Coupled Model Sea Surface Temperature Biases and Their Influence on Tropical Cyclone Environmental Conditions in an Atmospheric General Circulation Model

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COUPLED MODEL SEA SURFACE TEMPERATURE BIASES AND THEIR INFLUENCE ON TROPICAL CYCLONE ENVIRONMENTAL CONDITIONS IN AN ATMOSPHERIC GENERAL CIRCULATION MODEL

By

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Most climate models participating in the Coupled Model Intercomparison Project, Phase 5 (CMIP5) struggle to accurately simulate all aspects of the climatological global sea surface temperature (SST) distribution, especially in regions of coastal and equatorial upwelling. Of particular interest in this thesis are coupled model SST biases in the tropics and their potential influence on environmental conditions associated with tropical cyclone (TC) genesis and intensity. To evaluate this, two atmospheric general circulation models (AGCMs), the ECHAM5 and CAM5, were employed, first to examine their ability to capture observed TC characteristics when forced with observed SSTs (control runs) and then by comparing these results with output from model runs forced with observed SSTs plus the climatological, multi-model (31) mean CMIP5 monthly SST bias (bias runs), both covering the period 1979-2004. Three TC indices were evaluated, two of which were statistically based that relate atmospheric and SST conditions to TC formation and the third was physically based which evaluates the potential intensity of a TC (maximum near-surface windspeed) based on SST and vertical profiles of atmospheric data. All three indices were evaluated over the near global domain. The statistically based indices were the Tropical Cyclone...
Genesis Index (TCGI) and the Genesis Potential Index (GPI) whereas the physically based index was the Potential Intensity (PI).

Results using monthly mean atmospheric conditions from the control runs of ECHAM5 and CAM5 were found to produce similar results with those obtained from using daily NCEP reanalysis data, especially in terms of the spatial patterns of the three TC indices. Results between ECHAM5 and CAM5 control runs were found to be very similar and therefore in order to avoid being repetitive, only ECHAM5 was subsequently used for the analysis of the response to coupled model SST biases. While the AGCMs were found to generally produce too many cyclones as compared to NCEP reanalysis data they were able to capture the observed pattern of TC behavior very well. Pattern correlations were calculated between ECHAM5 control run results and NCEP reanalysis data for TCGI, GPI, and PI with values of 0.98, 0.56, and 0.86 obtained, respectively. These values increased confidence that despite the coarse resolution of the AGCM it was doing a good job at capturing the observed spatial patterns of the TC indices considered.

Comparing annual average results from the bias and control runs, the CMIP5 climatological SST biases were found to result in statistically significant regional changes in TCGI, PI, and GPI. In some locations, the proxies for TC frequency (TCGI, GPI) and intensity (PI) are enhanced, in others they are reduced. Generally, the regions of overestimated (underestimated) TCGI, GPI, and PI were found to be collocated with areas of positive (negative) SST biases. There were a few notable exceptions, but these were generally localized in nature. The sensitivity of the TCGI to the individual component variables from the bias runs was also examined and tested for statistical significance. Results from this sensitivity testing showed that the relative SST was the most influential term whereas absolute vorticity had the smallest overall impact. Seasonal analyses were also conducted for PI and GPI, owing to the different hurricane seasons
across each ocean basin. Results generally showed a strong correlation between regions of over (underestimated) TCGI, PI, and GPI to regions of negative (positive) SST biases.

The results obtained from this study indicate that ECHAM5 and CAM5 are able to accurately simulate observed TC behavior when forced with observed SSTs, especially in terms of spatial patterns of the TC indices. When comparing these results to those obtained when ECHAM5 is forced with observed SST plus the multi-model mean SST bias it becomes apparent that the SST biases are indeed having an impact on these simulations. Results between ECHAM5 control runs and observations showed that despite the coarse resolution of the coupled climate models, they can be used to realistically capture TC characteristics. When examining the influence of the coupled model SST biases on the three TC indices, it was found that the index with the greatest sensitivity to these biases was the TCGI. Regions of over/underestimated TCGI were generally found to be collocated with positive/negative SST biases despite a few exceptions. These impacts were generally the greatest in the Pacific Ocean, with lesser impacts across other ocean basins. This was particularly true across the eastern and western tropical Pacific where in some regions the over/underestimated number of TC genesis events exceeded 10 on an annual time scale.
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CHAPTER 1

