi et al. 2006; Smith et al. 2010; Sugi et al. 2002; Zhao et al. 2009). However, GCMs typically are of too coarse a resolution to directly infer climatology of high-impact weather at local scales and it is common to downscale over regions of interest using either statistical techniques or dynamical downscaling (Regional Climate Models - RCMs).

RCMs are also based on established physical laws, with the added benefit of high-resolution enabling them to better simulate local effects and high-impact weather. One of their weaknesses is the cost of running the models, making it near impossible to run enough simulations to fully define uncertainty.

This research utilizes the Weather Research and Forecasting Model (WRF; Skamarock et al. 2008) as a climate model, using GCMs to downscale to regional scales (Bender et al. 2010; Knutson et al. 2007, 2008; Walsh et al. 2004). The paper “Modeling High-Impact Weather and Climate: Lessons from a Tropical Cyclone Perspective” (Chapter 6: Done et al. 2013), presented here describes the development and implementation of the WRF model as a regional climate model. This paper also addresses the lessons learned and some best practices for using WRF as a regional climate model.

It is known that GCMs suffer from biases (Liang et al. 2008; Xu and Yang 2012). Unfortunately, biases that may be acceptable at global scales may irretrievably change - or even destroy - extreme weather signals, when used as driving data for RCMs (Ehret et al. 2012). The focus of this study is not to merely run the WRF model as an RCM, but finding improved ways to utilize these biased GCM data as RCM drivers. The paper “Bias Corrections of Global Models for Regional Climate Simulations of High-Impact Weather” (Chapter 5: Bruyère et al. 2013) presented here describes in detail the problems associated with driving RCMs with GCM data containing biases. A new bias correction method, whereby the climate change signal and variability are retained from the GCM while removing the systematic mean errors, is presented in this paper.

Statistical models encapsulate empirical relationships and enable inferences of extremes from low-resolution data. These, combined with low-resolution global models provide a low-cost method of downscaling and assessing uncertainty. The major disadvantage is that they do not directly encapsulate the laws of physics.
Building on work previously done by Emanuel and Nolan (2004) and Emanuel (2010), the North Atlantic basin is used as a test case to develop an improved basin specific empirical tropical cyclone genesis index. This is presented in the paper “Investigating the Use of a Genesis Potential Index for Tropical Cyclones in the North Atlantic Basin” (Chapter 3: Bruyère et al. 2012). Using this initial development, similar indices are developed for the other tropical cyclone basins. This work is presented in the paper “Exploring Genesis Potential Indices” (Chapter 4: Bruyère and Holland 2014).

A Hybrid Statistical-Dynamical approach provides an attractive way to harness the strengths from both statistical techniques and nested regional climate models. With this approach dynamical models are used as a baseline, while the statistical models provide additional local information and an improved assessment of uncertainty.

With the use of this hybrid statistical-dynamical approach we can make better inferences regarding the effect climate change will have on rare and small-scale extreme events, with tropical cyclones used as a single example.

**Keywords:** Dynamical Downscaling, Statistical Downscaling, Regional Climate Models, Climate Change and Variability, Tropical Cyclones.
Acknowledgements

“A leader leads by example, whether he intends to or not.”
- John Quincy Adams

First and foremost I would like to thank my advisors **Prof. Stuart Piketh (North-West University, South Africa)** and **Dr. Greg Holland (National Center for Atmospheric Research, USA)**.

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**Marcel**, words are inadequate to convey my feelings, but without a doubt I would not have been here today if not for you by my side. I am incredibly fortunate you have you in my life.

Thank you. *Je t’aime de tout mon coeur.*
Preface

The article model adopted by the Faculty of Natural Sciences in terms of the General Rules of the North-West University has been followed as the research component of this post-graduate study. The work presented in this thesis was conducted by the author between 2012 and 2014 and contains original data that has never been published or previously submitted for degree purposes to any university.

The author was personally involved in the conceptualization, research and the writing of the thesis and journal articles. Where use has been made of work by other researchers, such work is duly acknowledged in the text.

The overarching format and reference style in this thesis is in accordance with the specifications provided in the Manual for Post-graduate Students of the North-West University. This thesis is presented in article format, utilizing articles that have already been peer-reviewed and published. These articles are included with permission from the journals in which they appear, with the requirement that no parts of the articles may be altered from their original content. Thus, the articles in Chapters 3 through 6, although reformatted to the same style as the rest of the thesis, retained their original content as published. The thesis includes four manuscripts that have already been published by the following journals:

Manuscript 1:

Manuscript 2:

Manuscript 3:
Manuscript 4:

Data created during the research of manuscript 4 was published as:
Bruyère, C.L., J.M. Done, S. Fredrick, and A. Suzuki-Parker. 2013. *NCAR Nested Regional Climate Model (NRCM)*. Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory, http://dx.doi.org/10.5065/D6Z899DW.

All co-authors gave written permission for the manuscripts to be submitted for degree purposes (see Addendums).

Journal of Climate gave permission that manuscript 1 can be submitted for degree purposes.
OTC gave permission that manuscript 2 can be submitted for degree purposes.
Springer Science+Business Media B.V. gave permission that manuscripts 3 and 4 can be submitted for degree purposes. Manuscripts 3 and 4 were published with open access and the author’s retained full copywrite.
# Glossary

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<th>Description</th>
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<tr>
<td>AMJ</td>
<td>Season Apr-May-Jun</td>
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<tr>
<td>ASO</td>
<td>Season Aug-Sep-Oct</td>
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<tr>
<td>CCSM(3)</td>
<td>Community Climate System Model (version 3)</td>
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<td>CDF</td>
<td>Community Climate System Model version</td>
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<td>CGI</td>
<td>Cyclone Genesis Index</td>
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<td>CMIP3</td>
<td>Coupled Model Intercomparison Project 3</td>
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<td>DJF</td>
<td>Season Dec-Jan-Feb</td>
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<tr>
<td>ECMWF</td>
<td>European Centre for Medium-Range Weather Forecasts</td>
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<td>EMDR</td>
<td>Extended Main Development Region</td>
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<tr>
<td>ENSO</td>
<td>El Niño–Southern Oscillation</td>
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<tr>
<td>ERA</td>
<td>ECMWF Reanalysis</td>
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<tr>
<td>ERA40</td>
<td>40 Year ECMWF Reanalysis Project data</td>
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<tr>
<td>GCM</td>
<td>Global Circulation Model</td>
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<tr>
<td>GFDL</td>
<td>Geophysical Fluid Dynamics Laboratory</td>
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<tr>
<td>GOM</td>
<td>Gulf of Mexico</td>
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<tr>
<td>GP</td>
<td>Genesis Potential (EN, 2004)</td>
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<tr>
<td>GPI</td>
<td>Genesis Potential Index (E 2010)</td>
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<td>GPIx</td>
<td>Modified GPI</td>
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<tr>
<td>IBTrACS</td>
<td>International Best Track Archive for Climate Stewardship</td>
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<tr>
<td>IPCC</td>
<td>IPCC - Intergovernmental Panel on Climate Change</td>
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<tr>
<td>MDR</td>
<td>Main Development Region</td>
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<tr>
<td>MOS</td>
<td>Model Output Statistics</td>
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<tr>
<td>NAM</td>
<td>Northern Annular Mode</td>
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<td>NAO</td>
<td>North Atlantic Oscillation</td>
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<td>NARCCAP</td>
<td>North American Regional Climate Change Assessment Program</td>
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<td>NCAR</td>
<td>National Center for Atmospheric Research</td>
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<td>NCEP</td>
<td>National Centers for Environmental Prediction</td>
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<td>NNRP</td>
<td>NCEP-NCAR Reanalysis Project</td>
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<tr>
<td>NOAA</td>
<td>NOAA - National Oceanic and Atmospheric Administration</td>
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<td>NRCM</td>
<td>Nested Regional Climate Model</td>
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<td>NSF</td>
<td>National Science Foundation</td>
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<tr>
<td>NWP</td>
<td>Numerical Weather Prediction</td>
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<td>OI-SST</td>
<td>Optimum Interpolation SST</td>
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<tr>
<td>Abbreviation</td>
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<td>--------------------------------------------------</td>
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<tr>
<td>OND</td>
<td>Season Oct-Nov-Dec</td>
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<tr>
<td>PDF</td>
<td>Probability Density Function</td>
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<td>PI</td>
<td>Potential Intensity</td>
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<td>RCM</td>
<td>Regional Climate Model</td>
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<tr>
<td>RH</td>
<td>Relative Humidity</td>
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<tr>
<td>RMSE</td>
<td>Root Mean Square Error</td>
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<tr>
<td>RPSEA</td>
<td>Research Partnership to Secure Energy for America</td>
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<tr>
<td>SABC</td>
<td>South African Broadcasting Corporation</td>
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<tr>
<td>SST</td>
<td>Sea Surface Temperature</td>
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<tr>
<td>TC</td>
<td>Tropical Cyclones</td>
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<tr>
<td>WRF</td>
<td>Weather Research and Forecasting Model</td>
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1. Introduction and Literature Review

“A changing climate leads to changes in the frequency, intensity, spatial extent, duration, and timing of extreme weather and climate events.”

IPCC, 2012

1.1 Extreme Weather

Evidence of extreme weather events is numerous. Just recently SABC News (November 2013), reported: "Massive hailstorm showers Johannesburg (South Africa) - Hailstones the size of golf balls have pelted across the West Rand damaging cars and causing traffic chaos.,” while the Daily Camera (September 2013) reported: “Eight days, 1,000-year rain, 100-year flood – The story of Boulder County’s (Colorado, USA) Flood of 2013.” And the impacts on society are increasing markedly. For example a survey by Munich Re in 2013 found that: “Weather-related losses and damage have risen from an annual average of about $50 billion in the 1980s to close to $200 billion over the last decade.”

The Anthropogenic Connection

The question we need to ask is if these observed events are anthropogenic in nature, or merely natural variability. Meehl et al. (2004, 2007, 2012) compared global climate model simulations with and without anthropogenic forcing (Fig. 1.1), which include both warming gases such as CO₂ and cooling aerosols such as SO₄. The simulations found a near balance between the cooling and warming components up to the 1960s, but since about 1970 the simulations with anthropogenic forcing track the observed global surface warming, while the runs with only natural forcing cooled back to the temperatures of the nineteenth century. This anthropogenic signal is especially evident (Fig. 1.2) when the difference between simulations with and without anthropogenic forcing (blue diamonds; i.e. the difference between the red and blue lines from Fig. 1.1) is plotted against the observed global surface temperature anomalies (black line). These show unequivocally that observed increases in global mean temperature are due to anthropogenic forcing and that the rate of increase has accelerated in recent decades. This does not mean we can yet positively attribute any single extreme event to anthropogenic forces, although the pattern of increasing extremes is an expected response to climate change (IPCC 2013).
Figure 1.1: Annual-mean global surface temperature with (red) and without (blue) anthropogenic forcing, together with the observed global surface temperatures (black). Shading indicates ensemble uncertainty (after Fig. 1a of Holland and Bruyère 2014; and Fig. 2d of Meehl et al. 2004).

Figure 1.2: Annual-mean global surface temperature difference between simulations with and without anthropogenic forcing (blue diamonds), and the observed global surface temperatures anomalies (black). A five-year running mean has been applied to the data.
**Tropical Cyclones**

One example of changes in extreme weather events is changes in the frequency and intensity of tropical cyclones. An unprecedented 28 tropical storms developed in the North Atlantic basin in 2005, with Hurricane Katrina (*the costliest Atlantic tropical cyclone on record*) causing nearly a $100 billion in damages in Louisiana, Mississippi, and Alabama alone. Five of the ten most intense Atlantic tropical cyclones on record developed since 2000, with 3 occurring during the 2005 season (Beven *et al*. 2008). With a pressure of 882 hPa, Hurricane Wilma (2005) is the strongest Atlantic tropical cyclone on record. The 2005 tropical cyclone season was responsible for over a $150 billion in damages in the United States alone, and approximately 2000 deaths (Beven *et al*. 2008). In November 2012 Hurricane Sandy made landfall on the East Coast. This storm killed more than 100 people, destroyed whole communities in coastal New York and New Jersey, left tens of thousands homeless, and crippled mass transit (*The New York Times, November 2012*).

There is general consensus in the literature that it is likely that the frequency of intense tropical cyclones will increase with anthropogenic climate change (Knutson *et al*. 2010; IPCC 2012; Holland and Bruyère 2014; Bender *et al*. 2010; Done *et al*. 2012). Webster *et al*. (2005) showed that over the last 30 years there has been a trend toward a larger proportion of the most intense tropical cyclones (TCs). Holland and Bruyère (2014) showed that the proportion of Category 4 and 5 tropical cyclones (*on the Saffir Simpson scale*) has increased at a rate of nearly doubling for 1°C of global warming. They also found that both the total number of tropical cyclones and the intensity of the most intense tropical cyclones were changing only slowly, leading to development of a secondary peak in tropical cyclone activity around Category 4 and 5 and a decrease in weaker systems.

Human induced changes lead to warmer oceans, which make more energy available, thus leading to more frequent intense tropical cyclones (Emanuel 2007; Peterson *et al*. 2013). Compounding this is an increasing population and development in vulnerable coastal areas. Thus the economical cost and human impact due to tropical cyclones will increase in the future, regardless of the effects of climate change. Climate change will simply exacerbate the cost and damage associated with these events (Sussman 2009).

In the light of this evidence it is important that we improve our understanding of the variability of extreme weather events in a changing climate and their impacts. Climate change is global in it origins, but local in its effects, necessitating the understanding and predictions of how these local effects will change in time.
In this thesis, through the use of tropical cyclones as an example, the current methods available to model future climate change are evaluated. This thesis also introduces a hybrid statistical-dynamical approach that enables us to examine predicted changes to rare and often small extreme weather systems.

1.2 Modeling Methods

A number of modeling methods have been developed over the years and they can be broadly categories into 3 groups: 1) Global Climate Models (GCMs), 2) Regional Climate Models (RCMs), and 3) Statistical Models. All of these models are powerful and valuable tools, which allow us to explore and understand individual aspects of our changing world.

An alternative numerical modeling approach is variable-grid resolution models. These models are similarly to GCMs, but directly incorporate high-resolution in areas of interest, as oppose to dynamically downscaling using RCMs. Some of the earliest development of these grids dates back to work by Sadourny et al. (1968). A more recent example is the Model for Prediction Across Scales (MPAS – Ringler et al. 2008 and Thuburn et al. 2009). These models avoid some of the problems associated with traditional grid nesting, but introduce new uncertainties in the form of upscaling impacts (Skamarock et al. 2012), and the effects due to using physics across various grid resolutions (Gustafson et al. 2013). As these uncertainties have not yet been quantified, variable-resolution models will not be discussed further in this thesis. A details summary of recent developments in variable-resolution modeling can be found in McGregor (2013).

Numerical models (GCMs and RCMs), are built on the fundamental laws of physics, and can be used as virtual laboratories allowing us to perform experiments that we cannot conduct in the real world. These models are unrivalled tools with which we can assess not only the interactions between interconnecting components of the earth system, but also potential changes in the climate and understand how climate change will affect our day-to-day weather, and most importantly how it will change extreme weather events.

Knutson and Tuleya (2005) note that “if we had observations of the future, we obviously would trust them more than models, but unfortunately observations of the future are not available at this time”.

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1.2.1 Global Climate Models

Global Climate Models (GCMs) are mathematical representations of the general circulation of the atmosphere based on the laws of physics applied to the earth system (Bjerknes 1904; Phillips 1956; Collins et al. 2004). Due to the nature of these equations they can only be solved numerically, consequently, GCMs supply us with predictions that are discrete in time and space. Meaning that all results obtained represent regional and temporal averages on a scale dependent on model resolution and conservation properties. Typically, a model spatial resolution of $x$ km will not resolve any features $<6-7x$ km in scale (Skamarock 2004; Hohenegger et al. 2006; Hohenegger and Schär 2007; Davis et al. 2010b; Rummukainen 2010). The GCMs used in IPCC (2013) have typical resolutions of 100-200 km, meaning that they do not resolve many nation states, or substantial mountain ranges.

Phillips (1956) developed the first successful climate model, which could realistically depict monthly and seasonal tropospheric patterns. This lead to the development of a number of general circulation models, with NOAA (Manabe and Bryan 1969) developing the first coupled atmosphere-ocean model in the late 1960s. By the 1980s NCAR (National Center for Atmospheric Research, USA) developed the first community climate model (Washington 1982; Williamson 1983). This model has been under development since, and is still one of the major community climate models used today (Collins et al. 2004).

Despite their coarse resolution, a requirement for enabling long simulations with available computing capacity, climate models are able to capture many aspects of our real climate system. Climate models are able to realistically reproduce many of the important natural climate processes, including seasonal and daily cycles (for a detailed summary see, Randall et al. 2007). For example, Figs. 1.1 and 1.2 show that GCMs are able to capture the recorded global temperature variations over the past 100 years (Meehl et al. 2004; Holland and Bruyère 2014). At a continental or ocean basin scale, these models also are able to give us good guidance as to the impact due to climate change. Fyfe et al. (1999) and Shindell et al. (1999) showed that GCMs are able to simulate many aspects of the NAM (Northern Annular Mode) and NAO (North Atlantic Oscillation) patterns. Robertson (2001), Achatz and Opsteegh (2003) and, Selten and Branstator (2004), reported that most GCMs simulate hemispheric climate regimes that resemble those found in observations. D’Andrea et al. (1998) showed that GCMs realistically simulate the location of blocking events, although they tend to be somewhat shorter and rarer in GCMs compared to observations (Pelly and Hoskins 2003). However, resolutions of climate models are still much too coarse to represent small-
scale processes or the interactions of the circulation with local-scale topographical features. Deser et al. (2012 and 2013) examined temperature and precipitation uncertainty in GCMs and concluded that precipitation has a much higher noise to signal ratio than temperature. Kharin et al. (2005) found that GCMs generally simulate temperature extremes reasonably well, but have serious deficiencies in simulating precipitation extremes. Sun et al. (2006) showed that GCMs produce more light precipitation than observed, while under-predicting heavy precipitation events. They also showed that these errors tend to cancel each other out, resulting in seasonal mean precipitation amounts that are fairly realistic.

A downside of GCMs is that, while they can simulate changes with some accuracy, they contain systematic errors, which can be sufficiently large at the local scale to severely impact regional climate assessments (e.g. Ehret et al. 2012; see also Chapter 5: Bruyère et al. 2013 and Chapter 6: Done et al. 2013).

Since most extreme events are generally short lived, relatively limited in spatial scale, and responsive to local conditions, GCM predictions of their intensity, frequency and distribution contain substantial errors. For example, coarse-resolution GCMs are able to produce tropical cyclone-like vortices (Manabe et al. 1970; Bengtsson et al. 1982, 1995), but many authors (e.g., GFDL GAMDT 2004; Knutson and Tuleya 2004; Camargo et al. 2005), have reported on the errors in GCMs in simulated tropical storm frequency and intensity. Oouchi et al. (2006) suggested that predictions of tropical cyclones in GCMs are likely to improve only once GCMs have sufficient resolution to explicitly resolve at least the large convective systems without using parameterizations for deep convection. Walsh et al. (2009) stated that the direct simulation of tropical cyclones in GCMs is still in its infancy.

The coarse resolution of GCMs is not entirely a weakness, as it enables them to be run over long time periods and with multiple ensembles for assessing uncertainty. GCMs (like our world) are complex, chaotic, and non-linear, thus small changes could result in vastly different outcomes. Running ensembles allows us to create multiple realizations of the future and thus to capture some spread in the predicted outcome. Historically this has been the preferred approach for estimating the uncertainty of model predictions.
1.2.2 Regional Climate Models

As discussed in section 1.2.1, Global Climate Models alone are not sufficient for local impact studies, adaptation or mitigation strategies, as they only resolve features with length scales in the order of several hundred kilometers.

To overcome this problem downscaling methods are used to obtain information at much higher spatial and temporal scales. Dynamical downscaling (Leung et al. 2006; Feser et al. 2011) is a technique whereby limited area or regional numerical models (RCMs) are nested within GCMs. Limited area models are based on the same fundamental laws of physics as GCMs, but whereas GCMs are run at spatial resolutions of 100s of kilometers, limited area models are typically run at resolutions of kilometers to 10s of kilometers. In addition to the large-scale conditions supplied by the GCMs, the local climate in RCMs is strongly influenced by well-resolved complex orography and the small-scale atmospheric features that can develop.

Dickinson et al. (1989), and Giorgi and Bates (1989) were some of the first to successfully demonstrate the use of Regional Climate Models (RCMs). Since this time, numerous studies showed the added value that can be obtained through the use of RCMs. Diffenbaugh et al. (2005), Frei et al. (1998), Früh et al. (2010), Jones et al. (1995, 1997), Salathé et al. (2008), and Semmler and Jacob (2004), showed that RCMs with high resolution complex terrain are much more skillful at simulating precipitation than GCMs. Kunz et al. (2010) used very high resolution RCMs to correctly simulate the frequency and intensity of wind gusts associated with severe mid-latitude winter storms. Leung and Qian (2009) used a 20-year RCM run to study the effect of atmospheric rivers and land surface conditions on heavy precipitation events and floods. They found that they could only capture the extreme precipitation events when utilizing high resolution in their simulations. Rauscher et al. (2008) investigates snowmelt-driven runoff and found that the snow-albedo feedbacks driven by complex orography are more accurately resolved in high-resolution RCMs.


Regional climate simulation is in essence a weather diagnosis and forecasting issue and the sheer experience that has gone into numerical weather prediction models give them a big advantage when
used for dynamical downscaling (Rummukainen 2010). Most of these models have non-hydrostatic dynamical cores, and high-order, conserving numerical characteristics, making it possible to run these models from large-eddy scales to hemispheric applications (Leung et al. 2006; Rotunno et al. 2009). Thus high-resolution regional climate simulations can provide more realistic simulations of extreme events that can be used by decision makers and environmental managers for impact assessments. The article “Modeling High-Impact Weather and Climate: Lessons from a Tropical Cyclone Perspective” (Chapter 6: Done et al. 2013), describes the development and implementation of the Weather Research and Forecasting model (WRF; Skamarock et al. 2008) as a regional climate model. This paper addresses the lessons learned and best practices in adapting this weather model as a regional climate model.

There are also a number of significant weaknesses associated with the use of regional climate models. First, the lateral boundary conditions in RCMs are not a ‘well-posed’ problem (Rummukainen 2010), meaning that since a unique solution does not exist it is not possible to specify the conditions exactly right. Driving data used at the boundaries are of coarser resolution both temporally and spatially, necessitating interpolation to the finer resolution of the RCM. These interpolations could lead to unbalanced conditions in the boundary zone that might result in model instabilities. The driving model also typically uses different physical parameterization options. These are not prohibitive problems, as long as care is exercised when designing a regional climate model domain (Warner 2011). The domain needs to include all the features of the climate that are being simulated. For example, if one is interested in simulating tropical cyclones over the North Atlantic, the placement of the eastern boundary may need to also take into consideration the development of African Easterly waves (the precursors to tropical storms in this region). The domain must be large enough that the boundaries are far enough away from the area of interest to allow the model to correctly develop mesoscale features in the area of interest, while care must be taken to avoid placing the boundaries over regions containing complex terrain as our experience is that this can lead to the development of model instabilities. Done et al. (2014) used internal model variability to demonstrate the impact of inflow boundaries, making a case for large domains with lateral boundaries far removed from the area of interest.

The quality of the RCM simulations is highly dependent on the quality of the driving data. GCMs have skill in producing reliable large-scale anomalies, but suffer from biases (Ehret et al. 2012). Driving RCMs with data containing biases could have disastrous consequences for obtaining realistic simulations. The article "Bias Corrections of Global Models for Regional Climate Simulations of High-Impact Weather” (Chapter 5: Bruyère et al. 2013) describes in detail the problems associated
with driving RCMs with GCM data containing biases. This article also poses a bias correction method whereby the climate change signal and variability are retained from the GCM, while removing the systematic mean errors. An area of active research is the question of stationarity of biases under non-stationary conditions (Maraun 2012; Vannitsem 2011; Buser et al. 2009). Ehret et al. (2012) suggested that biases might be sufficiently stationary to make them acceptable for climate change impact studies. In Chapter 5 (Bruyère et al. 2013) we demonstrated that for the 40-year period 1960-2000 the bias was indeed stationary, thus increasing our confidence that the bias will not change substantially in the future.

Unlike GCMs, RCMs are able to resolve many key features of tropical cyclones (Bengtsson et al. 2007; Murakami and Sugi 2010; see also Chapters 5 and 6), however, correctly simulating the most intense tropical cyclones require horizontal resolutions of around 1km (Davis et al. 2010a and 2010b). Although some RCM transient runs are becoming available, limited computer resources still restrict the practical use of such high-resolution RCMs for extended periods of time. To enable us to capitalize on the strengths of RCMs, we often need to compromise on resolution and length of simulations. Thus, typically RCMs are run for horizontal resolution of rounds 20-40km, and a time-slice approach is followed instead of the traditional transient runs performed for GCMs. This limits our ability to explicitly study changes in tropical cyclone intensities and it leave gaps in the available high-resolution model data. Some of these limitations can be improved by combining the RCMs with statistical techniques (section 1.2.4).

### 1.2.3 Statistical Methods

Statistical downscaling of climate models developed out of the Model Output Statistics (MOS; Glahn et al. 1972) approach has been used in numerical weather forecasting for decades. MOS was introduced in the 1960’s when Numerical Weather Prediction (NWP) models were of high enough resolution to accurately predict large-scale weather patterns, but still contained substantial forecast errors and limitations. MOS, the combination of NWP models and statistical tools generally always outperformed either pure NWP or statistical techniques.

Statistical downscaling techniques for regional climate are designed to provide information on the long-term statistics of weather extremes and employ a number of potential approaches. Empirical relationships can be used to related large-scale atmospherically variables to local observations, or even directly to impacts (e.g. Maraun et al. 2010, Pryor 2005; Chapter 3: Bruyère et al. 2012). Extreme value statistics and related approaches also can provide an objective method of filling out
the unresolved component of intense weather-system frequency (Tye et al. 2014; Bürger et al. 2012; Elsner et al. 2008).

A major strength associated with statistical techniques is that they are computationally efficient. Thus, large numbers of realizations can be generated by applying statistical downscaling to coarse GCM ensembles or even relatively coarse RCMs, enabling us to quantify uncertainty, something which is hard to achieve with the much more expensive high-resolution RCMs.

The weaknesses associated with these techniques include: they are very sensitive to the choice of predictors, and therefore to the GCM’s ability to simulate these predictors; they tend to under predict temporal variations; they are based on the assumptions that the developed relationships between the large scale climate and the local predicted variable remain stationary under climate change scenarios; and they are sensitive to the robustness of the observational record. Detailed reviews of popular statistical downscaling techniques can be found in Hennessy et al. (2011) and Hewitson et al. (2014).

The article “Investigating the Use of a Genesis Potential Index for Tropical Cyclones in the North Atlantic Basin” (Chapter 3: Bruyère et al. 2012) describes the use of an empirical relationship in the developing of an index to predict North Atlantic cyclone frequency. This work is motivated by the relationships describe by Gray (1979) and Emanuel and Nolan (2004). But whereas they were mainly focusing on indices describing seasonal variations in cyclone frequencies, we concentrated on developing an index that can be used in the prediction of interannual cyclogenesis specific to the North Atlantic basin.

In the article “Exploring Genesis Potential Indices” (Chapter 4: Bruyère and Holland 2014) we expand on the concepts established in the first statistical downscaling paper, by examining how we can improve the prediction of interannual cyclogenesis in other cyclone basins.

1.2.4 Hybrid Statistical-Dynamical Approach

The objective of this thesis is to capitalize on the strengths of both regional climate models and statistical downscaling methods, but overcome the major weaknesses associated with each method. To accomplish this a hybrid statistical-dynamical approach is proposed. This approach depends on the separate, but complementary development of both a dynamical modeling component and
statistical methods, which are then combined to improve predictions of rare and extreme phenomena. Here tropical cyclone frequency is used as an example.

Dynamical downscaling (as described in Chapter 6 - "Modeling High-Impact Weather and Climate: Lessons from a Tropical Cyclone Perspective"), especially for very high-resolution are expensive, thus often restricting us to a few, or even a single realization and only for a select number of time slices. However, combining this with statistical downscaling using the approach developed in Chapters 3 and 4 can provide excellent added value in assessing potential future changes. For example, Figure 1.3 shows the number of North Atlantic tropical storms predicted using: 1) the CGI (Cyclone Genesis Index) index developed in Chapter 3 ("Investigating the Use of a Genesis Potential Index for Tropical Cyclones in the North Atlantic Basin") applied to an ensemble of coarse-resolution GCMs (blue and black lines and shaded area); and 2) the average number of storms obtained through the dynamical downscaling approach from Chapter 6 (red lines). The black line in Fig. 1.3 represents current climate (simulated 20th century) tropical cyclone frequency prediction using the CGI index. The shaded area represents the CGI applied to a number of IPCC A2 and A1B scenarios, with the solid blue line the mean of the ensemble. The horizontal red lines depict the average tropical cyclone frequency for each of the dynamically downscaled time slices.

Figure 1.3: Predictions of tropical cyclone frequency for the North Atlantic. Solid lines represent predictions using statistical downscaling techniques (black – simulated climate of the 20th century; blue - average of 8 IPCC A2 and A1B scenarios). The shaded area indicates ensemble uncertainty. Time slice average tropical cyclone frequency from dynamical downscaling is depicted with the solid red horizontal lines.
Clearly the hybrid statistical-dynamical approach adds value and credibility to both methods. The dynamical snapshots verify and anchor the statistical results, while the statistical methods can be used to fill in the gaps left by dynamical downscaling.

Additionally, since the statistical techniques are inexpensive we can apply them to large numbers of GCM ensembles, thus we can not only fill in the gaps between the dynamical downscaling results but also derive a measure of uncertainty (shaded areas in Fig. 1.3).

In this thesis a single example, namely tropical cyclone frequency, is used to demonstrate the strength in utilizing a Hybrid Statistical-Dynamical approach. However, this approach is not limited to tropical cyclone frequency. It can be applied equally efficiently to, for instance, tropical storm intensity, extreme wind predictions, precipitation and many more.
2. Data and Methods

For the development and assessment of Genesis Potential Indices (Chapters 3 and 4), we use two reanalysis products: the NCEP-NCAR Reanalysis Project (NNRP; Kalnay et al. 1996) and the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis (ERA; Uppala et al. 2005; Simmons et al. 2006). The base data are in 6-h intervals and these are averaged for the period August–October (ASO) to represent the broad climate variability. Tropical cyclone observations are taken from the International Best Track Archive for Climate Stewardship (IBTrACS; Knapp et al. 2010), also at 6-h intervals. Data deficiencies in the early years (1948–1957, where very few upper-air observations were made) made the reanalysis less reliable compared to later years (Kistler et al. 2001; Emanuel 2010). These early years were also a period of questionable tropical cyclone data (e.g., Knutson et al. 2010). Thus we have restricted our analysis to the years 1960–2009, a period of reasonable data quality that is also sufficiently long to enable a robust climate variability analysis.

The bias correction method was developed using the NNRP together with the merged Hadley Centre and NOAA’s Optimum Interpolation (OI) Seas Surface Temperature (SST) data set (Hurrell et al. 2008). The GCM used is the Community Climate System Model version 3 (CCSM3; Collins et al. 2006) run at T85 (~1.4° atmosphere and 1° ocean). CCSM3 is a coupled climate model with components representing the atmosphere, ocean, sea ice, land surface and biosphere as described in detail in Collins et al. (2006). The simulation was initialized in 1950 and run under twentieth century emissions till 2000. Thereafter a number of ensembles were generated for IPCC A2, A1B and B1 scenarios. In this study we make used to the A2 and A1B Scenarios.

The NCAR Weather Research and Forecasting model (WRF; Skamarock et al. 2008) was adapted as a Nested Regional Climate Model (NRCM). The WRF model is a fully non-hydrostatic model, and is routinely used for real-time tropical cyclone forecasting (Davis et al. 2008). The WRF model was previously used in seasonal simulations over the United States, and these studies have shown realistic features, including low-level jets and diurnal cycles of rainfall (Leung et al. 2005) as well as development of orographic precipitation (Done et al. 2005; Prein et al. 2013).

For our regional climate simulations we used a large model domain, extending from 10S to 60N, and from 160W to 50E, with a nominal grid resolution of 36 km, and 51 levels in the vertical, up to a height of 10mb. All model simulations used the Kain–Fritsch convective parameterization scheme (Kain 2004), WSM6 microphysics scheme (Hong and Lim 2006), CAM long- and shortwave radiation
Data and Methods

schemes (Collins et al. 2004), Yonsei University planetary boundary layer scheme (Hong et al. 2006), and Noah land surface model (Chen and Dudhia 2001).

The model was run for three time slices: 1995-2005, 2020-2030, and 2045-2055. The data generated have been made available to the community and can be freely downloaded from the NCAR Research Data Archive (Bruyère et al. 2013).

Details of the data and methods pertinent to each publication are discussed in more depth within the individual articles in chapters 3 through 6. These include how the dynamical models were configured as well as the development of data mining and statistical techniques.
3. **Journal Article**: *Investigating the Use of a Genesis Potential Index for Tropical Cyclones in the North Atlantic Basin*

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This paper has already been published in the Journal of Climate  

Consent from co-authors is attached as an addendum.

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Thesis Objective

*General Circulation Models (GCMs) are typically run for very long time periods. GCMs are also typically used to generate ensembles of future projections. This wealth of data makes them ideally suited to study long-term climate trends while simultaneously providing a measure of uncertainty. Unfortunately GCMs, due to their low resolutions, do not contain information regarding rare and often small extreme weather systems. Developing statistical methods to infer information regarding these extreme events directly from the large-scale environment will enable us to utilize this extensive source of data at a relatively low cost. To achieve this objective, we demonstrate here the development of a basin-specific Genesis Potential Index used to predict tropical cyclone frequency from large-scale environmental conditions. This approach, when combined with high resolution dynamical model results will not only anchor the dynamical results, but can be utilized to fill in gaps between the dynamical model results as well as providing a measure of uncertainty.*

Abstract

Large-scale environmental variables known to be linked to the formation of tropical cyclones, have previously been used to develop empirical indices as proxies for assessing cyclone frequency from large-scale analyses or model simulations. Here we examine the ability of two recent indices, the Genesis Potential and the Genesis Potential Index to reproduce observed North Atlantic cyclone annual frequency variations and trends. These skillfully estimate the mean seasonal variation of observed cyclones, but they struggle with reproducing interannual frequency variability and change. Examination of the independent contributions by the four terms that make up the indices finds that potential intensity and shear have significant skill, while moisture and vorticity either do not contribute or degrade the indices capacity to reproduce observed interannual variability. We also find that for assessing basin wide cyclone frequency, averaging indices over the whole basin is less skillful than its application to the general area off the coast of Africa broadly covering the Main Development Region (the MDR).

These results point to a revised index, the Cyclone Genesis Index (CGI) comprised of only potential intensity and vertical shear. Application of the CGI averaged over the MDR demonstrates high and significant skill at reproducing interannual variations and trends in all-basin cyclones across both reanalyses. The CGI also provides a more accurate reproduction of seasonal variations than the original GP. Future work applying the CGI to other tropical cyclone basins and to the downscaling of relatively coarse climate simulations is briefly addressed.
3.1 Introduction

Improving our understanding of the variability of tropical cyclones is important both scientifically and socially, and this becomes more important in a changing climate. With increasing computer power, global and regional climate models are approaching the capacity to reproduce the mesoscale processes occurring in cyclogenesis (Bender et al. 2010; Bengtsson et al. 2007; Gualdi et al. 2008; Knutson et al. 2007, 2008; Oouchi et al. 2006; Smith et al. 2010; Sugi et al. 2002; Zhao et al. 2009). These dynamical models bring in-depth perspective and understanding to the problem, but remain expensive and therefore limited in their use. An alternative approach to downscaling tropical cyclone activity involves embedding a 2-D hurricane model with ocean interaction into a statistical representation of the large-scale fields (Emanuel et al. 2008). This hybrid statistical-dynamical approach is cheaper to run and has been shown to have skill at reproducing observed tropical cyclone activity (Emanuel et al. 2008). Another alternative discussed here is that of statistical downscaling using empirical relationships.

That the large-scale environment has a role in determining tropical cyclone genesis has been understood since the earliest analyses of the association between cyclones and the general circulation in the tropics (e.g. Palmen, 1948; Riehl, 1954). Gray (1979) summarized the state of science and demonstrated the potential for assessing genesis potential utilizing such environmental parameters as ocean thermal content (strictly to a depth of ~60 m to account for ocean mixing by the cyclone, but often Sea Surface Temperature, SST, is used as a proxy), mid-level moisture, a conditionally unstable atmosphere, low-level vorticity, and vertical wind shear through a deep atmospheric layer. It is notable that Gray considered these to be necessary but not sufficient conditions for genesis to occur, nevertheless a number of subsequent studies have either utilized the Gray parameters directly in assessing cyclone frequency from analyzed or modeled fields (e.g. Ryan et al. 1992; Watterson et al. 1995), or as a basis for further genesis indices based on the same physical principles (e.g. Emanuel and Nolan 2004).

Emanuel and Nolan (2004; see also Emanuel et al. 2006) used a statistical fitting procedure, based on the seasonal cycle and spatial variation of the mean genesis climatology of the NCEP-NCAR Reanalysis data (NNRP - Kalnay et al. 1996), to develop the following refinement of Gray’s genesis parameters into a new Genesis Potential index (GP):
where, $\eta$ is absolute vorticity ($s^{-1}$) at 850 hPa, RH is relative humidity (%) at 700 hPa, PI is the Potential Intensity (ms$^{-1}$, Emanuel 1995) and $V_{\text{shear}}$ is the vertical wind shear (ms$^{-1}$) between 850 and 200 hPa. The normalizing factors render the index dimensionless and the values were selected to keep the individual terms within the same order of magnitude.

Since the GP index was formulated from a number of environmental variables that are known to be associated with tropical cyclone formation (e.g. Gray 1968, 1979), it is reasonable to argue that it would be suitable for use as a predictor in both current and future climate studies. Several studies have examined this approach: Emanuel and Nolan (2004) demonstrated skill with the GP in reproducing the hemispheric seasonal variations in the observed frequency of tropical cyclone genesis; Nolan et al. (2006) investigated hurricane formation under global warming conditions from the GP perspective; and Camargo et al. (2007a, 2007b) and Murakami and Wang (2010) used the GP to assess tropical cyclone genesis in global climate models.

Emanuel and Nolan (2004) developed the GP to reproduce the hemispheric seasonal variations in observed tropical cyclone frequency only. They did not examine its ability to capture inter-annual variability, nor did they test the GP’s skill in individual basins. Camargo et al. (2007b) showed that the GP has some skill in reproducing El Niño and La Niña impacts on observed annual frequency and location of genesis in several basins.

In recent years Emanuel (2010), Tippett et al. (2011) and McGauley and Nolan (2011) investigated improved generalized GP indices. Emanuel (2010) suggested that the genesis index should not depend directly on relative humidity, but rather on the mid-level saturation deficit. His new index comprises absolute vorticity, potential intensity, shear, and a measure of the moist entropy deficit of the middle troposphere, as is discussed further in Section 3.4. Tippett et al. (2011) evaluated the use of a clipped absolute vorticity term and concluded that increased vorticity beyond a defined minimum value does not increase the likelihood of cyclogenesis. They also considered satellite-observed column-integrated relative humidity, SST anomaly relative to the global tropics, and shear and suggested prudence in the use of relative humidity. McGauley and Nolan (2011) took the approach of using only threshold values in an index that checked for the fraction of time that
thresholds for PI, vorticity, shear and saturation deficit are exceeded locally. Genesis potential is then derived from the product of these fractional exceedence values.