INTRODUCTION

1.1 Sea Surface Temperature and Climate: Background

Oceans cover greater than 70% of Earth’s surface and are a fundamental component of the global climate system. The oceans store an enormous amount of heat, with estimates that over 90% of the heat gained between 1971-2010 has been absorbed by the global oceans (Zanna et al. 2019). They also serve as the world’s largest natural carbon sink, absorbing about one quarter of all anthropogenic carbon emissions (Doney et al. 2014). In addition, the oceans provide roughly 90% of all water vapor (H\textsubscript{2}O) in the atmosphere, which is crucial for the development of clouds and precipitation (Gleick 1996). Sea surface temperatures (SSTs) are particularly important to the study of climate given that they serve as the interface between the atmosphere and ocean. Climatologically, SSTs show considerable spatial variation, primarily due to ocean circulations, which near the ocean surface are largely driven by atmospheric winds. The spatial variations in climatological SSTs can be seen in Figure 1, which shows the 1950-2004 annual average global SST field (shaded) using the fifth version of the Extended Reconstructed Sea Surface Temperature (ERSSTv5) from the National Oceanic and Atmospheric
Figure 1 also shows the annual average precipitation (contours), and a few interesting features can be observed. One such feature is that generally speaking, the regions of heaviest precipitation in the tropics tend to coincide with comparatively warm SSTs. This is due in part to the increase in surface evaporation from the sea surface and the tendency for rising motion over warm waters leading to condensation, clouds and precipitation. One example of this is a narrow band near the equator in the Atlantic and eastern Pacific where the trade winds from both the Northern and Southern Hemispheres converge, which leads to copious amounts of precipitation, in a region which is commonly referred to as the Intertropical Convergence Zone (ITCZ; Wang and Wang, 1999).

Of particular interest in this thesis are SSTs throughout the tropics, given their contributing role in precipitation and regional climate patterns. For example, rainfall is abundant.
in the Western equatorial Pacific “warm pool” region whereas it is comparatively dry in the equatorial Eastern Pacific “cold tongue” region. On interannual timescales, SST variability, particularly in the tropics, plays a vital role in modulating precipitation both within and outside the tropical belt. The prototypical example is the El Niño Southern Oscillation (ENSO) phenomenon. ENSO is characterized by a coupled interaction between the atmosphere and underlying ocean in the equatorial Pacific Ocean (e.g., Cane et al. 1986) and can influence SSTs in the Indian and Atlantic oceans as well. During El Niño, or the ENSO warm phase, the Pacific trade winds weaken, which reduces equatorial upwelling in the east-central Pacific, allowing anomalously warm water to flow eastward and resulting in an increase in SSTs in the east-central Pacific and a deepening of the thermocline there. The increase in SSTs results in an eastward shift in atmospheric convection, and through associated changes in atmospheric heating, this can alter the atmospheric circulation and seasonal precipitation patterns across many parts of the globe (e.g., Ropelewski and Halpert 1987). During the cold phase of ENSO, otherwise known as La Niña, the equatorial Pacific trade winds are strengthened, thereby enhancing equatorial upwelling in the east-central Pacific Ocean which results in anomalously cool SSTs there. Convection is enhanced in the western equatorial Pacific and reduced further east, with anomalous, global precipitation patterns generally opposite from those identified during El Niño (Ropelewski and Halpert 1987, 1989). Figure 2 shows the average SST anomaly (departure from climatology) from June of 1997 to May of 1998 (a strong El Niño event) using a 1979-2005 SST base period and ERSSTv5 data. To generate the figure, the observed, average SST for the period June 1997 to May 1998 was computed and then the 1979-2005 average value was subtracted. The magnitude of the calculated SST anomaly for this event approaches 4 degrees centigrade
warmer than average near the west coast of South America and about a half of a degree colder than average across the western equatorial Pacific.

![Image of SST anomaly map](image)

Figure 2: June 1997-May 1998 SST anomaly (deg. C) calculated as the difference from a 1979-2005 SST climatology using ERSSTv5 data.

Of particular interest to this thesis, ENSO can also influence the development, intensity, and tracks of tropical cyclones (TCs). For example, during an El Niño event, tropical Atlantic hurricane activity is often reduced as a result of increased vertical wind shear and trade winds (Gray 1984). TC behavior is also influenced directly by local SSTs, as will be investigated in this thesis. Other examples of SST variations that influence regional climate include the Indian Ocean Dipole (IOD), the Atlantic Multidecadal Oscillation (AMO), and the Pacific Decadal Oscillation (PDO). The Indian Ocean Dipole (IOD) is defined as the SST gradient between the western and eastern equatorial Indian Ocean and has been shown to influence precipitation patterns over Australia, eastern Africa, and the Indian monsoon (Ashok et al. 2001; Behera et al. 2005; Cai et al. 2011). On decadal timescales, the Atlantic Multi-decadal Oscillation (AMO) and the Pacific Decadal Oscillation (PDO) have been shown to influence regional climate. The AMO and PDO can broadly be described as the North Atlantic and Pacific basin-wide SST fluctuations that occur on multi-decadal time scales (Knight et al. 2006; Newman et al. 2016). The AMO has been found to have a wide range of climate impacts, including its influence on rainfall variability in the Sahel and TC activity in the North Atlantic (Folland et al. 1986; Patricola et al. 2014).
Warmer than normal tropical North Atlantic SSTs have also been found to reduce North American precipitation, particularly west of about 90°W by up to 30% on interannual time scales (Kushnir et al. 2010). Among other impacts, the PDO has been found to influence the frequency of tropical cyclones throughout the Caribbean and Gulf of Mexico (Lupo 2000).

1.2 Climate Models and Model SST Biases

A particularly important tool that is often used to study the influence of SST anomalies on regional climate conditions is a climate model. Climate models have evolved substantially in recent decades and now include coupling between the atmosphere and ocean, land surface and biosphere. A coupled model allows for the two-way, dynamical interaction between the atmosphere and the underlying surface. In a coupled ocean model, for example, the atmosphere can influence ocean conditions, while changes in ocean conditions can alter the behavior of the atmosphere. Coupled climate models are necessary to capture phenomena such as ENSO, and while they are continually being improved, they still exhibit several errors in simulating the observed climate. Of particular interest here are coupled model biases in tropical SSTs. These biases are defined as the difference between modeled and observed values of climatological SSTs over the same time (base) period. Given that observed variations in tropical SSTs are often associated with regional climate variations, including the behavior of TCs, it seems plausible that the biases in coupled model SSTs may influence environmental conditions for TCs as well. For example, Figure 3 shows the difference between monthly, climatological (1979-2005) SSTs averaged over 31 models in the Coupled Model Intercomparison Project phase 5 (CMIP5; Taylor et al. 2012) and observations (ERSSTv5) for the September-November season. Computed as such, these differences represent the multi-model mean CMIP5 SST bias. The largest positive
biases seen in Figure 3 are typically located in regions of observed upwelling, particularly along the west coasts of South America, Africa, and Mexico and the western Indian Ocean. Negative SST biases are seen in the tropical equatorial Atlantic, Gulf of Mexico, and equatorial and subtropical central Pacific.

Figure 3: Multi-model average, climatological SST bias for September-November based on CMIP5 historical runs (1979-2005; deg. C).

Positive SST biases of over 4 degrees centigrade are seen off the west coast of South America, Africa, and Mexico. There are also negative SST biases of around 1 degree in the central equatorial Pacific, Gulf of Mexico, and tropical Atlantic. Note that the multi-model mean CMIP5 SST biases are of similar magnitude to the largest SST anomalies observed during the strong 1997-1998 El Niño event in Figure 2, which again suggests the former may play a role in altering regional climate.

In this thesis, I examine the influence of the multi-model mean CMIP5 climatological SST biases on environmental conditions that affect TCs, including vertical wind shear, atmospheric humidity, atmospheric vorticity, and the direct influence of SST itself. These factors can all affect the development and intensity of TCs. For example, as previously alluded to, during an El Niño event, tropical Atlantic hurricane activity is often reduced due to increases in the vertical wind shear in response to SST changes in the tropical Pacific (e.g., Patricola et al. 2014). Given that the coupled model SST biases can be of the same order of magnitude as SST
anomalies associated with a strong El Niño event, it is possible that they can also alter TC environmental conditions, which will be examined here within a climate model framework.