Our overall goal is to utilize the genesis parameter approach for assessing potential future climate variations and trends in tropical cyclones directly from the data available from coarse-resolution climate models. In this preliminary study we first assess the capacity of the GP and each of its components (Eq. 3.1) to describe interannual and longer-term tropical cyclone variations and trends in the North Atlantic when applied to reanalysis data. Based on this assessment we develop a revised genesis parameter that utilizes fewer predictors and is applied to a selected region of the basin. This is shown to provide an improved downscaling to observed climatological tropical cyclone variability compared to the GP. Section 3.2 describes our method and data used; the index is developed using North Atlantic data in Section 3.3; and a preliminary assessment of its global uses, together with a comparison with the Emanuel (2010) index and some discussion of limitations are made in Section 3.4.

3.2 Data and Method

a. Data

We use two reanalysis products: the NNRP (NCEP-NCAR Re-Analysis Project, Kalnay et al. 1996) and the European Centre for Medium range Weather Forecasting Re-Analysis (ERA, Uppala et al. 2005; Simmons et al. 2006). The base data are in 6-hour intervals and these are averaged over a range of spatial scales for the period August-October (ASO) to represent the broad climate variability. Monthly averages are used for the analysis of intraseasonal variation. Tropical cyclone observations are taken from the International Best Track Archive for Climate Stewardship (IBTrACS, Knapp et al. 2010), which is also at 6-hour intervals.

The NNRP analysis archive covers the period from 1948 to present and can be divided into three periods corresponding to the evolution of the major observing systems: the early years from 1948-1957, where very few upper-air observations were made; the rawinsonde era from 1958-1978, and the satellite era from 1979 to present day. Data deficiencies in the early years made the analyses demonstrably less reliable compared to later years (Kistler et al. 2001; Emanuel 2010) and this was also a period of questionable tropical cyclone data (e.g. Knutson et al. 2010). Thus we have restricted our analysis to the years 1960-2009, a period of reasonable data quality that is also sufficiently long to enable a robust climate variability analysis.
The ERA covers two overlapping analysis periods: the ERA40 from 1958-2001 (Uppala et al. 2005) and ERA-Interim from 1989-2009 (Simmons et al. 2006). The ERA40 was produced using 3D-variational analysis on a roughly 125km grid, while the ERA-Interim uses a 4D-variational analysis on a roughly 80km grid. Nevertheless, we consider these to be sufficiently similar to enable merging to a continuous set from 1960-2009. In doing this, we arbitrarily spliced the analysis series together at 1997. We also note that the GP was developed entirely on NNRP data, so the ERA provides an independent model and analysis approach, albeit one that is based on the same basic observations.

The atmospheric differences between NNRP and ERA are generally small. Studies comparing them with observations (Mooney et al. 2011; Davey et al. 2008; Chase et al. 2000; Chelliah and Ropelewski 2000) concluded that the average reanalysis trends generally fall within the variance in observational trends. One exception is relative humidity: Daoud et al. (2009) reported unrealistic low-level relative humidity in the ERA40, but not the NNRP; comparisons between NNRP, ERA40 and observations also showed markedly different behavior for extreme relative humidity values, with ERA40 poorly correlated with observations. These inconsistencies are shown to introduce large GP errors in Section 3.3.

In summary, both NNRP and ERA are considered suitable for climate variability and trend analysis and both are similar in character. There are some quality issues and those of importance are addressed in the analysis.

For the purposes of this study, the tropical cyclone data since 1960 are considered to be of good quality and free of major observational bias (e.g. Holland and Webster 2007). A recent study (Landsea et al. 2010) suggested that the upsurge in cyclone activity from 1995 might be due to changing observing practices that now identify a larger number of short-lived tropical cyclones. This finding is controversial and we present evidence that it is incorrect in Section 3.4.

b. Method

Four regions are used in assessing the GP, as shown in Fig. 3.1: the North Atlantic (American to African coast; 0-40°N), the Main Development Region (MDR, 10-20°N, 60-15°W), an Extended MDR (EMDR, 5-20°N, 60-15°W), and the Gulf of Mexico (GOM, 17.5-32.5°N, 100-80°W). The reasoning behind selection of the sub-regions is as follows.
The MDR has been shown in a number of studies to be important in the differentiation of long-period tropical cyclone variability across the whole basin and in seasonal forecasting techniques (e.g. Gray 1984a, 1984b; Elsner et al. 2006; Klotzbach 2011). Vimont and Kossin (2007) and Kossin and Vimont (2007) provided strong evidence that the local changes in the MDR region correspond to changes in the Atlantic Meridional Mode (e.g. Nobre and Shukla 1996; Chiang and Vimont 2004). This provides a further association with a number of other environmental changes known to affect tropical cyclone variability in the North Atlantic. The MDR is also a region of potentially increasing importance with climate change as there has been a migration of cyclone developments to this region in the past couple of decades and models indicate a continuation of this migration in the future (Holland and Webster 2007; Holland et al. 2010; Done et al. 2011a). This migration is potentially associated with the expansion of the Atlantic oceanic warm pool towards Africa (Webster et al. 2005).

Figure 3.1: Sub-regions used for exploring ASO GP relationship with tropical cyclone frequency.

Emanuel (2005, 2007) extended the MDR to 6-18°; 60-15°W, similar to our EMDR, for his power dissipation analysis. Power dissipation relates frequency, duration and intensity into a single seasonal activity parameter, which Emanuel showed to be highly correlated with EMDR SSTs.

The Gulf of Mexico was chosen as the region of highest GP (see Section 3.3) with values well above those in other parts of the basin. It is also the region most affected by intraseasonal variations (Maloney and Hartman 2000), which could be a contributor to interannual variations.
We considered other potential processes in addition to those encapsulated in Eq. 3.1: in-situ SST, which is included in the PI but examined separately for completeness; relative SST (the difference between Atlantic and global tropical SSTs, Vecchi and Soden 2007); low and high atmospheric-level vertical windshear; low- and mid-level temperature, relative humidity and water vapor; and mid-level moisture saturation deficit (Emanuel 2010 and Rappin et al. 2010). Of these the only terms to show any potential as predictors were in-situ and relative SST. In-situ SST is a quite good predictor (in agreement with Tippett et al. 2011) and is already included in the PI. Relative SST provided a good discriminator, in agreement with earlier findings (Vecchi and Soden 2007), but the in-situ SST provided a better predictor, and the cyclone-frequency relationship with relative SST largely disappeared when the in-situ SST linear correlation was removed. This is a different finding to Vecchi and Soden (2007), who suggested that relative SSTs were more important; we are examining this difference in a separate study.

The in-situ SST provided nearly the same level of skill as PI for past climate and we suggest that this is a valid substitute for earlier periods where atmospheric information is lacking. We do consider that the atmospheric contribution may become more important for future climate assessments, where there are substantial changes in atmospheric as well as oceanic conditions (IPCC 2007).

To test the contributions of the genesis parameters as predictors of storm frequency, linear correlations were calculated and tested for significance using a standard 2-sided t-test.

Figure 3.2: Mean seasonal variations in monthly cyclogenesis frequency (bars) and monthly-mean GP for the North Atlantic basin calculated from NNRP (solid line) and ERA (dashed line) over the period 1960 to 2009 ($R^2 = 0.87$ for NNRP and $R^2 = 0.95$ for ERA; both at 99% significance level).
3.3 Use of Genesis Parameters as a Proxy for Current and Past North Atlantic Tropical Cyclone Climatology

a. Application of the full GP

The GP averaged over the entire North Atlantic basin skillfully reproduces the seasonal variation of monthly-mean cyclone frequency (Fig. 3.2) with $R^2=0.87$ for NNRP and $R^2=0.95$ for ERA, both at 99% significance level. This is an expected result, as the GP was originally developed for this purpose (Emanuel and Nolan 2004).

However, as shown in Fig. 3.3, the basin-average ASO GP provides a poor predictor of climate variability in observed annual tropical cyclone frequency ($R^2=0.21$). The skill is particularly poor before 1975 and there is a wide difference between the two reanalyses, with neither providing a good assessment of the observed cyclone frequency variations or trend. We suggest that there are two major contributors to this lack of relationship: reanalysis errors, and large intra-basin variations and inconsistencies in the GP. The reanalysis errors are discussed in relation to the component terms of the GP in Section 3.3b.

![Figure 3.3: Five-year running mean of observed annual tropical cyclone frequency (black) and basin-wide ASO GP for NNRP (red), and ERA (blue), with dashed trend lines superimposed.](image)

The intra-basin variations and inconsistencies in the GP are obvious from Fig. 3.4, which shows GP values overlain with genesis locations. Of the local GP values across the basin, 75% are less than one (Fig. 3.5a), whereas the Gulf of Mexico (GOM) has GP consistently >6 and occasionally much higher (Fig. 3.4). Yet the GOM only produces ~20% of the basin cyclones and the maxima in observed genesis frequency are in the eastern tropical Atlantic and off the US east coast, both areas of
relatively lower GP values. Thus, proportionally small changes in GP over the GOM may dominate the overall basin average without being associated with a concomitant change in overall genesis frequency.

Kossin and Camargo (2009) noted that the PI along the actual cyclone track was a better indicator of cyclone intensity than aerial averages. A similar comparison for GP values at actual genesis locations (Fig. 3.5b) indicates that these values are normally <5, with values of 2-3 being most common. This is even more noticeable when GOM storms are excluded from the analysis (Fig. 3.5b, grey line).

Figure 3.4: ASO NNRP GP (color) overlay with observed genesis locations (black dots) for the period 1960-2009. ERA GP is similar (not shown).

Figure 3.5: ASO GP PDF for the period 1960 to 2009: a) NNRP for the entire basin, b) NNRP at genesis locations (grey line similar, but excluding GOM storms). (Similar for ERA, not shown).
Table 3.1: Variance ($R^2$) in annual tropical cyclone frequency explained by ASO GP (for NNRP, top; and ERA, bottom), with 5-y running-mean variance in parenthesis. The regions are shown in Fig. 3.1, bold indicates the highest $R^2$ in any given row, bold-italic indicates highest overall $R^2$ for each reanalysis, and significance is indicated by * 95% and ** 99%.

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<tr>
<th></th>
<th>Average ASO GP in</th>
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<tr>
<td></td>
<td>Basin</td>
<td>GOM</td>
<td>MDR</td>
<td>EMDR</td>
<td>Basin - GOM</td>
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<tr>
<td><strong>Annual TC Frequency</strong></td>
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<tr>
<td>All storms in NA basin</td>
<td>0.21 **</td>
<td>0.03 (0.29 **)</td>
<td>0.37 **</td>
<td>0.37 **</td>
<td>0.26 **</td>
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<tr>
<td>Storms that move through the GOM</td>
<td>0.19 **</td>
<td>0.07 (0.34 **)</td>
<td>0.18 **</td>
<td>0.19 **</td>
<td>0.19 **</td>
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<tr>
<td>Number of storms forming in the MDR</td>
<td>0.08 **</td>
<td>0.04 (0.18 **)</td>
<td>0.23 **</td>
<td>0.19 **</td>
<td>0.07 **</td>
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<tr>
<td>Number of storms forming in the EMDR</td>
<td>0.08 **</td>
<td>0.04 (0.14 **)</td>
<td>0.23 **</td>
<td>0.19 **</td>
<td>0.07 **</td>
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<tr>
<td>Number of storms that move through the MDR</td>
<td>0.12 **</td>
<td>0.07 (0.17 **)</td>
<td>0.23 **</td>
<td>0.19 **</td>
<td>0.10 **</td>
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<tr>
<td>Number of storms that move through the EMDR</td>
<td>0.12 **</td>
<td>0.07 (0.17 **)</td>
<td>0.23 **</td>
<td>0.19 **</td>
<td>0.10 **</td>
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<tr>
<td><strong>All storms in NA basin</strong></td>
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<tr>
<td></td>
<td>0.32 **</td>
<td>0.29 (0.52 **)</td>
<td>0.32 **</td>
<td>0.35 **</td>
<td>0.27 **</td>
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<tr>
<td>Storms that move through the GOM</td>
<td>0.15 **</td>
<td>0.24 (0.20 **)</td>
<td>0.11 **</td>
<td>0.14 **</td>
<td>0.10 **</td>
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<tr>
<td>Number of storms forming in the MDR</td>
<td>0.10</td>
<td>0.10 (0.30 **)</td>
<td>0.26 **</td>
<td>0.21 **</td>
<td>0.08 **</td>
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<td></td>
</tr>
<tr>
<td>Number of storms forming in the EMDR</td>
<td>0.13 **</td>
<td>0.13 (0.32 **)</td>
<td>0.28 **</td>
<td>0.24 **</td>
<td>0.10 **</td>
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</tr>
<tr>
<td>Number of storms that move through the MDR</td>
<td>0.17 **</td>
<td>0.16 (0.37 **)</td>
<td>0.31 **</td>
<td>0.28 **</td>
<td>0.14 **</td>
</tr>
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</tr>
<tr>
<td>Number of storms that move through the EMDR</td>
<td>0.17 **</td>
<td>0.16 (0.37 **)</td>
<td>0.31 **</td>
<td>0.28 **</td>
<td>0.14 **</td>
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</table>

We thus suggest that skewing of basin-averaged GP by the small area of extreme values in the GOM, combined with the smoothing provided by the large number of GP values less than one, is a major contributor to the lack of a solid relationship between basin-wide average GP and annual tropical cyclone frequency in Fig. 3.3. This is examined further in relation to the individual GP components in Section 3.3b. It also provides one explanation for the finding by Emanuel (2010) that the application of a genesis parameter improved substantially as the scale of the domain of averaging was decreased.

For climate prediction applications it is not feasible to calculate GP at genesis locations, but we can utilize sub-regions of the most common genesis frequency (Fig. 3.1 and for completeness, a basin-wide GP average that excludes the GOM is also included). For each region we compare ASO GP with tropical cyclone annual frequencies for all storms, for storms forming within the MDR or EMDR regions, and for storms moving through the GOM, MDR, or EMDR regions at some point (Table 3.1).
Clearly, averaging the GP over smaller domains is an improvement on the basin-wide average. Comparing domains, the MDR and EMDR regions overall have the highest relationship regardless of storm family and explain 35-45% of the observed North Atlantic frequency. This improvement is partly due to the MDR/EMDR GP picking up the overall increases in cyclone frequency since 1995 (Fig. 3.6), a not surprising result as the bulk of this has occurred through increased equatorial developments (Kimberlain and Elsner 1998; Holland and Webster 2007). However, both the EMDR and MDR provide an improved ability to estimate all basin storms over those that just forms within the EMDR/MDR region. This implies some downstream impact of favorable conditions in this area, as is discussed further in Section 3.4.

b. Contributions by Each Term in the GP

The contributions of the individual terms in Eq. 3.1, and their products, to explaining storm frequency variations are shown in Table 3.2 and Fig. 3.7. For simplicity, we limited Table 3.2 to just the whole basin and EMDR, as these provided the greatest clarity of comparison.

![Figure 3.6: Five-year running mean of observed annual tropical cyclone frequency and that estimated from the ASO EMDR GP applied to NNRP and ERA.](image)

It is clear that the relative humidity and vorticity terms do not exhibit an association with annual variations in tropical cyclone frequency. The relative humidity term alone has a negative correlation and explains essentially no variance. PI, vertical shear or their product explains substantially higher variance in observed annual frequency and this is significant for all except the basin wide ERA reanalysis. Thus, variations in the EMDR, specifically PI and shear, dominate tropical cyclone development across the basin, a curious result since both are normally associated with in-situ
development and intensification rather than the remote association found here (e.g. Kossin and Camargo 2009); possible reasons are discussed in Section 3.4.

The lack of a vorticity relationship is consistent with the finding of Tippett et al. (2011) that increases in the value of absolute vorticity beyond a threshold minimum do not increase the probability of tropical cyclone genesis. That the main role of vorticity is as a limiting factor is consistent with its original inclusion by Gray (1968) based on observations that tropical cyclones do not generally form close to the equator.

The lack of a RH signal also agrees with the findings of Tippett et al. (2011), but appears to be in conflict with other studies that have found a strong relationship (e.g. Gray 1968, 1979; Cheung 2004; Emanuel and Nolan 2004; Emanuel 2010). There are obvious detrimental impacts of very dry air on the ability of deep convection to develop, and if convection develops on the associated development of cool downdrafts that limit the available boundary-layer thermodynamic energy (e.g. Emanuel 1993; Tang and Emanuel 2010). But do these impacts carry over to the interannual variations that...
are of interest to our study? We suggest not, and we further suggest that the varying findings on the importance of RH arise largely from the differing applications being investigated.

Table 3.2: Variance ($R^2$) in annual tropical cyclone frequency explained by components of ASO GP, with 5-y running-mean $R^2$ in parenthesis. The parameters are: $v$ for vorticity term, $r$ for relative humidity term, $p$ for PI term, and $s$ for vertical wind shear term. Geographical regions are shown in Fig. 3.1, bold indicates equal or higher correlation than the full GP, bold-italic indicates highest overall correlation for NNRP and ERA, * indicates negative correlations, and significance is indicated by * 95% and ** 99%. Line 6, highlighted by the bold box, is the CGI index.

<table>
<thead>
<tr>
<th></th>
<th>NNRP</th>
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<th>ERA</th>
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<td></td>
<td>basin</td>
<td>EMDR</td>
<td>basin</td>
<td>EMDR</td>
</tr>
<tr>
<td>GP</td>
<td>$0.21^{**}$ (0.29*)</td>
<td>$0.27^{<strong>}$ (0.46</strong>)</td>
<td>$0.32^{<strong>}$ (0.52</strong>)</td>
<td>$0.35^{<strong>}$ (0.44</strong>)</td>
</tr>
<tr>
<td>$r<em>p</em>s$</td>
<td>$0.34^{<strong>}$ (0.55</strong>)</td>
<td>$0.36^{<strong>}$ (0.56</strong>)</td>
<td>$0.40^{<strong>}$ (0.69</strong>)</td>
<td>$0.40^{<strong>}$ (0.76</strong>)</td>
</tr>
<tr>
<td>$v<em>p</em>s$</td>
<td>$0.15^{<strong>}$ (0.38</strong>)</td>
<td>$0.45^{<strong>}$ (0.66</strong>)</td>
<td>$0.15^{<strong>}$ (0.31</strong>)</td>
<td>$0.40^{<strong>}$ (0.59</strong>)</td>
</tr>
<tr>
<td>$v<em>r</em>s$</td>
<td>$0.06$ (0.00)</td>
<td>$0.11^{<strong>}$ (0.12</strong>)</td>
<td>$0.04$ (0.03)</td>
<td>$0.01$ (0.04)</td>
</tr>
<tr>
<td>$v<em>r</em>p$</td>
<td>$0.11^{**}$ (0.13*)</td>
<td>$0.17^{<strong>}$ (0.18</strong>)</td>
<td>$0.22^{<strong>}$ (0.46</strong>)</td>
<td>$0.32^{<strong>}$ (0.53</strong>)</td>
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<tr>
<td>$p*s$</td>
<td>$0.36^{<strong>}$ (0.67</strong>)</td>
<td>$0.52^{<strong>}$ (0.83</strong>)</td>
<td>$0.29^{<strong>}$ (0.61</strong>)</td>
<td>$0.41^{<strong>}$ (0.74</strong>)</td>
</tr>
<tr>
<td>$r*p$</td>
<td>$0.04$ (0.00)</td>
<td>$0.07$ (0.05)</td>
<td>$0.01$ (0.00)</td>
<td>$0.02$ (0.00)</td>
</tr>
<tr>
<td>$r*p$</td>
<td>$0.14^{**}$ (0.19*)</td>
<td>$0.13^{**}$ (0.13*)</td>
<td>$0.29^{<strong>}$ (0.58</strong>)</td>
<td>$0.35^{<strong>}$ (0.69</strong>)</td>
</tr>
<tr>
<td>$v*p$</td>
<td>$0.05$ (0.18**)</td>
<td>$0.36^{<strong>}$ (0.55</strong>)</td>
<td>$0.11^{<strong>}$ (0.41</strong>)</td>
<td>$0.38^{<strong>}$ (0.72</strong>)</td>
</tr>
<tr>
<td>$v*r$</td>
<td>$0.03$ (0.04*)</td>
<td>$0.00$ (0.00)</td>
<td>$0.00$ (0.00)</td>
<td>$0.00$ (0.10*)</td>
</tr>
<tr>
<td>$v*s$</td>
<td>$0.14^{<strong>}$ (0.20</strong>)</td>
<td>$0.31^{<strong>}$ (0.48</strong>)</td>
<td>$0.04$ (0.00)</td>
<td>$0.18^{**}$ (0.13*)</td>
</tr>
<tr>
<td>$p$</td>
<td>$0.16^{<strong>}$ (0.44</strong>)</td>
<td>$0.48^{<strong>}$ (0.77</strong>)</td>
<td>$0.22^{<strong>}$ (0.66</strong>)</td>
<td>$0.38^{<strong>}$ (0.76</strong>)</td>
</tr>
<tr>
<td>$r$</td>
<td>$0.01$ (0.07*)</td>
<td>$0.00$ (0.01*)</td>
<td>$0.00$ (0.02*)</td>
<td>$0.00$ (0.06*)</td>
</tr>
<tr>
<td>$s$</td>
<td>$0.26^{**}$ (0.30*)</td>
<td>$0.38^{<strong>}$ (0.53</strong>)</td>
<td>$0.10^{**}$ (0.08)</td>
<td>$0.26^{<strong>}$ (0.41</strong>)</td>
</tr>
<tr>
<td>$v$</td>
<td>$0.09$ (0.42*)</td>
<td>$0.07$ (0.19*)</td>
<td>$0.06$ (0.38*)</td>
<td>$0.03$ (0.00)</td>
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</table>

For example, Gray (1968, 1979) and Emanuel and Nolan (2004) were focused on the intra-seasonal variation in tropical cyclone formation. There is an obvious and large change as relatively dry winter conditions change over to the moister conditions that prevail during the tropical cyclone season (e.g., Emanuel and Nolan 2004; Cheung 2004; Tippett et al. 2011). We have demonstrated that these large seasonal relationships do not carry over into interannual variations, where the RH changes are much smaller.