In order to quantify the influence of coupled model SST biases on TC environmental conditions, I will use the output from two atmospheric general circulation models (AGCMs). Running the AGCMs requires that the SST conditions are first specified in the model. In this thesis I will first utilize output from the AGCMs where the models are run with (or “forced” by) observed monthly SSTs from 1979-2005. These runs will constitute a set of “control runs.” In a second set of runs (the “bias runs”) the monthly climatological CMIP5 multi-model mean SST biases are added to observed SSTs before running the two AGCMs. Differences in atmospheric conditions between the bias and control runs will thus indicate the influence of the SST biases on different environmental conditions that influence TCs, at least to the extent that the response to the latter are properly captured in the AGCMs. Of particular interest are conditions that influence the genesis of TCs as well as their potential Intensity. Details of the overall approach will be provided in Chapter 2.

1.3 Study Goals

This thesis has two main goals. The first is to determine the extent to which AGCMs are able to properly capture the observed climatological conditions that relate to TC development and potential intensity as captured by three widely used TC indices. The second goal is to then use these same AGCMs to determine the influence of the CMIP5 climatological SST biases on the same indices. Each of the chapters in this thesis outline the specific objectives necessary to meet these goals. Chapter 2, “Assessing the Ability of Atmospheric General Circulation Models to Capture Observed Environmental Conditions for Tropical Cyclones” is focused on the first
goal, examining how well AGCMs simulate the observed regional-scale environmental conditions affecting the development and potential intensity of TCs. The chapter begins by providing some background on the design and use of the AGCM control runs. Next, the three TC indices are described that relate environmental conditions in the atmosphere and ocean surface to TC genesis and potential intensity. Computed values of these indices based on the AGCM control runs will then be compared with those obtained from observationally-based data. In Chapter 3, “Influence of Coupled Model SST biases on TC Environmental Conditions,” I analyze the three TC indices using output from the bias runs of the two AGCMs and compare the results to those obtained from the control runs. All differences between results obtained from the bias and control runs will be tested for statistical significance. Although there has been considerable research conducted to evaluate systematic SST biases in coupled climate models, very little research has been conducted to determine the potential influence of such biases on TC environmental conditions. One exception to this was Hsu et al. (2018), which was a study that examined the influence of coupled model SST biases on TCs using a tropical channel atmospheric model. This is the main motivation for the study from a scientific perspective. Given the impacts that TCs frequently have on societies around the globe, the results will have broader implications, particularly regarding the direct use of coupled climate model output in climate risk assessments without considering some important caveats in doing so.
CHAPTER 2
ASSESSING THE ABILITY OF ATMOSPHERIC GENERAL CIRCULATION MODELS TO CAPTURE OBSERVED ENVIRONMENTAL CONDITIONS FOR TROPICAL CYCLONES

2.1 Overview

Chapter one of this thesis outlined the significant role that the global oceans have on observed climate conditions, especially within the tropics. As was noted, there are large regional variations in observed SSTs around the globe due to oceanic currents, upwelling and other factors. In order to increase our understanding of the role of oceans (and SSTs) in the climate system, we often use coupled climate models. These models couple the ocean and atmosphere, allowing for an interaction between the two so that they dynamically influence one another. For example, the atmospheric circulation may alter SSTs, while changing SSTs may also influence conditions in the atmosphere. While coupled models have shown significant improvements in simulating the observed climate over the years, they still have known limitations and biases. The focus of this thesis is on coupled model biases in climatological SSTs. Specifically, this thesis will determine if the climatological SST biases in the current generation of coupled climate models have an impact on environmental conditions that influence the behavior of tropical cyclones (TCs). This will be accomplished by using two atmospheric general circulation models (AGCMs) where SSTs are specified before the models are run.

A key first step in this research is to determine the extent to which the AGCMs are able to capture observed climate conditions that relate to TCs. These conditions will be quantified using three widely used TC indices (described in detail in Section 2.3). The ability of these atmospheric models to accurately simulate regional climate conditions relating to TCs is of
utmost importance before I later use them to examine the potential impact that coupled model SST biases have on TC environmental conditions. Although I will initially examine model output from two AGCMs, it will be shown in section 2.4.1 that the results obtained from the two models were found to be very similar and therefore in order to simplify the study and avoid repetition, the results from only one AGCM is used in subsequent analyses that are presented.

2.1.1 Climate Models

Some general background information on climate models is warranted before proceeding with the details of the study. As mentioned earlier, in an AGCM the sea surface temperature must be specified before the model is run. To examine the influence of observed SSTs on atmospheric conditions in an AGCM, time-varying, observed SSTs are specified to the model. In this case, all changes in SST with time in the AGCM are simply due to changes in the observed SST, from one month to the next (the observed, monthly SSTs are actually first interpolated in time to obtain time-varying, daily values). The atmospheric conditions in the AGCM can be affected by the underlying distribution of SSTs, but the modeled atmospheric conditions don’t change the SST.

As mentioned earlier, a coupled climate model is one in which there is an exchange of “information” (heat, momentum, etc.) between the atmosphere (atmospheric model component) and ocean (ocean model component). This exchange occurs in both directions (the ocean influences the atmosphere and vice versa). Other than such regular exchanges, the atmospheric and ocean models run separately. In a coupled climate model, SSTs are not specified since the model simulates its own ocean conditions, including the SST field. Climatological values of SST in a coupled model, however, are computed in the same manner as done for observations, by
computing the multi-year mean of monthly average SSTs values over a desired base period (here, 1979-2005). Monthly biases in coupled model climatological SSTs are then quantified by subtracting the observed monthly climatological values from the coupled model values (both computed over the same base period). In this study, the multi-model mean biases are computed from the output of 31 CMIP5 coupled models are used. Additional details on the specific CMIP5 models used to identify the monthly SST biases are detailed in Lyon (2020).

Two AGCMs are used in this thesis. The first AGCM is the fifth-generation of the European Centre Hamburg Model (ECHAM5), which was developed by the Max Planck Institute for Meteorology (MPIM; Roeckner et al. 2003). The model evolved from the spectral weather prediction model of the European Centre for Medium Range Weather Forecasting (ECMWF), where it was modified for climate studies. The version of ECHAM5 used is an atmospheric model where ocean conditions (SSTs and sea ice concentration) are specified (Roecker et al. 2003). Greenhouse gas concentrations are held fixed at 2000 levels. The model is configured to resolve the atmosphere from the surface up to 10 hPa and has a horizontal spatial resolution of about 2.8° lat/lon.

The second AGCM used is the fifth generation of the Community Atmosphere Model (CAM5; Neale et al. 2012), which is the latest version of the global atmospheric model produced at the National Center for Atmospheric Research (NCAR). CAM5 is the atmospheric component of the coupled Community Earth System Model (CESM). CAM5 has 26 vertical layers in the atmosphere with a horizontal spatial resolution of about 1.4° lat/lon. CAM5 is a spectral model with SSTs and sea ice concentrations both prescribed prior to running the model (CAM5; Neale et al. 2012). In addition, greenhouse gas concentrations were fixed at 2000 levels, similar to that of ECHAM5.
2.2 Observational Data Used and Setup of AGCM Control Runs

2.2.1 Observational Data

Two observed SST datasets are used in this study. The first is the Extended Reconconstructed Sea Surface Temperature version four (ERSSTv4; Huang et al. 2015), which is a monthly global dataset with a spatial resolution of 2° latitude/longitude. Version 4 has several improvements over the previous version, including a decade’s worth of data from Argo floats and a new estimate for continental sea ice from the HadISST2 dataset (Huang et al. 2015). The Argo floats that were utilized in ERSSTv4 originate from the Global Data Assembly Centre in France. These floats were released ocean-wide with the goal of obtaining a better representation of the ocean’s subsurface temperature and salinity structure for the top 2,000 meters (Riser et al. 2016). There have also been bias corrections made to this dataset, as well as extensive quality control and interpolation mechanisms including updated ship measured SST biases using the Hadley Centre Nighttime Marine Air Temperature dataset v2 (HadNMAT2). As a result, a more accurate and representative reconstructed SST dataset has been obtained with improved high-latitude SSTs, and ship observation bias corrections made with respect to higher accuracy buoy measurements (Huang et al. 2015). Comparisons with direct and independent observations suggest that the updates incorporated in ERSSTv4 have resulted in better representation of the global spatial variability in SST and the magnitude of ENSO related phenomena such as El Niño and La Niña (Huang et al. 2015). This dataset has a long record period, from January of 1854 to the present day but only data for the period 1979-2005 will be used here.
A second observed SST dataset utilized is version two of the weekly, 1° spatial resolution Optimally interpolated SST analysis (OIv2) created at the National Oceanic and Atmospheric Administration (NOAA) using a combination of in situ and satellite observations from November of 1981 to the present (Reynolds et al. 2002). Since 1998 the in-situ SST observations used in this product come primarily from ship and buoy data, with data prior to 1998 originating from the Comprehensive Ocean-Atmosphere Data Set (COADS; see Slutz et al. 1985; Woodruff et al. 1998). Bias corrections have been conducted on this dataset to ensure accuracy. Monthly SST fields were created through an interpolation between daily and weekly data, with the monthly product used in this thesis (Reynolds et al. 2002).