The poor interannual relationship cannot be attributed to the RH and vorticity terms as these are simply too small to emerge above the reanalysis noise. As is clear from Fig. 3.7, the RH term is essentially constant throughout the entire period and there is no relationship with tropical cyclone frequency on any time scale, either interannual or decadal. The vorticity is also very flat, though there could be a weak decadal relationship.
One alternative interpretation for RH is that there is a minimum threshold required to enable sustained deep convection within the incipient disturbances that may become a tropical cyclone. The required moistening of the atmosphere to enable cyclogenesis can then follow in the protected Lagrangian volume where regular convective processes moisten the atmosphere to levels well above the local climatological norm (e.g. Dunkerton et al. 2009). This view is supported by Rappin et al. (2010), who examined the time-to-genesis in a modeling study using an atmosphere in radiative-convective equilibrium. They found essentially no relationship with either vorticity or mid-level RH, in agreement with our findings. However, there is a strong negative relationship between the time to genesis and PI. This implies that weak pre-cyclone disturbances have a higher chance of development before coming into contact with a region hostile to development. Since PI is highly dependent on SST, it also follows that this is indicative of a more rapid moistening of the Lagrangian environment, also aiding cyclone development.

The use of thresholds as the basis of a genesis parameter has been comprehensively examined by McGauley and Nolan (2011) and will not be examined further here. Rather we acknowledge that this and previous studies point towards both vorticity and RH being a threshold requirement above which there is little relationship with cyclogenesis, and for which there is essentially zero interannual signal. This leads in the next section to the development of a revised, simplified cyclone genesis index.

**c. A Revised Cyclone Genesis Index (CGI)**

Removing vorticity and RH from Eq. 3.1 gives:

$$CGI = \left( \frac{PI}{70} \right)^3 \left( 1 + 0.1(V_{\text{shear}}) \right)^{-2}$$  \hspace{1cm} (3.2)

The CGI is dimensionless, and can be converted to cyclone frequency by matching the means of the CGI with the mean annual cyclone count over a defined base period.

As shown in Table 3.2 Line 6 (indicated by the bold box), this index explains the greatest variance ($R^2=0.83$) for smoothed annual tropical cyclone frequency of all combinations of the factors in Eq. 3.1.

However, the implicit assumption in the GP that the contribution from vertical shear is maximized at $V_{\text{shear}}=0$ may not be correct. For Rossby-mode waves the vertical wavenumber following a ray varies
according to \( \frac{dm}{dt} = -k \frac{\partial U}{\partial z} \), where \( m/k \) are the vertical/zonal wavenumbers, and \( U \) is the zonal wind (e.g. Lighthill 1978; Webster and Chang 1988; Done et al. 2011b). For westerly vertical shear (\( \frac{\partial u}{\partial z} < 0 \)) wave energy can propagate upwards and leak out of the shear layer, but for easterly shear the waves are evanescent and will tend to be trapped in the shear layer. Thus there is a potential asymmetry in the manner in which a disturbance will respond to shear: for easterly shear the trapping of wave energy may counterbalance the detrimental shearing effect, but they complement each other to the detriment of the cyclone for westerly shear. Adding to this asymmetry is the westerly vertical shear that is generated over a cyclone core by the beta effect (Holland 1983). This self-generated vertical shear may be counteracted by an opposite easterly shear in the environment (Ritchie and Frank, 2007). From observations, Zheng et al. (2010) also confirmed that easterly shear has a lower effect on cyclone intensification than does westerly shear. In order to evaluate this potential asymmetry we add a new parameter \( a \) to the shear term of equation 3.2, i.e.,

\[
CGI = \left( \frac{PI}{70} \right)^3 \left( 1 + 0.1(V_{\text{shear}} + a) \right)^{-2}
\]

(3.3)

We varied parameter \( a \) to examine if including the sign of the shear is important and found a small, but clear relationship. Changing the maximum impact for the EMDR from westerly shear through to easterly shear by varying \( a \) from 5 to -5 produces a steady increase of variance explained for annual cyclone frequency by ~8% when shear alone is used. However the dominance of the PI term means that this effect is minimal for the full CGI. This is an area that warrants further investigation, but for now we set \( a = 0 \) (i.e., defaulting back to equation 3.2).

Figure 3.8: Five-year running mean of observed TC storm frequency (black), and that estimated from ASO CGI for NNRP (red) and ERA (blue), with dashed linear trend lines superimposed.
As shown in Fig. 3.8, for both reanalyses CGI reproduces realistic trend lines and very good assessments of decadal variations. The summary results in Table 3.3 indicate that, overall, EMDR CGI explains 83% (NNRP) and 74% (ERA) of the observed smoothed interannual storm variance. The CGI applied to either the MDR or the EMDR also explains >50% of the variance regardless of which subset of years is selected. The best relationships are for the satellite era, however, when compared to the GP (Eq. 3.1) there is less sensitivity to analysis errors in earlier years. For example, for the 5-γ smoothed NNRP EMDR, $R^2=0.92, 0.83$ and $0.81$ for the periods since 1980, 1960 and 1950, respectively; this compares to $0.86, 0.29$ and $0.15$ for the basin-wide GP. Unsmoothed annual frequencies also typically have $R^2>0.5$. Whether the reduction between smoothed and interannual correlations is due to factors from known relationships, such as ENSO, or to stochastic process requires further investigation.

As shown in Fig. 3.8, these correlations arise from both a trend across the period of analysis and a number of shorter-period variations. After removing the trend, CGI explains 65% of the smoothed variability (significant at 99%) and 38% of the unsmoothed variability (significant at 95%). This implies that CGI can be used both for analysis of long-term trends and also for shorter period fluctuations.

![Figure 3.9: Seasonal variation in monthly-mean tropical cyclone frequency together with that estimated by monthly mean basin-wide GP (black) and EMDR CGI (red) for NNRP (solid) and ERA (dashed).](image)

Applying CGI to assessing seasonal changes in the monthly mean frequency of tropical cyclones also provides an improvement over the original GP (Fig. 3.9). The early season build-up, peak in September and late season ramp-down are all improved, with the one outlier month being due to an underestimate of the August frequency.
3.4 Discussion

a. CGI

The large bulk of the CGI success comes from the PI term (Table 3.2), which is strongly influenced by local SST and to some extent by upper-atmospheric temperature and atmospheric moisture. For example using 5-y smoothed data, the NNRP EMDR PI term alone explains 77% of the annual cyclone frequency variance and shear adds only 6% to this. A valid question arises as to whether this additional variance explained truly adds relevant new information. Taken separately, shear explains 53% of the smoothed annual frequency changes, but shear is also correlated directly with PI (R^2=0.36). In essence, both are responding to internal atmospheric changes as SST increases and the warm pool expands (e.g. Wang et al. 2006, 2007), and both are thus indicators of these SST changes. Since SST is the major factor in the PI correlation (Section 3.2), shear can be considered to be following the PI.

Further, there is an interesting bifurcation in the CGI component relationships when the annual number of tropical cyclones exceeds 11 (Fig. 3.10). For both predicted and observed annual cyclone counts <11 there is little real relationship with either the CGI or its component terms. The PI, and thus CGI, predicts years with >11 cyclones very well, whereas the shear term relationship is nearly flat and contributes little to the overall variance explained.

![Figure 3.10: Scatter plot showing annual storm frequency estimates using ASO CGI, Potential Intensity and Shear (for NNRP data).](image-url)
Consistent with the original GP index (Eq. 3.1), the revised CGI is developed from the product of the PI and shear terms. For completeness, we also tested alternative approaches. These included taking the sum of the PI and shear terms as well as using different exponents for each of the PI and shear terms. But none of these produced any significant change in skill.

A further evaluation can be made by comparing CGI with the Emanuel (2010) GPI:

\[
GPI = \left[ \eta \chi^{-4/3} \max((PI-35),0)^2 (25+V_{shear})^{-4}, \right.
\]

(3.4)

where \( \chi \) is the moist entropy deficit in the middle atmosphere. The GPI has units of rate/unit area, so when it is normalized to fit the mean annual cyclone frequency it assumes the same basin-wide frequency character as the CGI.

The GPI retains moisture and vorticity terms that were dropped in the CGI, and it has different normalizations and exponents for the PI and shear terms. Yet its reproduction of historical cyclone frequency on both interannual and decadal time scales is very close to that of the CGI (Fig. 3.11). Further, removing the moisture and vorticity parameters from GPI (notated as \( \text{GPI}_x \), dashed green line, Fig. 3.11) make essentially no difference to its capacity to predict interannual variations, which is consistent with our findings in Section 3.3b.

The lack of real difference in reproducing historical annual cyclone frequency across diverse formulations clearly indicates that, whilst it is important to include PI and shear in any genesis index formulation, the precise nature of that combination is not particularly important. For historical consistency and parsimony, we opt to retain Eq. 3.2 as our genesis index.

**b. Data Quality**

In Section 3.2 we referred to the Landsea et al. (2010) study that suggested the recent upsurge in tropical cyclone frequency in the North Atlantic was due to an anomalous increase in short-lived storms associated with improved observing and analysis systems. This is a marked change from a large number of other studies, which have concluded that the cyclone data have been quite reliable since 1970 (e.g. Owens and Landsea 2003; Chang and Guo 2007; Vecchi and Knutson 2008; Holland and Webster 2007). The close relationship between the CGI, GPI and storm activity in Fig. 3.11 (see also Table 3.3) also argues for the increase being real, as was suggested earlier by Emanuel (2010). Here we note that neither the CGI nor the GPI was tuned to fit the annual cyclone frequency sequence, aside perhaps from some implicit tuning in the selection of averaging area.
That environmental changes occur in association with the observed increase in annual tropical cyclones is evidenced by changes in other cyclone characteristics, such as the marked shift towards more equatorial developments (Kimberlain and Elsner 1998; Holland and Webster 2007). Emanuel (2005) noted a very close relationship between annual power dissipation (which is influenced by frequency, intensity and duration) and SST (which we have shown to be essentially the basis of the PI term in Eq. 3.2). Emanuel (2007) investigated the observed recent increases in power dissipation in the North Atlantic and concluded that they “strongly covary and are highly correlated with SST”. Knutson et al. (2007) and Chen and Lin (2011) also simulated the recent increases in tropical cyclones lasting >2 days using the GFDL model embedded in reanalysis and with internal nudging, indicating that recent tropical cyclone activity has responded to observed environmental changes.

Further checking reveals that the observed recent change in short-lived storms was mirrored by similar proportional changes in the remaining long-lived storms as is evident from Fig. 3.12. The only disproportionate change in short-lived tropical cyclones occurred between roughly 1950 and 1960. This was during the introduction of aircraft reconnaissance and we concur there is a strong case for this change to have arisen from observational and analysis changes. However, there has been no observable change in the proportion of short-lived tropical cyclones since 1970. The proportion of short-lived storms has remained relatively constant at ~20% of the total since 1970 and thus their numerical increase is consistent with the changes in CGI and GPI (Fig. 3.11).
Thus, assuming that short-lived tropical cyclones have increased due to observing and analysis changes requires an explanation for why the long-lived cyclones have also increased, and an explanation for why so many independent studies have found a real increase associated with observed environmental changes. Invoking Occam’s razor, the most likely explanation is that short-lived tropical cyclones have simply followed an overall, real increase in all cyclones.

Table 3.3: Variance ($R^2$) in annual tropical cyclone frequency explained by ASO GP (for NNRP, top; and ERA, bottom), with 5-y running-mean variance in parenthesis. The regions are shown in Fig. 3.1, bold indicates the highest $R^2$ in any given row, bold-italic indicates highest overall $R^2$ for each reanalysis, and significance is indicated by * 95% and ** 99%. For simplicity, only $R^2$ values for the Basin, MDR and EMDR regions are shown.

<table>
<thead>
<tr>
<th></th>
<th><strong>Average ASO CGI in</strong></th>
<th><strong>NNRP</strong></th>
<th><strong>ERA</strong></th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Basin</td>
<td>MDR</td>
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<tr>
<td></td>
<td>Annual TC Frequency</td>
<td></td>
<td></td>
</tr>
<tr>
<td>All storms in NA basin</td>
<td>0.34*</td>
<td>0.49**</td>
<td>0.52**</td>
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<tr>
<td></td>
<td>(0.64**)</td>
<td>(0.72**)</td>
<td>(0.83**)</td>
</tr>
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<td>0.22,</td>
<td>0.25,</td>
<td>0.29,**</td>
</tr>
<tr>
<td></td>
<td>(0.53*)</td>
<td>(0.58**)</td>
<td>(0.58**)</td>
</tr>
<tr>
<td>Number of storms forming in the MDR</td>
<td>0.15</td>
<td>0.29,**</td>
<td>0.27,</td>
</tr>
<tr>
<td></td>
<td>(0.45)</td>
<td>(0.56**)</td>
<td>(0.49**)</td>
</tr>
<tr>
<td>Number of storms forming in the EMDR</td>
<td>0.17</td>
<td>0.34,**</td>
<td>0.32,**</td>
</tr>
<tr>
<td></td>
<td>(0.48)</td>
<td>(0.58**)</td>
<td>(0.55**)</td>
</tr>
<tr>
<td>Number of storms that move through the MDR</td>
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<td>0.38,**</td>
<td>0.37,**</td>
</tr>
<tr>
<td></td>
<td>(0.56)</td>
<td>(0.66**)</td>
<td>(0.64**)</td>
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<tr>
<td>Number of storms that move through the EMDR</td>
<td>0.21</td>
<td>0.38,**</td>
<td>0.37,**</td>
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<tr>
<td></td>
<td>(0.56)</td>
<td>(0.66**)</td>
<td>(0.64**)</td>
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<tr>
<td></td>
<td><strong>Average ASO CGI in</strong></td>
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<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Basin</td>
<td>MDR</td>
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<td>0.41,**</td>
<td>0.42**</td>
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<td></td>
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<td>(0.62**)</td>
<td>(0.74**)</td>
</tr>
<tr>
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<td>0.23,</td>
<td>0.27,**</td>
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<tr>
<td></td>
<td>(0.58**)</td>
<td>(0.59**)</td>
<td>(0.66**)</td>
</tr>
<tr>
<td>Number of storms forming in the MDR</td>
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<td>0.25,**</td>
<td>0.20,**</td>
</tr>
<tr>
<td></td>
<td>(0.40**)</td>
<td>(0.49**)</td>
<td>(0.41**)</td>
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<td>0.25,**</td>
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<td>(0.41)</td>
<td>(0.49**)</td>
<td>(0.46**)</td>
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<tr>
<td>Number of storms that move through the MDR</td>
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<td>0.30,**</td>
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<tr>
<td></td>
<td>(0.55**)</td>
<td>(0.61**)</td>
<td>(0.58**)</td>
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<td>0.30,**</td>
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<td></td>
<td>(0.55**)</td>
<td>(0.61**)</td>
<td>(0.58**)</td>
</tr>
</tbody>
</table>

c. **Global and Climate Change Application**

The CGI has demonstrated considerable skill in predicting interannual variations in North Atlantic cyclones, but a more stringent test will apply for application to other basins where widely different environments are found. This is a complex task, requiring careful attention to varying data quality and also an understanding of the appropriate sub-regions that are representative of the basin as a whole. The detailed results will be presented in a companion publication, but some preliminary
comments can be made here. We constrain the analysis period to post-1975 due to significant data issues prior to the satellite era, and we normalize the CGI to the average annual global cyclone frequency for this period.

Figure 3.12: Variation in annual proportion of short-lived tropical cyclones from 1880 (diamonds) together with the 5-y running mean (black line) and the linear trends from 1890-1940 and 1960-2008 (dashed lines). Original tropical cyclone data from IBTrACS (Knapp et al. 2007 has been adjusted for early missing storms following Vecchi and Knutson (2007)).

The CGI reproduces the global patterns of cyclone development reasonably well (Fig. 3.13). These patterns are close to the observed, but the details are not always so. For example, the central Pacific has too many near-equatorial developments. Nevertheless, the CGI provides a better global assessment than does the GP. Similarly, GPIx (GPI after removal of the moisture and vorticity parameters), reproduces the global cyclone development patterns reasonably well. It is similar to the patterns seen for CGI and is an overall improvement over the patterns for the original GPI.

There is considerable variability in the capacity of CGI applied to different basins in reproducing annual variations and trends, with the Northern Hemisphere basins faring better than those in the Southern Hemisphere. This reflects our experience in the Atlantic where an all-basin average was quite poor at reproducing observed annual frequency. The variability across basins is similar to findings by Menkes et al. (2012), who showed that different indices tend to under/overestimate
different basins. The accuracy increases when specific sub-regions are selected, again similarly to the findings with the EMDR here, but a full discussion is beyond the scope of this study.

Emanuel (2010), Rappin et al. (2010), Korty et al. (2012) and Tang and Emanuel (2010) all argued that saturation deficit, although relatively stable for current climates may play a bigger role under climate change scenarios. We suggest caution with this assessment. Whilst the climatological mean saturation deficit can be expected to change with global warming, there is no à priori reason to assume that this will impact cyclone frequency in any significant way.

Both this climate change aspect and the global applicability details will be reported in a separate publication.
3.5 Conclusions

Tropical cyclone genesis indices capture the major environmental controls, or contributors, to cyclone formation and reduce them to a single parameter that can provide a valuable way of assessing cyclone changes from large-scale analyses or model simulations. Our overall motivation for examining such indices is to establish a solid parametric relationship that can be applied to climate model output in assessing potential cyclone changes associated with varying and changing future climate. Here we reported on the first phase to investigate existing indices and developing a revised index.

Gray's (1979) work established the benchmark for those physical and dynamical processes contributing to the necessary conditions for tropical cyclogenesis in the first seasonal genesis parameter. His four main parameters of SST (or more correctly ocean thermal content), vorticity, mid-level humidity, and vertical shear of the wind have formed the basis for all subsequent applications and developments of genesis indices.

We first examine in detail a recent, widely-used Genesis Potential (GP) index developed by Emanuel and Nolan (2004, our Eq. 3.1), together with a recent revision, the Genesis Potential Index (GPI) developed by Emanuel (2010, our Eq. 3.4). This examination included the GP and GPI applicability to seasonal, interannual and longer-term cyclone frequency changes in the North Atlantic. We find that the GP and GPI accurately reproduce the variation of monthly cyclone frequency throughout a composite of hurricane seasons, but that they are far less suitable for interannual or longer-term variations. There are several potential reasons for this:

- Part of the limitation lies in the choice or area over which to average the indices. Taking the whole basin is a quite poor approach largely due to the marked variations in amplitude across the basin, and we find that for the North Atlantic annual cyclone frequencies taking the mean in the general area of the Main Development Region (MDR) offers the best choice;

- Another problem lies in the inclusion of mid-level moisture and low-level vorticity as explicit predictors, which we find to be quite poor predictors of interannual or longer-term changes, adding either nothing or negative skill to the GP and GPI. We concur with Gray (1979) and more recent work by Tippett et al. (2011) that these parameters are more of a necessary condition in that they must lie in a specific range, but beyond this they appear to add nothing to interannual variations.
• The Potential Intensity (PI) provides the bulk of the skill in predicting climate variations and trends in North Atlantic annual cyclone frequency. Once the PI relationship is removed, shear adds a small, but useful, level of skill.

• Careful differentiation must be made between this climatological finding and the importance of humidity and shear in the immediate environment of the developing tropical cyclone, where there does appear to be a strong moisture and shear signal (e.g. Tang and Emanuel 2010).

Based on this analysis, we suggest a revised Cyclone Genesis Index (CGI; Eq. 3.2), which is derived from the GP but includes only potential intensity and vertical wind shear as predictors, and which is best when applied to a slight meridional extension of the MDR to assess basin-wide cyclone variability and change. In this configuration, the CGI explains ~50% of the interannual variance in North Atlantic cyclone frequency for NNRP reanalysis (~40% for ERA); smoothing the series to remove El Niño variations increases these to ~80% (NNRP) or ~75% (ERA). All are significant at 99%. These results contain a combination of trend and shorter-period variability. When the linear trend is removed the CGI explains ~40% of the interannual variance at 95% significance level) or ~65% of the variance after application of a 5-y running mean (99% significance) when using NNRP (similar for ERA). The CGI also provides an improved fit to the monthly changes in cyclone frequency throughout the season compared to the original GP.

These strong relationships of CGI with annual cyclone variability and trend points to the presence of a strong forcing from the large-scale environment on cyclogenesis in agreement with Gray (1979). This does not rule out the role of small scales and stochastic elements for individual cyclone development (e.g. Holland 1995; Tang and Emanuel 2010), but when taken over long-periods, the large scales appear to dominate.

This first phase provides us with confidence that the CGI can provide a robust way of assessing variations in changes of tropical cyclone frequency from both reanalyses and climate model simulations. The next stage of the work will address the global use of the CGI and its application to future climate scenarios. We provide some initial indications here (e.g. Fig. 3.13) but the full details will be reported in a follow-up publication.

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AGS-1048841 and AGS-1048829. Erin Towler acknowledges the support of the Postdocs Applying Climate Expertise (PACE) program, funded by the NOAA Climate Program Office and the USGS, and administered by the UCAR Visiting Scientist Program. Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the US Government.

REFERENCES


Genesis Potential Index for North Atlantic


4. **Journal Article:** *Exploring Genesis Potential Indices*

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*National Center for Atmospheric Research, Boulder, CO*

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**Thesis Objective**

The article showcased in Chapter 3 gave a single example of the development of a basin specific Genesis Potential Index to predict tropical cyclone frequency from large-scale environmental conditions. The objective here is to take this general concept one step further by expanding the prediction of tropical cyclone frequency to other TC basins. Although tropical cyclone frequency is used as a canonical example, this method can be applied equally well to other rare and small weather systems, which in turn can be used to add value to dynamical model results.

To insure that the data mining technique does not simply identify random areas that correlate to the tropical cyclone frequency of individual basins, any area identified that could not be physically justified was rejected, and areas were only retained if they showed a significant correlation to tropical cyclone frequency. Interestingly, the highest correlated area for most basins were found to be upstream of the basin in regions that could be loosely defined as the main development region for the basin, increasing our confidence that the identified areas were not merely random. The one exception is the South Indian Ocean, where no clear area of high correlation could be defined, but this is also the basin that suffers most from data quality issues.

**Abstract**

That the large-scale environment has a role in determining tropical cyclone genesis has been understood since the earliest analyses of the association between cyclones and the general circulation in the tropics. Gray (1968, 1979) summarized the state of science and demonstrated the potential for assessing genesis potential utilizing such environmental parameters as ocean thermal content, midlevel moisture, an unstable atmosphere, low-level vorticity, and vertical wind shear through a deep atmospheric layer. Building on this earlier work, a number of cyclone genesis indices have been developed and are being utilized to assess potential hurricane changes over climate time-scales. A recent index developed for North Atlantic tropical cyclones combines an index of available energy for cyclone development with the negative influences of strong vertical shear and has demonstrated skill in assessing annual cyclone frequency variations (Bruyère et al., 2012). Following on from this study, here we examine a number of global cyclone regions with the goal of establishing similar predictors of annual cyclone counts.
4.1 Introduction

It is well known that tropical cyclone formation – and thus annual frequency – is determined partially by the prevailing state of the large-scale environment (e.g., Gray, 1968, 1979). Factors that have been associated with cyclone development include: a warm mixed layer in the upper ocean with temperatures greater than 26°C; moderate wind shear in the vertical, with winds changing by less than 10 ms⁻¹ between the lower and upper levels that cyclones can penetrate; low-level convergence of moist air and an unstable atmosphere to support the clouds that maintain the cyclone; sufficient background rotation, usually requiring a location poleward of approximately 5° latitude; and a cold upper atmosphere, with some level of divergence (Emanuel, 1995). Once a tropical cyclone has developed, the primary factors that influence its continued existence are the availability of heat and moisture supplied from the surface, continuing weak vertical windshear and an absence of dry-air intrusion (Holland, 1995; Dare and Davidson, 2004).

Cyclone genesis indices that encapsulate these favorable large-scale conditions have been used in various forms for assessing cyclone frequency from analyses and climate models (see Bruyère et al., 2012 for a full summary). Emanuel and Nolan (2004) developed a Genesis Potential (GP) index that includes low-level vorticity, mid-level relative humidity, potential intensity (a measure of available energy for the cyclone), and vertical windshear. This original GP has been developed further by Emanuel (2010), Tippett et al. (2011), and McGauley and Nolan (2011). Emanuel (2010) suggested a modified index that depended on midlevel saturation deficit, in place of relative humidity. Tippett et al. (2011) evaluated the use of a clipped absolute vorticity term and also suggested prudence with regard to the use of relative humidity. McGauley and Nolan (2011) developed an index that checked for the fraction of time that thresholds for potential intensity, vorticity, vertical windshear, and saturation deficit are exceeded.

Bruyère et al. (2012) examined the skill of the components of genesis indices for the Atlantic Basin and found that only potential intensity and vertical windshear provided skill. These were combined in a new index, which provided substantial skill in assessing interannual variations in cyclone frequency for the entire North Atlantic when applied to a region just west of Africa - often referred to as the Main Development Region (MDR, Goldenberg and Shapiro 1996). This success is considered to be due to African easterly waves being the dominant source of seedlings for Atlantic tropical cyclones, so that favorable conditions in the MDR lead to enhance development potential of these waves as they leave Africa.
However, easterly-wave type disturbances are not the main source of seedlings in other parts of the globe, where monsoonal disturbances, intraseasonal oscillations and interactions with subtropical weather systems have all been shown to be important (Ritchie and Holland, 1999; Schreck et al., 2012).

Here we examine the use and applicability of three published indices to assessing annual cyclone frequency over all tropical cyclone regions of the globe. Specifically, we are interested in assessing if there are specific locations where application of the indices provides improved skill in a similar manner to that discovered for the MDR in the Atlantic.

4.2 Data and Method

Definitions
We break the global tropics down into six tropical cyclone basins, following World Meteorological Organization1. We further divide the South Indian basin into an eastern and western section and we add a sub-basin centered on the Gulf of Mexico (Fig. 4.1).

The annual cycle of tropical cyclone occurrence in each of these basins is shown in Fig. 4.2. The North Indian Ocean is unique in as much as it has two peak seasons (Fig. 4.2a), May/June and then end of the year, around October to December. With the most active months been Nov/Oct/May. This makes

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1Atlantic Oceanographic and Meteorological Laboratory, Hurricane Research Division. "Frequently Asked Questions: What regions around the globe have tropical cyclones and who is responsible for forecasting there?". NOAA. http://www.aoml.noaa.gov/hrd/tcfaq/F1.html
it difficult to pick an appropriate season to use when calculating a potential genesis index. The early period (AMJ) accounts for 30 percent of the annual number of storms, while the later season (OND) account for nearly 60 percent of the annual number of storms. For the purpose of this study we chose October-November-December. For all other basins we chose the three months that contain the bulk of the storms: August-October (ASO) for the Northern Hemisphere basins; and December-February (DJF) for the Southern Hemisphere basins.

Figure 4.2: Mean annual cyclone of observed tropical cyclones in each of the basins in Fig. 4.1: Left, Northern Hemisphere; right, Southern Hemisphere.

Data

We use the global reanalysis from the National Centers for Environmental Prediction and the National Center for Atmospheric Science (designated the NNRP Kalnay et al., 1996) to provide the large-scale data for the genesis indices. The base data are in 6-h intervals and these are averaged into three-month periods to represent the broad climate of the hurricane seasons. Tropical cyclone observations are taken from the International Best Track Archive for Climate Stewardship (IBTrACS; Knapp et al., 2010), also at 6-h intervals. The NNRP analysis archive covers the period from 1948 to present, but data deficiencies in both the analysis and tropical cyclone data make the earlier years somewhat unreliable (Kistler et al., 2001; Emanuel, 2010; Knutson et al., 2010). We therefore restricted our analysis to the years 1975 – 2012.
Exploring Genesis Potential Indices

Method

We use three genesis potential indices to evaluate their capacity to reproduce annual tropical cyclone frequency within the designated basins:

Cyclone Genesis Index (Bruyère et al., 2012):

\[
CGI = \left( \frac{PI}{70} \right)^3 \left( 1 + 0.1(V_{shear}) \right)^{-2}
\]  
(4.1)

Genesis Potential index (Emanuel and Nolan, 2004):

\[
GP = \left[ 10^5 \eta \right]^{5/2} \left( \frac{RH}{50} \right)^3 \left( \frac{PI}{70} \right)^3 \left( 1 + 0.1V_{shear} \right)^{-2}
\]  
(4.2)

Revised Genesis Potential Index (Emanuel, 2010):

\[
GPI = \left| \eta \right|^{3/2} \chi^{-4/3} \max((PI - 35),0)^2 (25 + V_{shear})^{-4},
\]  
(4.3)

Here: \( \eta \) is absolute vorticity (s\(^{-1}\)) at 850 hPa, RH is relative humidity (%) at 700 hPa, PI is the Potential Intensity (ms\(^{-1}\), a measure of available energy for cyclone development, Emanuel 1995), \( V_{shear} \) is the vertical wind shear (ms\(^{-1}\)) between 850 and 200 hPa, and \( \chi \) is the moist entropy deficit in the middle atmosphere (Emanuel, 2010).

First we evaluate the effectiveness of the different genesis indices, and their components, as proxies for tropical cyclone frequency when averaged over the entire basin. Then we investigate if specific regions show more skill than these basin averages. This is accomplished by a data-mining technique in which each component of the indices is evaluated at each grid point in the global analysis and then correlated to the annual tropical cyclone frequency of the basin of interest. An example data-mining result for the western North Pacific basin is provided in Fig. 4.3. This shows that regions outside the cyclone basin generally provide the best assessment of tropical cyclone frequency inside the basin. The results from this data mining exercise for all ocean basins and each of the cyclone indices are present in the next section.
4.3 Analysis

Table 4.1 summarizes the results of the use of the three indices across all ocean basins. The North Atlantic is the only basin where basin-wide averages have skill (*left three columns*). However, the data mining (*right three columns*) identified regions of potential skill for almost all cyclone basins. In all but the North Indian basin, the CGI demonstrated the highest skill, supporting the finding by Bruyère *et al.* (2012) that the additional components of the other indices reduce, rather than add to the skill.

The summaries in Table 4.1 are for the entire period of analysis, from 1975 - 2012. Of more interest is how well the indices can explain the interannual variability of tropical cyclone frequency. These are shown in Fig. 4.4.

Without exception, the data mining exercise provided improved relationships over using basin averages of the indices. For the basin averages (left group in Fig. 4.4) the genesis indices accurately reproduced the interannual variability only in the North Atlantic, though there was some limited skill in the western North Pacific for all indices and in the western South Indian for the CGI. The data mining provided improved assessments in the western North Pacific, western South Pacific, North Atlantic and Gulf of Mexico. There was no real improvement in the North Indian, and eastern South Indian – each of which had essentially no predictability; and mixed results were found for the eastern North Pacific and western South Indian Ocean. Overall, the CGI provided the best relationship with annual cyclone frequency.
Exploring Genesis Potential Indices

Table 4.1: Summary of the variance explained (square of the correlation) by each cyclone index. The first three columns are for basin-wide average and the last three columns for the optimal regions identified by the data mining. Bold indicate the best index in each basin and parentheses indicate negative correlations.

<table>
<thead>
<tr>
<th>Basin</th>
<th>GP</th>
<th>GPI</th>
<th>CGI</th>
<th>GP</th>
<th>GPI</th>
<th>CGI</th>
</tr>
</thead>
<tbody>
<tr>
<td>North Indian</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.22</td>
<td>0.00</td>
<td>0.20</td>
</tr>
<tr>
<td>West North Pacific</td>
<td>(0.18)</td>
<td>(0.09)</td>
<td>(0.04)</td>
<td>0.14</td>
<td>0.14</td>
<td>0.38</td>
</tr>
<tr>
<td>Eastern Pacific</td>
<td>0.25</td>
<td>0.02</td>
<td>0.16</td>
<td>0.36</td>
<td>0.31</td>
<td>0.37</td>
</tr>
<tr>
<td>North Atlantic</td>
<td>0.37</td>
<td>0.37</td>
<td>0.51</td>
<td>0.54</td>
<td>0.56</td>
<td>0.60</td>
</tr>
<tr>
<td>GOM</td>
<td>0.09</td>
<td>0.22</td>
<td>0.01</td>
<td>0.36</td>
<td>0.35</td>
<td>0.44</td>
</tr>
<tr>
<td>South Indian</td>
<td>0.00</td>
<td>(0.01)</td>
<td>(0.12)</td>
<td>0.20</td>
<td>0.22</td>
<td>0.23</td>
</tr>
<tr>
<td>West South Indian</td>
<td>(0.02)</td>
<td>(0.01)</td>
<td>(0.19)</td>
<td>0.22</td>
<td>0.20</td>
<td>0.36</td>
</tr>
<tr>
<td>East South Indian</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>0.01</td>
<td>0.01</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>West South Pacific</td>
<td>0.00</td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>0.20</td>
<td>0.00</td>
<td>0.23</td>
</tr>
</tbody>
</table>

For those regions that showed improvement from the data mining, the areas of highest correlation were:

- Western North- and South-Pacific cyclones were best related to areas immediately to their east
- The North Atlantic was best predicted by the MDR region – a well-known result (e.g., Bruyère et al. 2012)
- The highest GOM correlations were slightly west of the MDR

4.4 Concluding Discussion

This initial analysis of the use of cyclone genesis indices for assessing annual tropical cyclone frequency has indicated considerable variability in skill. In almost all cases, basin index averages provided worse results than selected regions of optimal performance. Of the three indices, the CGI performed consistently best. Comparing ocean basins, no useable relationships were found for the North Indian, and eastern South Indian basins. The best relationships were found for the North Atlantic and the Gulf of Mexico.

The Gulf of Mexico relationship is being developed further for use in future climate assessments for the offshore energy industry in this region. Here we are utilizing a combination of high-resolution modeling and the CGI applied to global climate models to assess the likely cyclone response to both climate variability and change over the next 50 - 100 years. Continuing work also is assessing
whether other environmental indices can provide an improved assessment, particularly for those basins where the traditional index approach has proven to be unsatisfactory.

The excellent North Atlantic relationship between cyclone frequency and the MDR environment arises from African easterly waves being a major source of seedlings for tropical cyclones in this region (see, e.g., Bruyère et al. 2012 for discussion). The physical processes leading to the relationships in the western North- and South-Pacific, and the western South Indian basins are being investigated and some preliminary results will be reported in the presentation.

Figure 4.4: Observed annual tropical cyclone frequency per basin (black dashed lines), and tropical cyclone frequency as predicted by GP (blue line), GPI (green line), and CGI (red line) with basin averages on the left and optimal regions from the data mining on the right. All curves have been smoothed by a 5-year running mean.
Acknowledgments: NCAR is funded by the National Science Foundation and this work was partially supported by the Research Program to Secure Energy for America (RPSEA). Funding for the project is provided through the “Ultra-Deepwater and Unconventional Natural Gas and Other Petroleum Resources Research and Development Program” authorized by the Energy Policy Act of 2005. This program—funded from lease bonuses and royalties paid by industry to produce oil and gas on federal lands—is designed to assess and mitigate risk enhancing the environmental sustainability of oil and gas exploration and production activities. RPSEA is under contract with the U.S. Department of Energy’s National Energy Technology Laboratory to administer three areas of research. RPSEA is a 501(c) (3) nonprofit consortium with more than 180 members, including 24 of the nation’s premier research universities, five national laboratories, other major research institutions, large and small energy producers and energy consumers. The mission of RPSEA, headquartered in Sugar Land, Texas, is to provide a stewardship role in ensuring the focused research, development and deployment of safe and environmentally responsible technology that can effectively deliver hydrocarbons from domestic resources to the citizens of the United States. Additional information can be found at www.rpsea.org.

REFERENCES


5. **Journal Article**: *Bias Corrections of Global Models for Regional Climate Simulations of High-Impact Weather*

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This paper has already been published in Climate Dynamics  

Consent from co-authors is attached as an addendum.

Journal information and guidelines are available from:  

Open Access and copy write information is available here:  
http://www.springer.com/open+access/open+choice?SGWID=0-40359-0-0-0
The objective of the article is to demonstrate how to remove biases by utilizing the predictive changes from the GCM models as boundary conditions for regional climate models. Statistical methods to remove biases from the boundary conditions are not perfect and have the potential for introducing new errors. For example, dynamical fields will no longer be in balance since each field is bias corrected independently. These imbalances are small and no more significant than the imbalances introduced through interpolating low-resolution driving data to the higher resolutions of RCMs.

A second, important potential uncertainty to acknowledge is the question of stationarity of biases under non-stationary conditions. Ehret et al. (2012) suggested that biases might be sufficiently stationary to make them acceptable for climate change impact studies. In this article we demonstrated that for the 40-year period 1960-2000 the bias was indeed stationary, thus increasing our confidence that the bias will not change substantially in the future.