Observationally-based atmospheric data was obtained from two different so-called reanalysis datasets that assimilate observations into climate model-based fields. The specific datasets used are ERA40 and NCEP reanalysis. ERA40 is second-generation reanalysis dataset based on meteorological observations from September 1957 to August 2002 (Uppala et al. 2005). This dataset is produced by the European Centre for Medium Range Weather Forecasts (ECMWF) with input from many other institutions. ERA40 is the first reanalysis dataset to successfully assimilate satellite data, which began to accelerate during the 1970s (Uppala et al. 2005). Bias corrections have been made in ERA40 to account for changes in instrumentation type and quality (Uppala et al. 2005). This dataset has a horizontal spatial resolution of 2.5° x 2.5° with data at 23 vertical pressure levels. The National Center for Environmental Prediction (NCEP) reanalysis dataset has global coverage from 1948 to present. This dataset is compiled through the use of numerous in situ and satellite-based observations, including those from ground-based weather stations, ships, radiosondes, pibal, and aircraft (Kalnay et al. 1996). Bias corrections have been made to account for changes in measuring techniques and instrumentation.
For both ERA40 and NCEP reanalyzeres, the primary variables used are humidity, temperature, horizontal wind and relative vorticity at different pressure levels. All climate data used in this study, including SST and reanalysis data, were accessed through Columbia University’s International Research Institute’s (IRI) Climate Data Library, which can be accessed at: https://iridl.ldeo.columbia.edu.

2.2.2 AGCM Control Runs

The first set of AGCM runs utilized here will be a set of control runs, where ECHAM5 and CAM5 have been “forced” with observed monthly SSTs from ERSSTv4 covering the period January 1979-December 2004. For each model, the control runs consist of 16 ensemble members, each member generated by running the models using slightly different initial atmospheric conditions. Generating an ensemble of runs was done in order to account for “noise” resulting from random weather events generated by the models, which can result in differences between single model runs. This noise is reduced by computing ensemble averages from the 16 ensemble members before undertaking analyses of the model data. Ensemble means were calculated by using both Matlab and the International Research Institute’s (IRI) Climate Data Library software. If the observed monthly SST is written as the sum of the climatological monthly mean SST plus a monthly anomaly (i.e. departure from the climatological mean) then the observed SSTs (SST\textsubscript{OBS}) used to force the ECHAM5 and CAM5 in the control runs can be expressed as:

\[ \text{SST}_{\text{OBS}} = \overline{\text{SST}}_{\text{obs}} + \text{SST}'_{\text{obs}} \]

where \( \overline{\text{SST}}_{\text{obs}} \) and \( \text{SST}'_{\text{obs}} \) are the observed, monthly SST climatology (1979-2004) and monthly anomaly, respectively. Other conditions, such as sea ice extent, greenhouse gas concentrations,
aerosols, and land surface condition were all held at fixed, climatological values when generating each ensemble member and over the course of the model integration (1979-2004). The ECHAM5 and CAM5 control runs were both generated at Columbia University, with output stored at the International Research Institute’s (IRI) Climate Data Library, which can be accessed at: https://iridl.ideo.columbia.edu. For all model variables, both daily averages and monthly averages were archived.

In order to conduct the required analyses, in this thesis the output from the AGCM control runs, and all reanalysis data, were first re-gridded to a common 2.0° x 2.0° lat./lon. grid using bilinear interpolation. As mentioned earlier, output from the AGCM control runs will be used to evaluate how well the AGCMs perform in simulating the observed environmental conditions associated with tropical cyclones. As outlined in the next section, three different TC indices will be used to make these comparisons. An overall description of the indices will first be described.