Abstract

All global circulation models (GCMs) suffer from some form of bias, which when used as boundary conditions for regional climate models may impact the simulations, perhaps severely. Here we present a bias correction method that corrects the mean error in the GCM, but retains the six-hourly weather, longer-period climate-variability and climate change from the GCM. We utilize six different bias correction experiments; each correcting different bias components. The impact of the full bias correction and the individual components are examined in relation to tropical cyclones, precipitation and temperature. We show that correcting of all boundary data provides the greatest improvement.
5.1 Introduction

Global Circulation Models (GCMs) provide the basis of our capacity to simulate, understand and predict climate variability and change. These models are based on established physical laws and have proven fidelity for assessing changes to global quantities (Randall et al. 2007; Anderson et al. 2004; Collins et al. 2004; Déqué et al. 1994; Flato et al. 2013; Pope et al. 2000; Roeckner et al. 2003). However, GCMs typically are of too a coarse resolution to directly infer climatology of high-impact weather at local scales and it is common to downscale over regions of interest using statistical techniques or nested regional climate models. Unfortunately, biases that may be acceptable at global scales can be problematic for these downscaling applications to regional and extreme weather climate scales (e.g. Liang et al. 2008; Ehret et al. 2012; Xu and Yang 2012; Done et al. 2013).

One approach is to apply combined bias-correction and downscaling methods directly to the GCM data in the form of empirical relationships between the large scales and high impact weather (Camargo et al. 2007; Walsh et al. 2007; Bruyère et al. 2012). An obvious shortcoming of this method is that this bias correction is applied independently across time, space and variable, without taking into account feedback mechanisms between atmospheric processes. It is important to also remember that the GCM data were generated at a coarse resolution, where local processes and terrain heterogeneity were not taken into account. It also is possible that statistical downscaling methods developed on past climate might not hold true under climate change conditions.

An alternative, widely-used approach is to nest a Regional Climate Model (RCM) within GCM boundary conditions (Laprise et al. 2008; Bender et al. 2010; Knutson et al. 2007, 2008; Walsh et al. 2004; Done et al. 2013). Because of their smaller domain, RCMs can operate at higher resolution than GCMs to enable simulation of much finer scale features, which are required for assessment of many extreme weather phenomena. One shortcoming of this approach is the transmission of GCM biases through the RCM lateral and lower boundaries, which may have a severe impact on the interior climate (e.g. Warner et al. 1997; Done et al. 2013).

One approach to correcting these regional biases is to apply a correction to the RCM output (e.g. Dosio and Paruolo 2011). This approach suffers from the same limitations as the aforementioned statistical bias correction of GCMs and has the additional complication that GCM biases may irretrievably change - or even destroy - the high-impact weather signal of interest (Ehret et al. 2012; Done et al. 2013).
An alternative bias-correction approach is to construct boundary conditions from a current climate reanalysis plus a climate change perturbation, a technique known as pseudo-global-warming (Schär et al. 1996; Rasmussen et al. 2011). This approach is simple to apply and takes advantage of the improved ability of GCMs to simulate trends compared to absolute climates (Randall et al. 2007). However, there are substantial disadvantages arising from the inherent assumption of no change in synoptic and climate variability. Biases from current GCM simulations also may change into the future and alias into the imposed climate change perturbation.

A more recent approach takes advantage of the strengths in both the GCMs and RCMs by performing bias correction on the GCM boundary data. Using a common bias-correction method applied to all variables provides more balanced atmospheric conditions to drive the RCM. Variance is free to change into the future (within the resolution constraints of the driving GCM) and the RCM has the freedom to develop its own interior solution within the bias corrected boundary data. A number of variations on this theme have been attempted including; correcting bias in the mean and variance (Xu and Yang, 2012), quantile-quantile mapping (Colette et al. 2012), and feature location correction (Levy et al. 2012). White and Toumi (2013) tested both the mean bias correction and quantile-quantile mapping methods, and found that the mean bias correction method is a more reliable and accurate method compared to the quantile-quantile mapping method.

In this study we investigate the applicability of bias correcting the boundaries in RCM simulations of high-impact weather. The environments for Atlantic tropical cyclones and North American summer precipitation and temperatures are used as examples, but the results are applicable to a wide range of weather extremes.

In Section 5.2 a bias correction method for GCM boundary conditions is developed that successfully reproduces the statistics of high-impact weather in the regional climate simulation. We then develop physical insight into the role of bias correction for the downscaled regional climate in Section 5.3 through analysis of the simulation sensitivity to bias correction of specific variables or sets of variables in the driving data. The results are presented in Section 5.4. Section 5.5 contains our conclusions.
5.2 Methodology

5.2.1 Models and Data

The GCM used here is the Community Climate System Model version 3 (CCSM3; Collins et al. 2006) run at T85 (~1.4° atmosphere and 1° ocean). CCSM3 is a coupled climate model with components representing the atmosphere, ocean, sea ice, and land surface as described in detail in Collins et al. (2006). The simulation was initialized in 1950 and run under 20th Century emissions.

The NCAR Weather Research and Forecasting model (WRF; Skamarock et al. 2008) is nested into CCSM3 for downscaling as the Nested Regional Climate Model (NRCM, Done et al. 2013). The WRF model is a fully non-hydrostatic model, and is routinely used for real-time hurricane forecasting (Davis et al. 2008) and regional climate studies (see the discussion in Done et al. 2013). The NRCM domain (Fig. 5.1) extends from 10S to 60N, and from 160W to 50E. Grid resolution is ~36 km with 51 vertical levels. All model simulations used the Kain–Fritsch convective parameterization scheme (Kain 2004), WSM6 microphysics scheme (Hong and Lim, 2006), CAM long- and shortwave radiation schemes (Collins et al. 2004), the Yonsei University planetary boundary layer scheme (Hong et al. 2006), and the Noah land surface model (Chen and Dudhia, 2001).

The atmospheric reanalysis used to bias correct the CCSM3 data is the National Centers for Environmental Prediction–National Center for Atmospheric Research (NCAR) Reanalysis Project (NNRP, Kalnay et al. 1996). Analysis SST data utilize the merged Hadley Centre and NOAA’s optimum interpolation (OI) SST data set (Hurrell et al. 2008).

Figure 5.1: Regional domain used for all RCM simulations. Shading represents terrain height (m).
Figure 5.2: 20 year (1975-1994) Aug-Sep-Oct mean bias (CCSM3 – NNRP) for a) Sea Surface Temperature (K), b) 850-200 hPa Wind Shear (ms⁻¹), c) 700 hPa Relative Humidity (%), d) 200 hPa Temperature (K), and e) Cyclone Genesis Index.

5.2.2 Bias Correction

Note that here we are using the term bias in the context of systematic errors in the model, as compared to some base ‘truth’ (specifically the NNRP). We also partially consider the ‘bias’ that may arise from sampling from relatively short time periods within a climate that varies on long and short time scales (e.g. Mauran 2012). This is accomplished through our use of a limited set of longer simulations. A related ‘bias’ arising from the essentially nonlinear nature of climate, which means that more than one internal solution may result from the same imposed boundary conditions is the subject of a separate study.

The CCSM3 model output contains substantial mean biases compared to NNRP and OI-SST data (Fig. 5.2). A cold SST bias over the North Atlantic Ocean and a warm SST bias along the west coasts of the Americas (Fig. 5.2a; Large and Danabasoglu, 2006) results in a permanent El Niño-like condition and this drives a high vertical wind-shear bias (defined as the difference in winds between 200 and 850
hPa, Fig. 5.2b) over the tropical Atlantic through a modified Walker Circulation (e.g. Gray 1984). In addition, the CCSM3 is drier (Fig. 5.2c), and colder aloft (Fig. 5.2d) than the NNRP.

Figure 5.3: Tropical storms generated by the RCM over the 11-year period 1995-2005 when driven by a) raw CCSM3 data, b) bias corrected CCSM3 data, c) and observed TC tracks from an arbitrary 11 year current period.

Application of the Cyclone Genesis Index (CGI, Bruyère et al. 2012) indicates a significant low bias over the North Atlantic (Fig. 5.2e), a result of the combined cool SST and high vertical shear over the development region. This is confirmed when the NRCM is driven with the raw CCSM3 model data with resulting suppression of almost all tropical cyclone development (Fig. 5.3a) to an average of only 1.5 storms per year, compared to the observed average of ~9-12 (Knapp et al. 2010). The storms that
occur also tend to develop much further poleward than observed (Fig. 5.3c), away from the regions of high shear and low moisture shown in Fig. 5.2.

Bias correction of the CCSM3 boundary conditions uses the approach in Holland et al. (2010) (see also Xu and Yang, 2012; and Done et al. 2013), which can be applied consistently across variables and times. This corrects the mean bias from the GCM, but allows synoptic and climate variability to change and is similar to the approach used in Maraun (2012). Six-hourly GCM data are broken down into a mean seasonally-varying climatological component (\( \overline{GCM} \)) plus a perturbation term (\( GCM' \)):

\[
GCM = \overline{GCM} + GCM'
\]  

(5.1)

The mean climatological component is defined over a 20-year base period (to smooth out influence of short-period variations such as \( El \; Niño \)). Twenty years was chosen to avoid inclusion of any significant climate trends though we acknowledge that this may alias some decadal oscillations into the bias correction.

The NNRP reanalysis and OI-SST (Obs) is similarly broken down into a seasonally-varying mean climatological component (\( \overline{Obs} \)) and a six-hourly perturbation term (\( Obs' \)):

\[
Obs = \overline{Obs} + Obs'
\]  

(5.2)

The bias corrected climate data for the NRCM boundary conditions, \( GCM^* \), are then constructed by replacing the GCM climatological mean from Eq. 5.1 with the Obs mean from Eq. 5.2:

\[
GCM^* = \overline{Obs} + GCM'
\]  

(5.3)

These bias-corrected climate data thus combine a seasonally-varying climate, as provided by NNRP and OI-SST, with the six-hourly weather from the GCM. This approach also retains the GCM longer-period climate variability and climate change.

Equation 5.3 is applied to all the variables required to generate surface and lateral boundary conditions for NRCM: zonal and meridional wind, geopotential height, temperature, relative humidity, sea surface temperature and mean sea level pressure.
5.3 Results

5.3.1 CCSM Bias Corrections

Figure 5.4 illustrates the SST bias-correction changes to the CCSM3 data. Represented in this figure is the average Aug-Sep-Oct (ASO) SST over the hurricane Main Development Region (MDR, 5-20°N; 20-60°W) from observations, together with the raw and bias-corrected CCSM3 simulation. The MDR was chosen as an indicative example because of its importance as an indicator of Atlantic tropical cyclone activity (Bruyère et al. 2012). However, any region - including the entire model domain - together with other variables or time averages could equally well have been chosen. Compared with observations (black line), the CCSM3 raw data (grey line) have a cold bias of almost 2K. The bias correction procedure brings the revised CCSM3 time series (blue line) up to values within the observed SST error range (less than 0.1°C over the North Atlantic) as specified by Hurrell et al. (2008).

We next examine the sensitivity of the revised climate to the choice of the base period arising from a possible non-stationarity of the bias. Choosing different base periods (1960-79, 1965-84, 1970-89, and 1975-94) result in nearly identical bias corrections over the entire simulation period (Fig. 5.4). This increases confidence that the bias will not change substantially in the future. The validity of this assumption is further addressed in the climate projection discussion.

Figure 5.4: Aug-Sep-Oct mean Sea Surface Temperature over the MDR off the coast of Africa for: observations (black); raw CCSM3 (grey); mean bias corrected CCSM3 data using different base periods 1960-79, 1965-84, 1970-89, and 1975-94 (green, purple, teal and blue); and mean and variance bias corrected CCSM3 data using the base period 1975-94 (dashed red).
The dashed red line in Fig. 5.4 shows the affect of including variance bias correction in addition to the mean correction (following the method of Xu and Yang, 2012). Clearly, accounting for variance in addition to mean bias makes only a marginal difference. This is supported by the NRCM downscaling with mean bias-only correction. For current climate, the variance in 500 hPa temperature over the MDR is 0.88 for NNRP and 0.62 for the CCSM3 model. Yet, the NRCM with mean bias correction has a variance of 0.96, indicating that it is effectively spinning up realistic internal variance without the need for additional variance bias correction.

5.3.2 NRCM Downscaling

Sensitivity to choice of variables used for bias correction is examined using a series of NRCM simulations with the following boundary conditions: raw CCSM3 data (NO_BC); bias corrected winds only (BC_UV); bias corrected SST only (BC_SST); bias correction of both the winds and SST (BC_SSTUV); all variables excluding SST corrected (BC_NoSST); and all boundary data corrected (BC). These simulations cover a seven months period from May 1 to Dec 1, for an arbitrarily chosen year representative of current climate. Note that for the surface only the SST is prescribed, the land is free to evolve in NRCM.

Analysis of these sensitivity runs uses the ASO average large-scale flow, however, since the anomalies in a single year may not be representative of the anomaly over a longer period, we also compare the NO_BC and BC cases for a total of 11 years, using the first year as a spin-up year, and years 2 to 11 for the analysis period. These simulations are referred to as NO_BC10 and BC10.

Atlantic Tropical Cyclone Environment

Figure 5.5 depicts the ASO mean wind shear for the six sensitivity simulations. The NO_BC case (Fig. 5.5a) has anomalously high shear values (up to 40 ms-1) over the North Atlantic Ocean and especially in the MDR. This strong shear extends all the way to the North American coast and suppresses cyclogenesis to the point that not a single cyclone develops in the basin.

Applying bias corrections to individual or combinations of boundary variables results in the following:

- Winds (BC_UV, Fig. 5.5b) or SST (BC_SST, Fig. 5.5c) alone both reduce the shear bias substantially. This is expected: correcting the SST bias removes the anomalous Walker circulation that generates the strong vertical shear; applying wind corrections at the boundaries also suppresses this Walker circulation in the regional model. Notably, although both brought about a
similar reduction in shear magnitude, leaving the cold SST in place (BC_UV) still suppresses all cyclone activity, whereas the warm oceans (BC_SST) combined with reduced vertical shear generates three cyclones (not shown).

• Combining SST and wind corrections (BC_SSTUV, Fig. 5.5d) improves the shear values comparable to the sum of the shear improvement through correcting SST and winds independently (Figs. 5b and c). This improvement results in the genesis of five cyclones, some of which form in the MDR.

• All boundary variables (BC; Fig. 5.5e), produces shear patterns similar to those seen in observations (Fig. 5.5i), and results in the formation of 7 cyclones in the MDR and the Gulf of Mexico.

• Applying a bias correction to all boundary variables excluding SST (BC_NoSST, Fig. 5.5f) indicates the importance of getting the surface correct; the shear increases substantially and only 2 cyclones develop.

Longer period simulations for NO_BC10 and BC10 produces similar results to those of the single season simulations (NO_BC and BC), with ASO mean shear values over the North Atlantic too high for NO_BC10, and realistic values being simulated for BC10 (Fig. 5.5g,h). These longer simulations also produce similar annual cyclone numbers to those for single seasons: ~1.5 for NO_BC10 that developed too far north (Fig. 5.3a), and ~10 for BC10 with much more realistic genesis locations and storm tracks (Fig. 5.3b).

Figure 5.6 shows the ASO Root Mean Square Error (RMSE) profiles of temperature, relative humidity, height and zonal wind for the MDR, using 20-year NNRP as a basis. Since the 20-year mean is being compared with a single season, the RSME will reflect both the difference due to bias as well as interannual variability. In all cases the errors are reduced, as more boundary variables are bias corrected. This is especially notable in the upper-air. In general the NO_BC case results in the highest RMSEs and the BC the lowest. The exception is height, where results are somewhat mixed. BC_SSTUV also consistently performs well, although not as well as the BC case.
Figure 5.5: ASO mean wind shear (200-850 hPa, ms$^{-1}$) for cases with bias correction applied to: a) no variables (NO_BC), b) winds (BC_UV), c) SST (BC_SST), d) winds and SST (BC_SSTUV), e) all boundary variables (BC), f) all boundary variables excluding SST (BC_NoSST), g) no variables for a 10-year simulation (NO_BC10), h) all boundary variables for a 10-year simulation (BC10), and i) a 20-year (1975-1994) NNRP average.
Figure 5.6: RSME profiles for a) temperature (K), b) Relative Humidity (%), c) Height (m), and d) Zonal Wind (ms\(^{-1}\)).

The Taylor diagram (Taylor 2001) in Fig. 5.7 provides an alternative measure of the performance of the various boundary modifications. There is a wide spread in overall response to different boundary modifications, and this depends on the variable that is chosen, with the upper-air values, which originally showed the biggest errors, responding most to the bias correction. The one clear signal is that applying all boundary modifications (BC, black dots) consistently produces the best results. Clearly, applying a consistent correction across all relevant variables provides the best outcome for dynamical downscaling with the NRCM.
North American Summer Precipitation and Temperature

The impact of boundary bias corrections on summer precipitation over North America is shown by the ASO averages in Fig. 5.8(a-f), which can be compared with the CPC Unified Gauge-Based Analysis of daily precipitation (Fig. 5.8g; http://www.esrl.noaa.gov/psd/). A marked zonal gradient in the observed precipitation results from wet conditions along the east and Gulf coasts decreasing to generally dry conditions in the west. Although there is more noise due to the relatively short simulation periods, applying the full set of boundary conditions (BC, Fig. 5.8e) reproduces the observed pattern quite well. By comparison, using the raw boundaries (NO_BC, Fig. 5.8a) produces a simulation that is far too wet in the central and northeastern USA. Here the correction for SST has the largest single influence, as can be seen by comparing Figs. 8a,b,f (simulations without SST bias correction) with 8c,d,e (simulations with SST bias correction). When all boundary corrections are made except for SST, the bias-corrected simulation is substantially degraded (Fig. 5.8f).
Figure 5.8: ASO-average daily precipitation (mm/day) for cases with bias correction applied to: a) no variables (NO BC), b) winds (BC_UV), c) SST (BC_SST), d) winds and SST (BC_SSTUV), e) all boundary variables (BC), f) all boundary variables excluding SST (BC_NoSST), and, g) 20-year ASO-average daily CPC Unified Gauge-Based Analysis of Daily Precipitation.

North American temperature simulations, although more robust than other variables, are also improved by the application of a bias correction at the boundaries (Fig. 5.9). Figure 5.9 depicts the normalized distribution of ASO maximum daily surface temperature (2m level) over the continental
USA for the 6 sensitivity runs (color lines), as well as the 20-year mean distribution from observations (dashed grey line). The light grey shading indicates the variance over the 20 observed years. The observed mean daily maximum surface temperature is around 23°C, with the year-to-year variations from 21.5°C to 23.5°C. Applying raw boundary conditions results in a substantial regional cooling of 2-3°C in the NRCM simulations compared to observations. Applying bias correction to specific variables or sets of variables improved this cold bias and, as with other experiments, using all boundary condition corrections together provided the greatest improvement.

![Figure 5.9: Normalized distribution of ASO maximum daily surface temperature (2m level) over the continental USA for observations and the six different sensitivity runs. The dashed grey line is the 20-y distribution of observed surface temperatures, with the light grey shading indicating the variance over the 20 observed years.](image)

5.4 Conclusions
Biases in GCMs are transferred through lateral and lower boundary conditions to RCMs, impacting the downscaled results, sometimes severely. Here we examined application of a bias correction method that corrects the seasonally-adjusted mean error in the GCM but retains the weather
variance, longer-period climate variability, and climate change from the GCM. The correction is nearly independent of the period over which it is developed, giving confidence that such corrections will be somewhat invariant in future projections. Corrections to both mean and variance were considered, but the variance correction made very little difference, as the NRCM was able to successfully reproduce the observed variance internally.

The impact of both the full bias correction and individual components were examined in relation to simulations of the North Atlantic tropical cyclone environment and North American precipitation and temperatures.

A consistent result was achieved for all three components. Using the uncorrected climate model boundary conditions resulted in substantial errors, including suppressing almost all tropical cyclones. Applying the full correction to all boundary variables substantially improved the simulations compared to observations: simulated tropical cyclones had realistic spatial distributions and annual frequency; North American precipitation distribution and magnitude was substantially improved; and the probability distribution of surface temperatures moved from a distinct cold bias to a better approximation of observations.

Correcting individual and groups of boundary variables in isolation indicates that the biggest single improvement came through correcting the SST. Correcting both SST and winds at the horizontal boundary provided the majority of the improvement. But in all cases correcting all boundary variables in a consistent manner was better than correcting any subset of variables.

These findings suggest that application of a relatively simple bias correction to the GCM boundary conditions for a regional climate model - in which only seasonal variability is included - may suit many regional climate applications. A particular strength of this approach is that it enables current-climate variability within the GCM (weather, decadal and climate change) to vary with future simulations while correcting for the major biases that can cause serious issues for regional climate downscaling.

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REFERENCES


6. **Journal Article:** *Modeling High-Impact Weather and Climate: Lessons from a Tropical Cyclone Perspective*

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Thesis Objective

A weakness of GCMs is that due to their coarse resolution, these models are not able to represent small-scale processes or extreme events. On the other hand, Regional Climate Models (RCMs) typically have resolutions high enough to enable simulation of key features of extreme weather events. Even though RCMs are expensive to run, and therefore necessitate limited simulations, these runs can be used to validate statistical methods, which are much more cost effective to run. The objective of this article is to show how we applied the Weather Research and Forecasting (WRF) model, essentially a weather model, as a regional climate model, along with lessons learnt and best practices.

Abstract

Although the societal impact of a weather event increases with the rarity of the event, our current ability to assess extreme events and their impacts is limited by not only rarity but also by current model fidelity and a lack of understanding and capacity to model the underlying physical processes. This challenge is driving fresh approaches to assess high-impact weather and climate. Recent lessons learned in modeling high-impact weather and climate are presented using the case of tropical cyclones as an illustrative example. Through examples using the Nested Regional Climate Model to dynamically downscale large-scale climate data the need to treat bias in the driving data is illustrated. Domain size, location, and resolution are also shown to be critical and should be adequate to: include relevant regional climate physical processes; resolve key impact parameters; and accurately simulate the response to changes in external forcing. The notion of sufficient model resolution is introduced together with the added value in combining dynamical and statistical assessments to fill out the parent distribution of high-impact parameters.
6.1 Introduction

In recent years, society has faced a steep rise in economic and insured losses from weather and climate related hazards, largely due to significant increase in exposure (e.g. Kunreuther and Michel-Kerjan 2009). Projections of a continuing trend towards more intense systems (see Knutson et al. 2010; Holland and Bruyère 2013 for the case of tropical cyclones) point to a further increase in societal vulnerability. More accurate information on high-impact events, is thus a critical need of society. This requires assessments of the statistics of high-impact events and the associated uncertainty with regional clarity together with potential changes under climate variability and change.

Meeting these demands requires a combination of dynamical and statistical components. The traditional dynamical approach combines the capacity of regional high resolution to simulate weather events with the capacity of global coarse resolution to simulate climate by embedding high resolution within the global mesh over regions of interest (e.g. Laprise et al. 2008; Knutson et al. 2007). Increases in computational capacity have enabled such simulations in unprecedented detail (e.g. Bender et al. 2010). Regional modeling studies are subject to uncertainty and careful consideration is required of the balance between model complexity to resolve the relevant physical processes, ensemble size to sample uncertainty in the driving data, and simulation length to capture the full distribution. These competing demands for computational resources often results in a truncation of the full distribution of high-impact events and this has led to exploration of a variety of solutions including the use of empirical relationships between weather systems and the large-scale environment (e.g. Camargo et al. 2007), and assessment of errors in frequency distributions of weather events from dynamical models (e.g. Katz, 2010).

Meeting the societal demand of assessing high-impact events with regional clarity remains extremely challenging. This paper presents an overview of recent lessons learnt in modeling high-impact events on regional scales using the case of tropical cyclones. Tropical cyclones represent a hard test case for simulating high-impact weather owing to their rarity, regional variability and uncertain future regional changes (see for example large variations between the modeling studies of Knutson et al. 2007, 2010 and Bengtsson et al. 2007). The merits and limitations of the dynamical modeling approach are discussed and motivate, by way of illustrative examples, the need for combined dynamical-statistical approaches in order to provide credible and useful information.

The next section describes simulation experiments with the Nested Regional Climate Model (NRCM), a dynamical downscaling tool based on the Weather Research and Forecasting (WRF) model
Lessons Learned

(Skamarock et al. 2008) designed specifically to contribute to assessments of high-impact events. Atmosphere-only NRCM simulations of current and future North Atlantic tropical cyclone activity are presented to illustrate current limitations and sensitivities of the dynamical model approach. The value of complementary statistical approaches is illustrated in Section 6.3. Finally, key findings are summarized in Section 6.4.

6.2 Dynamical Assessments

Here multi-year NRCM simulations of high-impact weather are assessed using limited area domains to identify the impact of climate bias, domain size and resolution; and to explore and document critical sensitivities of this dynamical modeling approach.

Global climate data are provided by Community Climate System Model (CCSM, Collins et al. 2006) version 3 using the A2 scenario (IPCC SRES SPM 2000), from the Coupled Model Intercomparison Project 3 (CMIP3, Meehl et al. 2007). The CCSM is a full Earth system model, including atmosphere, ocean, cryosphere, biosphere, and land surface. These data are used to drive a NRCM 36 km domain using one-way nesting, which in turn is used to drive a 12 km domain (Fig. 6.1) to explore the additional information, if any, provided by the higher resolution. One-way nesting is chosen to avoid the unknown implications of using two-way nesting and for the practical reason of running each domain separately and checking the simulation prior to further downscaling. A description of the NRCM and physics used is provided in the supplemental online material (SOM) section S1.

The simulations cover three periods: a decade of ‘current’ climate conditions (1995-2005) referred to hereafter as ‘base climate’, and two future decades of 2020-2030 and 2045-2055. The time periods are nominal since the driving CCSM model was initialized in 1950 with no additional assimilated data. Thus, for example, model interannual and multidecadal variations are not expected to match those in the real world, though the historical anthropogenic trend associated with greenhouse gases should be captured.
6.2.1 *Domain Size, Location and Horizontal Resolution*

Domain size and horizontal resolution are key factors for regional climate simulation (e.g. Vannitsem and Chome 2005) and tropical cyclone simulation (e.g. Kumar *et al.* 2011). High resolution is required to adequately resolve the intensity of strong tropical cyclones (Bender *et al.*, 2010), particularly if they are small. Resolution also affects cyclone structure (Fig. 6.2). At 36 km the simulated cyclone has a simple circular structure whereas at 12 km sub-system-scale structure emerges in the form of eye-wall asymmetries and spiral rain bands. As the grid-spacing is reduced further the shift from parameterized towards explicit convection can additionally impact other cyclone characteristics including; genesis mechanism (Kieu and Zhang 2008), eye-wall replacement cycles and rapid intensification (Davis *et al.* 2008), and upscale impacts through vertical redistributions of heat and momentum (as discussed in Leung *et al.* 2006). Finally, cyclone frequency is also found to be sensitive to resolution (SOM text, section S3). Whether this is due to changes in small- or large-scale processes is unknown. Caron *et al.* (2010) and Caron and Jones (2011) found high resolution was necessary for the intensity of easterly waves and even for accurate representation of the large-scale environment over the eastern Atlantic.
Large nested domains have been shown to improve the simulation of all scales within the domain interior above those in the driving global data (Jones et al. 1995; Laprise et al. 2008) and reduce spatial spin-up issues by moving the inflow boundary far from the region of interest (Leduc and Laprise 2009). Critically, the domain needs to be sufficiently large to capture regional physical processes (Giorgi and Mearns 1999) not only to assess high-impact weather in current climate but also to capture the correct climate response. A domain that is smaller than the main external modes of variability is closely coupled to the driving model (somewhat similar to nudging), and where small scales are important to these modes, the domain size needs to be large to enable this upscale interaction to occur. For example, Caron and Jones (2011) constructed a domain to capture relationships between Atlantic SSTs, Sahelian rainfall and tropical cyclogenesis.

Guided by these findings, available resources for this study are directed to domain size and resolution at the expense of run length and ensemble size so a single simulation is run on each domain. The 36 and 12 km domains are far larger than North America, our target region, to ensure the majority of atmospheric processes that impact the region are handled by the higher resolution model rather than the coarser climate model. As a specific example, African easterly waves are not well captured by the CCSM simulation, necessitating the inclusion of the African wave source and development region within the 36 km domain (see SOM section S3 for discussion on the representation of easterly waves).

6.2.2 Climate Bias

Global climate models commonly contain climate bias and despite the large domain, the NRCM-generated climate driven directly by CCSM data contains substantial biases. Anomalously strong
large-scale flow at upper-levels over the tropical North Atlantic produces strong vertical wind shear, defined as the difference in winds between 200- and 850-hPa (Fig. 6.3a), thereby preventing tropical cyclogenesis. Sensitivity studies (not shown) reveal that this bias is transferred to the NRCM from CCSM, in part due to dynamical propagation from the east and west boundaries but also due to a warm eastern Pacific Ocean SST bias (Large and Danabasoglu 2006). This permanent El Niño-like condition contributed to the high vertical wind shear in the NRCM over the tropical Atlantic through a modified Walker Circulation (e.g. Gray 1984). One approach to correcting bias is to statistically correct the NRCM model output (Dosio and Paruolo 2011) but here this post-processing approach is not suitable since the biased climate did not generate any tropical cyclones, thereby necessitating bias correction of the driving CCSM data prior to NRCM simulation.

A popular approach to assessing regional climate change that implicitly removes bias is the pseudo-global-warming approach (Schär et al. 1996; Rasmussen et al. 2011). In this approach, reanalysis data are used for current climate and future climate is constructed by adding a perturbation, intended to represent the mean climate change, to the reanalysis data. This approach assumes no change in variability at the domain boundaries and for small domains will constrain the frequency of weather events to current climate only. An alternative bias correction technique is used here that allows synoptic and climate variability to change in the future. Six-hourly CCSM data for the entire simulation (1950-2100) are broken down into an average annual cycle plus a perturbation term:

\[
\text{CCSM} = \text{CCSM} + \text{CCSM}',
\]

where CCSM’ varies in time throughout the entire 150-year CCSM simulation period and includes both high-frequency variability and climate trends. The average annual cycle is defined over a 20-year base period (to smooth out any influence of El Niño) from 1975 to 1994. Twenty years may not be sufficient to smooth out influence of multi-decadal variability but is chosen to avoid inclusion of any climate trends. Similarly, 6-hourly NCEP/NCAR Reanalysis Project (NNRP; Kalnay et al. 1999) data for 1975-1994 are broken down into an average annual cycle plus a perturbation term:

\[
\text{NNRP} = \text{NNRP} + \text{NNRP}',
\]

The revised climate data, CCSM_R, are then constructed by replacing CCSM in Eq. 6.1 with NNRP in Eq. 6.2:

\[
\text{CCSM}_R = \text{NNRP} + \text{CCSM}',
\]
CCSM\textsubscript{R} therefore combines a base, seasonally varying climate provided by reanalysis data with day-to-day weather, climate variability (e.g. synoptic weather systems, ENSO) and climate change provided by CCSM. This approach is similar to the method used by Xu and Yang (2012) that additionally corrects for variability bias. We choose here to correct only the mean bias, specifically to reduce the strong wind shear. Although the variance in CCSM’ is generally slightly smaller than NNRP’ over the base period, the regional model driven by CCSM\textsubscript{R} recovers this difference in variance (not shown). Equation 6.3 is applied to variables needed to generate the lateral boundary conditions for NRCM; zonal and meridional wind, geopotential height, temperature, relative humidity, mean sea level pressure, and lower boundary condition of sea surface temperature. When driven by revised boundary conditions, the NRCM develops substantially improved wind shear over the tropical Atlantic (Fig. 6.3).

There may be sensitivity of the revised climate to the choice of the base period arising from non-stationarity of the bias, but fortunately this is not the case here. Sensitivity studies using different base periods result in nearly identical bias corrections over the entire simulation period. This increases confidence that the bias will not change substantially in the future, though the validity of this assumption needs further consideration. Further justification for this approach is provided by Mote \textit{et al.} (2011), who showed that for assessing changes between a current and future period, a biased model for current climate is as valid as an unbiased model. On the other hand, Dosio and Paruolo (2011) showed the assumption of constant bias in time may only be appropriate for ensemble mean quantities rather than for individual model projections.

\textbf{6.2.3 Future Changes in Tropical Cyclone Frequency}

NRCM simulated tropical cyclones are identified and tracked automatically following Suzuki-Parker (2012) and described briefly in the SOM section S2. On the 36 km domain the NRCM driven by revised CCSM data produces an average of 7.6 North Atlantic tropical cyclones annually for base climate. As noted earlier the model base climate period 1995-2005 is nominal. This introduces ambiguity as to the selection of observational period used for model evaluation. The selection of 1975-1994 as base period for the bias correction leads to this being one logical choice. In this case the comparative annual number of observed North Atlantic named tropical cyclones (including tropical storms and hurricane categories 1-5) is 8.9 (using IBTrACS data; Knapp \textit{et al.} 2010). Alternative choices are the average over, say, the recent 50 years (1958-2007) of 10.4, or the current (1995-2005) high period of 14.3 cyclones per year. Regardless of the choice of observational period for comparison, NRCM appears to underestimate the actual frequency. This frequency
underestimate could easily be corrected by tuning the detection criteria but the detection parameters are deliberately frozen at fixed values. Of importance to this study, Suzuki-Parker (2012) showed that the future changes in cyclone frequency are not impacted by the choice of detection values.

Figure 6.3: Three-month average vertical wind shear (200 – 850hPa, ms$^{-1}$) for the period August-October 1996 for (a) NRCM driven by raw CCSM data; (b) NRCM driven by revised CCSM data; (c) raw CCSM data, and (d) NNRP data. Adapted from Holland et al. (2010). Copyright 2010 OTC. Reproduced with permission of the copyright owner.
The NRCM predicts an increase in North Atlantic tropical cyclone frequency, with annual numbers on the 36 km domain increasing from 7.6 in the base climate to 8.5 in 2020-2030 and 10.4 in 2045-2055. This is a statistically significant increase (using the Wilcoxon-Mann-Whitney rank-sum test; Wilks 2006) at the 90% level and represents a 37% in North Atlantic tropical cyclone frequency over the next 50 years. Annual numbers of cyclones on the 12 km domain, using the same detection criteria as for 36 km, are higher at 17.3, 17.5 and 19.9 for the three time slices, but show a similar increase (though not significant) of 15% over the next 50 years. These results are different from those of other studies, which have tended towards predicting small changes and if anything a decrease in overall Atlantic tropical cyclone frequency over coming decades (e.g., Knutson et al. 2010; Bengtsson et al. 2007), and serves to highlight the large uncertainty in determining changes in high-impact events on regional scales.

The modeled spatial distribution of North Atlantic tropical cyclone track and genesis densities on both the 36- and 12 km domains for base climate are close to the observed long-term climatology (Fig. 6.4). The future climate prediction exhibits a consistent southeastward shift in track density, from a maximum in the mid-Atlantic in base climate, to a low-latitude maximum in 2045-2055 (Fig. 6.4). This prediction is a continuation of recent trends (Holland and Webster 2007) and agrees with Wu et al. (2010) who found that a relative increase in eastern Atlantic SSTs leads to changes in atmospheric circulation and near-equatorial tropical cyclone activity.

6.2.4 Future Changes in Tropical Cyclone Intensity

Modeled tropical cyclone intensity distributions show the most intense cyclones are weaker than observed (Fig. 6.5). This is a common problem due to the inability of the 36- and 12 km grids to resolve the inner core dynamics of a tropical cyclone (e.g. Knutson et al. 2008; Davis et al. 2010; Gentry and Lackmann 2010). Note also the related tendency to over-simulate moderate intensity systems, which to some extent is due to those storms that would have been more intense being held back in this region. Nevertheless, storms on the 36 km and 12 km domains experience modest future increases in mean wind speed of approximately 0.64 ms\(^{-1}\) and 0.90 ms\(^{-1}\) respectively. This increase is less than observational errors in the historical record; meaning current observation systems could not detect this change in the mean intensity.
Figure 6.4: Tropical cyclone track density (color shading) and genesis density (contours) normalized by the maximum value for (top) IBTrACS data 1975-1995, (left column) NRCM 36 km domain, (right column) NRCM 12km domain, (top row) base climate, (middle row) 2020-2030, and, (bottom row) 2045-2055. Density is defined as the number of cyclone tracks or genesis points within a 5 degree radius of a point per year. Non-normalized track and genesis densities are provided in the SOM section S4.
A more marked increase, however, is seen in the number and intensity of the most intense hurricanes that can be resolved by the model (Fig. 6.5). This is in agreement with other dynamical modeling and theoretical studies (Knutson et al. 2010) and for recent changes to current climate (Holland and Bruyère, 2013). These intensity increases may be due to future large-scale environment changes (indeed, Suzuki-Parker (2012) showed favorable future increases in SST, relative SST (Vecchi and Soden (2007) and decreasing shear in the driving CCSM data) but may also be due to the future southeastward shift of track density (Fig. 6.4) associated with potential changes in the proportion of tropical cyclones developing from easterly waves and cyclone track lengths.

Figure 6.5: Frequency distributions of 6-hourly tropical cyclone maximum wind speed (m/s) at 10m above the surface as simulated by the NRCM (top) 36km domain and (bottom) 12km domain for base climate (black line), the period 2020-2030 (dark gray), and the period 2045-2055 (light gray), and observations (IBTrACS data) for the period 1995-2005 (black dashed line). Adapted from Holland et al. (2010). Copyright 2010 OTC. Reproduced with permission of the copyright owner.
6.3 Statistical Assessments

Confidence in the variability and trends of high-impact events obtained through dynamical downscaling is limited in part by the relatively short period and small number of events that can be simulated. Fortunately, sample size can be increased substantially through statistical approaches and can aid uncertainty assessments. Such statistical assessments provide a valuable adjunct to the dynamical simulations and by way of illustration two approaches are discussed here.

6.3.1 Empirical Assessments of Tropical Cyclone Frequency

A popular statistical downscaling approach for tropical cyclone frequency is the use of empirical relationships with large-scale data taken from reanalysis or global model data (e.g., Gray 1968, 1984; Emanuel and Nolan 2004). These approaches were typically designed to capture the hemispheric seasonal cycle and typically do not do well on regional and interannual scales. For example, Menkes et al. (2011) applied four genesis potential indices to different reanalysis datasets and found poor reproduction of interannual amplitude and phase variability on regional scales. However, recent work has begun to show skill on regional, seasonal scales.

The Emanuel and Nolan (2004) index combines low-level vorticity, mid-level relative humidity, potential intensity (a measure of the vertical instability of the atmosphere, Emanuel 2000), and vertical wind shear. Bruyère et al. (2012) showed that for interannual variability and longer-term changes, the relative humidity and vorticity terms contribute nothing to the skill, though this could be due to the specific formulation of the index rather than having a physical interpretation (a general limitation highlighted by Menkes et al. 2011). Bruyère et al. (2012) also found care needs to be taken when selecting an index averaging area: for the North Atlantic, a basin-wide average was not optimal in explaining total basin cyclone frequency, whereas an average taken over the eastern tropical Atlantic (5-20°N, 60-15°W), was able to explain 72% of the annual variance of total basin cyclone frequency.

Suzuki-Parker (2012) applied the Bruyère et al. (2012) index to the same revised global data used to drive the NRCM simulations presented in section 6.2 and produced results in agreement with the NRCM dynamical results of an increase in tropical cyclone frequency of between 1 and 3 storms by the mid 21st century.
6.3.2 Extreme Value Assessment of Tropical Cyclone Intensity

One complimentary approach to assess changes to the most intense cyclones from the truncated regional climate simulations is to utilize extreme value statistics (Coles 2001). The NRCM-generated cyclone intensity distribution is truncated at maximum winds of around 43 ms \(^{-1}\) for tropical cyclones on the 36 km grid (Fig. 6.5). However, as stated earlier the NRCM predicts a shift of the truncated distribution towards more intense storms over the next 50 years (Fig. 6.5). Applications of the Weibull distribution (Weibull 1939) have been experimented with to assess associated changes in the intense cyclones. The Weibull is a stretched exponential distribution and is used here because of its history of application to modeling weather and climate extremes (e.g., Katz and Brown 1992; Mearns et al. 1984) and because it is bounded below at zero.

The Weibull Cumulative Distribution Function (CDF) and Probability Density Function (PDF) are:

\[
\text{CDF: } F(x) = 1 - e^{-\left(\frac{x}{\alpha}\right)^\beta}, \quad 0 \leq x \leq \infty \tag{6.5}
\]

\[
\text{PDF: } f(x) = \frac{\beta}{\alpha} \left(\frac{x}{\alpha}\right)^{\beta-1} e^{-\left(\frac{x}{\alpha}\right)^\beta}, \quad 0 < x < \infty \tag{6.6}
\]

The scale parameter \(\alpha\) and the shape parameter \(\beta\) both lie in the range \((0, \infty)\): \(\beta = 1\) corresponds to the exponential distribution, \(\beta = 2\) the Rayleigh distribution, and \(\beta = 3.5\) an approximation of the normal distribution. The mean and the variance of the Weibull distribution are given by:

\[
\text{Mean: } \mu = \alpha \Gamma \left(1 + \frac{1}{\beta}\right) \tag{6.7}
\]

\[
\text{Variance: } \sigma^2 = \alpha^2 \Gamma \left(1 + \frac{2}{\beta}\right) - \mu^2, \tag{6.8}
\]

where \(\Gamma\) is the Gamma function. Thus, a first-order approximation to future changes in tropical cyclone extremes can be obtained by first applying the Weibull to current tropical cyclones for the period 1995-2008 (where \(x\) in Eqns. 6.5 and 6.6 corresponds to cyclone lifetime maximum 10m wind speed, using IBTrACS; Knapp et al. 2010) to obtain current scale parameter \(\alpha = 37\) and shape parameter \(\beta = 1.8\) using the method of moments. Model-resolved future changes in the mean and standard deviation of tropical cyclone intensity are then used to estimate changes to these current scale and shape parameters and provide an assessment of future full intensity distributions. Finally, the changes in probability of various tropical cyclone intensities can be calculated from the Weibull exceedence probability:
\[
P(x > c) = 1 - F(c) = e^{-\left(\frac{c}{\mu}\right)^\mu},
\]

where \(c\) is the lower limit of the intensity range of interest (e.g. 69 ms\(^{-1}\) for Cat 5 hurricanes).

The small 36km NRCM-predicted changes in the resolved distribution result in a much greater change in the most intense cyclones (Fig. 6.6). Category 5 hurricanes are predicted to increase by 60% from a base climate period of 1980-1994 and by 30% from a base climate period of 1995-2008. In this application we make the assumptions that the modeled changes are indicative of the changes that would have been simulated in the full distribution, were it resolved; and there is no process that will cause a change in the unresolved tail of the distribution without any signal in the resolved component.

Another approach is to further dynamically downscale the NRCM to a resolution capable of resolving the full intensity distribution. Bender et al. (2010) took this approach using the Geophysical Fluid Dynamics Laboratory operational hurricane model to downscale to a resolution that captured the full intensity distribution and showed similar future changes to the most intense storms as reported here. This suggests that the statistical correction of the intensity distribution is a promising line of research that warrants further exploration, particularly with regard to understanding how the model intensity distribution relates to the observed intensity distribution.
6.4 Concluding Discussion

This discussion of dynamical and statistical approaches to assessing variability and change in high-impact weather events is intended to contribute to community discussion and collaboration on best practices. Key findings are:

1) Importance of domain size, location and resolution: These aspects of model setup need careful consideration in order to capture accurate regional climate and high-impact weather. Experience with the NRCM using large domains at different resolutions indicates that: higher resolution than is required to resolve the key characteristics of the high-impact events may produce little added value and may not be an optimal use of resources; and, to capture accurate regional climate and regional climate change the regional domain may need to include those forcings and circulations that directly affect the regional climate over the area of interest.

2) Treating bias: Regional climate simulations can be severely affected by biases in the driving global climate model, even when large domains are employed. A successful technique has been shown to remove such bias in a manner that retains the day-to-day weather, climate variability and change components. As climate models improve, there remains a need to treat regional biases (e.g. Muñoz et al. 2012). Further work is required to fully understand the implications of such techniques, to assess and remove changes in bias with time, and to develop new approaches to bias removal for emerging modeling tools such as regional atmosphere-ocean coupled models and global variable resolution meshes.

3) Incorporating statistics and assessing uncertainty: Confidence in high-impact weather assessments obtained through dynamical downscaling is limited by both truncation of the observed distribution and the small number of events that can be simulated. Ensemble modeling is an obvious approach to increase sample size and explore statistical uncertainty. Indeed, Strachan et al. (2013) show spread in annual TC counts in a small initial condition ensemble global atmospheric model, but this approach is computationally impractical for high resolution, large domains. The examples of empirical and extreme value approaches discussed here serve to demonstrate the high potential of combining dynamical modeling with statistical approaches in assessing high-impact weather. Their value lies in both assessments of events beyond the capacity of current dynamical models and the effective increase in sample size by the ability to use low-resolution ensembles. These lead to improved assessments of statistical uncertainty in the climatology of high-impact weather and future change.
Meeting the societal demand for assessments of variability and change in high-impact weather events with regional clarity is a challenge that extends well beyond simply improving climate simulations, and once the regional climate prediction has been made and the uncertainty quantified, there remains a huge gap regarding how this affects society. The past two decades of regional climate research outputs have largely been exploratory in nature and not directly aligned to the requirements of the end user. Exceptions include ensemble regional downscaling programs and bias corrected and statistically downscaled CMIP3 archives. Recent work by Towler et al. (2012) went a step further by incorporating NRCM-generated climate change data into a risk-based approach to assess ecological impacts and inform conservation efforts. The field is wide open to develop the concepts discussed here further and to more fully integrate with societal impact assessments.

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Supplemental Material

(NRCM), details of the automated tropical cyclone tracking algorithm, and presents results of simulations of the global tropics that were conducted to establish the capacity of the NRCM in simulating tropical cyclone activity.

S1. The Nested Regional Climate Model

The NRCM is based on the Weather Research and Forecasting (WRF) model (Skamarock et al. 2008) version 3.1 nested into either global reanalysis or a global climate model data with options selected for long-term simulation as described in Leung et al. (2005) including; a wide lateral boundary zone
(following Giorgi et al. 1993) with combined linear-exponential relaxation following Liang et al. (2001); and, updated lower boundary conditions of sea surface temperature, surface albedo and vegetation fraction. Atmosphere-ocean interaction is limited to one-way only from the ocean to the atmosphere. A hydrostatic pressure vertical co-ordinate is used with 51 levels such that levels are terrain following near the surface transitioning to pressure surfaces near the model top at 10 hPa. Resolution is highest in the boundary layer to capture small-scale variability.

Model physical parameterizations are chosen based on test simulations of seasonal rainfall totals and spatial distributions over the maritime continent when compared with Tropical Rainfall Measuring Mission Multisatellite Precipitation Analysis data (Huffman et al. 2007). Shortwave and longwave radiation is treated using the CAM3 radiation scheme (Collins et al. 2006), and includes the radiative effects of ozone and aerosol and time varying (yearly) greenhouse gases consistent with the A2 scenario of the boundary condition data. Cumulus convection is parameterized using the Kain-Fritsch scheme (Kain and Fritsch 1990), including a parameterization of shallow convection. Explicit precipitation processes are parameterized by the WRF single moment 6-class microphysics (Hong and Lim, 2006). Boundary layer and surface processes are represented by the non-local YSU boundary layer scheme (Hong and Pan, 1996), and the Noah land surface model (Chen and Dudhia, 2001) with 5 soil layers.

Figure 6.S1: NRCM model domains at 36 km grid spacing (large black box) and 12 km grid spacing (small black box). Model terrain height (shaded) is shown at the different model resolutions and extends beyond the 36 km domain to indicate the resolution of the NNRP driving data.
S2. Automated Tropical Cyclone Tracking

NRCM simulated tropical cyclones are identified and tracked automatically. Full details of the algorithm are provided in Suzuki-Parker (2012) and described briefly here. Local minima in surface pressure are first checked for 850hPa vorticity > $10^5 \text{s}^{-1}$ and 10m wind speed > 17ms$^{-1}$ within 1º radius of the surface pressure minima. Next, vortex structure is checked for: sum of temperature anomalies at 300-, 500- and 700-hPa > 0K; temperature anomaly at 300hPa greater than the temperature anomaly at 850hPa; and, wind speed perturbation larger at 850hPa than 300hPa. In addition, the cyclone phase parameters of Hart (2003) are checked for B (cyclone thermal symmetry) < 10, -VTL (lower tropospheric thermal wind) > 0 and –VTU (upper tropospheric thermal wind) > 0. Finally, a 2-day duration criterion is imposed.

S3. Global Tropical Cyclone Activity

Results are presented from simulations using NRCM configured as a tropical channel model. For this experiment the NRCM is driven by data from the NCEP/NCAR Reanalysis Project (NNRP; Kalnay et al. 1996) at 2.5º lat/lon grid spacing at the north and south lateral boundaries (45ºN and 45ºS, as shown in Fig. 6.S1), as well as prescribed sea surface temperatures (Hurrell et al. 2008). The model is initialized on 1st January 2000 and runs though 1st January 2006 using a grid spacing of 36 km. An additional simulation is conducted with a two-way nest at 12 km grid spacing over the North Atlantic (Fig. 6.S1) for the period 1st May 2005 through 1st Dec 2005 to probe the sensitivity of tropical cyclone simulation to model resolution. No nudging of the NRCM to NNRP data is applied in the interior of the domain.

The NRCM produces a reasonable temporal and spatial distribution of global tropical cyclone activity (Suzuki-Parker, 2012) but overproduces the total number by typically 20-30% depending on the year compared to observations (using IBTrACS data, Knapp et al. 2010). This bias is in part subject to details of the tracking algorithm (Suzuki-Parker, 2012); here the algorithm is not tuned to fit a specific model grid spacing to avoid interpreting the results of tuning as model skill. Tulich et al. (2009) suggested that the bias is correlated to generally overactive easterly waves, particularly over the Northwest Pacific. Over the tropical North Atlantic, however, further examination shows that the easterly waves are generally too weak and dry, contributing to reduced tropical cyclogenesis in the eastern Tropical North Atlantic.
Figure 6.S2: Tropical cyclone track density (color shading) and genesis density (contours) for (top) IBTrACS data 1975-1995, (left column) NRCM 36 km domain, (right column) NRCM 12km domain, (top row) base climate, (middle row) the time slice 2020-2030, and, (bottom row) the time slice 2045-2055. Density is defined as the number of cyclone tracks or genesis points within a 5 degree radius of a point per year.
Lessons Learned

The 12 km nested domain improves simulation of both the number and spatial distribution of tropical cyclones for the North Atlantic, with 20 storms at 12 km and 13 storms at 36 km compared to 25 tropical storms in the observations. Interestingly, at 12 km cyclogenesis occurs in the eastern tropical North Atlantic, but not at 36 km, suggesting the importance of local high resolution. Caron et al. (2010) and Caron and Jones (2011) noted a similar sensitivity of cyclogenesis in the eastern tropical North Atlantic to local resolution but found genesis to occur in this region at a grid spacing of 0.3° (approximately 30 km) rather than the higher resolution of 12 km found to be necessary in this study. This suggests local high resolution is not in itself sufficient. Cyclogenesis is influenced by large-scale, resolvable processes, (e.g. Gray 1968) but also by mesoscale processes below current model resolution.

S4. Future Changes in Tropical Cyclone Frequency

This section presents the non-normalized cyclone track and genesis densities as supplemental information to section 6.2.4 in the main manuscript. Figure 6.S2 shows a low bias in the 36km data and a high bias in the 12km data for the base climate period. We are not too concerned about model bias in tropical cyclone frequency since frequency can easily be changed by dialing up and down thresholds in the tropical cyclone detection algorithm (Suzuki-Parker, 2012).

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Lessons Learned


7. Conclusions

Lewis and Perkins (2013) colorfully stated: “In the absence of time-travelling climatologists, models are unrivalled tools for understanding our changing climate system”.

In the absence of future observation and more actual realizations of the climate of planet earth, numerical models, which are built on the fundamental laws of physics, can be used as virtual laboratories allowing us to perform experiments that we cannot conduct in the real world. These models are unrivalled tools with which we can assess not only the interactions between interconnecting components of the earth, but also potential changes in our climate and how climate change will affect our day-to-day weather, specifically rare and often-small extreme weather events. In this thesis tropical cyclones are used as an example of an extreme and relatively rare (in terms of events like tornadoes, floods, etc.), weather event.

Global Climate Models (GCMs) can be viewed as mathematical representations of the earth system, comprising the general circulation of the atmosphere and ocean, along with interacting processes over land and in the biosphere and cryosphere. The strengths of these models are:

- They are based on the fundamental laws of physics;
- They are global models and not dependent on lateral boundary conditions;
- These models are complex, chaotic, and non-linear, thus small changes could result in vastly different outcomes. This coupled with their relatively computationally efficiency enables the creation of ensembles with which we can assess a degree of uncertainty.

A weakness of GCMs is that due to their coarse resolution, these models are not able to represent small-scale processes or extreme events. On the other hand, Regional Climate Models (RCMs) typically have resolutions high enough to enable simulation of key features of extreme weather events. RCMs are also mathematical representations of the earth system. They have non-hydrostatic dynamical cores, and high-order, conserving numerical characteristics, enabling simulations ranging from large-eddy to synoptic scales.

In Chapter 6 we describe the application of the Weather Research and Forecasting (WRF) model as a regional climate model, along with lessons learnt for such applications. This paper uses tropical cyclones as an illustrative example in testing the WRF model as an RCM. We take a critical look at the domain size, location and resolution needed in simulating tropical cyclones. Some of key finding from this paper include:
• **Sufficient** resolution is needed to simulate key features of the event of interest. Resolutions of 10s of kilometers are needed to develop tropical cyclones in RCMs. Experiments with different resolutions showed that resolutions higher than required to resolve the key features may produce little added value and may not be the optimal use of available computer resources.

• Size and location are critical and domains should be designed such that it includes key regional climate processes. For example, a domain for simulating tropical cyclones over the Atlantic should consider the development of African Easterly waves, the precursors to tropical cyclones in this region. Domains should also be large enough to allow the development of mesoscale features.

Other weakness of GCMs are that these models often suffer from systematic errors, though the predicted changes are generally much more reliable than the absolute fields themselves. RCMs are dependent on lateral boundary conditions, and biases that may be acceptable at global scales may change or destroy extreme weather signals in regional climate models.

In Chapter 5 we describe a new bias correction method and tested its application over North America and the Atlantic basin. The bias correction method developed in this paper corrects the seasonally mean error in the GCM data, while retaining the variance as well as the long-term climate variability and change signal. We examined the impact of correcting individual variables and groups of variables. All cases showed consistent improvement over using the uncorrected climate data. Sea surface temperature and winds are the most critical, but correcting all variables in a consistent manner is better than correcting any subset of variables. Using uncorrected climate data as boundary conditions suppressed the development of tropical cyclones, while the application of the fully corrected boundary conditions resulted in realistic spatial distributions and frequency of tropical storms. The bias correction also improved the distribution and magnitude of North American precipitation and removed a distinct cold bias in the model.

Statistical methods used to remove biases from the dynamical fields are not perfect and they have the potential to introduce new errors. One such error is the introduction of imbalances in the boundary conditions as each dynamical field is bias corrected independently. Even so, these imbalances are far less significant that the large biases from the GCMs, and no more significant than the imbalances introduced through temporal and spatial interpolation of the lateral boundaries. In Chapter 5 we have shown that if the RCM has a significantly large domain, the model will be able to correct for these small imbalances.
When bias correctly RCM lateral boundary conditions, an important potential uncertainty to acknowledge is the question of stationarity of biases under non-stationary conditions. Ehret et al. (2012) suggested that biases might be sufficiently stationary to make them acceptable for climate change impact studies. In chapter 5 we demonstrated that for the 40-year period 1960-2000 the bias was indeed stationary.

A weakness of Regional Climate Models (RCMs) is that they are typically very expensive to run at high resolution, making them unsuitable for long runs or large ensemble predictions.

Statistical downscaling techniques use empirical relationships to relate large-scale atmospheric variables to local observations. Their strengths and weaknesses are:

- They are computationally efficient, and can therefore be applied to ensembles of GCMs to provide assessments of regional climate uncertainty;
- Empirical approaches are sensitive to the choice of predictors, and therefore also to the GCM’s ability to simulate these predictors;
- They tend to under-predict temporal variations;
- They are based on the assumptions that the developed relationships between the large scale climate and the local predicted variable remain stationary under climate change scenarios;
- They are sensitive to the robustness of the observational record.

Here we present 2 papers that make use of statistical techniques to relate large-scale atmospheric flow to tropical cyclone genesis. In the first of these (Chapter 3), we focused on the Atlantic basin and created a new basin specific index to predict interannual tropical cyclone frequency. In this paper we examined genesis potential indices and their application to interannual tropical cyclone frequency for the North Atlantic basin. Some key finding from this paper are:

- Whilst most genesis predictors work well for seasonal variability (for which they were originally designed), they explain less than 30% of the interannual variability.
- Moisture and low-level vorticity are poor predictors for North Atlantic tropical frequency.
- Potential Intensity explains the bulk of North Atlantic storm frequency, with shear contributing a small but useful component of the predictability.
- The choice of area to average these predictors over is critical. In this case an area just of the coast of Africa, known as the main development region (MDR) proved to be the most important for predicting Atlantic cyclone frequency.
- Using the newly developed index, applied only over the MDR, resulted in improved interannual predictions with over 80% variance explained.
In the second statistical downscaling paper (Chapter 4), we expanded to include all tropical cyclone basins. Here we developed a new data mining technique to explore areas that are correlated with cyclone genesis in these different basins. We found that for most basins there is a critical area over which the predictors must be averaged, and this area is not necessarily the basin of interest or even contained within the basin of interest. No major improvements were obtained for the North and South Indian oceans. The Western North- and South-Pacific cyclones were best related to areas immediately to their east. The Eastern Pacific, Gulf of Mexico and Atlantic were best related to smaller areas on the eastern edges of the basins.

These results support the development of Hybrid Statistical-Dynamical approach that is able to capitalize on the strengths and compensate for the weaknesses of both Regional and Global Climate Models, thereby increasing the fidelity of the results while decreasing the inherent uncertainty. This Hybrid Statistical-Dynamical approach has two main components:

- It utilizes extreme weather simulations from RCMs to predict future changes, verify and anchor statistical methods;
- Statistical approaches are then utilized to fill in the gaps between the dynamical time slices and to assess the level of uncertainty in the predictions.

In this thesis we demonstrate how, through a hybrid statistical-dynamical approach, we can obtain transient information, including a measure of uncertainty, for changes in North Atlantic tropical cyclone frequency.
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Done, J.M., C.L. Bruyère, M. Ge, and A. Jaye, 2014: Internal Variability of North Atlantic Tropical Cyclones. Submitted to JGR.


References


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March 18, 2014

To whom it may concern

Dear Sir / Madam,

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herewith give permission that this manuscript can be submitted as part of Cindy Bruyère’s PhD thesis. Although we were involved with the conceptualization of this work, Cindy Bruyère was primarily responsible for the execution and documentation of this research.

Sincerely

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- The design of the dynamical downscaling using the Weather Research and Forecasting (WRF) model;
- Research into tropical cyclone development in the Nested Regional Climate Model (NRCM);
- The design of the bias correction method; and
- Development of a statistical framework for tropical cyclone frequency.

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- The design of the dynamical downscaling using the Weather Research and Forecasting (WRF) model;
- Research into tropical cyclone development in the Nested Regional Climate Model (NRCM);
- The design of the bias correction method; and
- Development of a statistical framework for tropical cyclone frequency.

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