2.3 Statistical and Physically-Based Tropical Cyclone Indices

This thesis will utilize one physically-based, and two statistically-based, TC indices. The physically-based index uses physical principles to compute the potential intensity (PI) of a TC. The PI indicates the greatest TC intensity that could be theoretically achieved under given environmental conditions. The two statistically-based indices indicate the likelihood of TC genesis based on empirical relationships between the observed occurrence (frequency) of TCs and various environmental conditions (humidity, vorticity, wind shear, etc.). All three indices will first be computed using output from the AGCM control runs and then using observational data to assess AGCM performance in this regard. The three indices were calculated using both
daily and monthly average values for the input variables and it was found that the results were very similar. Therefore, in order to reduce the size of the data sets and computational expense, monthly average values were used in this thesis. In Chapter 3, changes from the control run values of these indices will examined when the AGCMs are subsequently run with SSTs that include the climatological biases from the CMIP5 coupled models. All computations in the thesis were made using MatLab software, utilizing the International Research Institute’s Climate Data Library software to first access the necessary archived data.

2.3.1 The Tropical Cyclone Genesis Index

The first statistically-based index considered is the Tropical Cyclone Genesis Index (TCGI; Tippett et al. 2011). This index is based on a statistical fit between the observed, climatological number of TCs in a given month and four different environmental inputs. The TCGI is based upon a log-linear model that may be written as:

\[ \mu = \exp(b + b_\eta \eta + b_H H + b_T T + b_V V + \log \cos \phi) \]

In the above expression, \( \mu \) is the expected number of TC genesis events per month in a 40-year record, \( \eta \) is the monthly average 850 hPa absolute vorticity, \( H \) is the 600 hPa relative humidity, \( T \) is the relative SST (i.e. the difference between the local SST at a grid point and the tropical average value of SST), \( V \) is magnitude of the vector vertical wind shear between 850 hPa and 200 hPa levels, and \( b \) is a constant intercept term. The last term (\( \log \cos \phi \)) relates to the dependence of TC formation on latitude, \( \phi \) (more TCs occur at low latitudes). The values of the coefficients used in the above expression came from line 6 in Table 1 of Tippett et al. (2011), with the coefficient subscripts in the above expression indicating the associated variable. The coefficients can be interpreted as the sensitivities of the index to each of the large-scale climate
variables (Tippett et al. 2011). The exponential of the summation of the individual climate variable terms is thus the statistical estimate of TC genesis at a particular grid point. The overall domain used was 88° south to 88° north latitude and 0° east to 2° west longitude.

While a statistical estimate of TC genesis, the TCGI is still based on physical reasoning, which warrants some further discussion of the terms used in its computation. Relative vorticity can generally be described as the spin, or rotation, in the atmosphere about the local vertical, which can either be clockwise or counterclockwise (negative, or positive). The absolute vorticity is the sum of the relative vorticity and the planetary vorticity at a given location, the latter being directly related to the rotation of the earth itself. TCs require some amount of initial vorticity in order to form, which is why TCs are not observed to originate at the equator. When used in computing the TCGI, the absolute vorticity has been “trimmed,” meaning that values above a specified threshold are capped, since planetary vorticity increases continually towards the poles but TCs are a tropical phenomenon and hence do not form at higher latitudes (extratropics). Thus, latitudinal increases in absolute vorticity do not equate to an increase in the likelihood of TC development outside the tropics (Tippett et al. 2011). Relative humidity is the percentage of the actual amount of water vapor in the air compared to how much could be present at a given temperature if the air were saturated at a given pressure level. The contribution of relative humidity throughout the vertical profile of a developing TC is not precisely known, and therefore the use of relative humidity at 600 hPa in this index is somewhat arbitrary (Tippett et al. 2011). Nonetheless, higher values of relative humidity at this mid-tropospheric level favor the development of TCs. Relative sea surface temperature is defined as the difference between the local (i.e., grid point) sea surface temperature and its tropical average (here, 25°S-25°N) value. The use of relative SST is different from Gray’s original work (Gray 1979) that considered
absolute values of SST, as the former allows for changes in the mean climate (e.g., as resulting from anthropogenic climate change). Lastly, vertical wind shear is computed as the magnitude of the difference in the vector wind between 850 and 200 hPa in the atmosphere. TC formation is known to be hindered when there is significant wind shear due to cumulus clouds not being able to reach their maximum potential height. The TCGI index expands upon the earlier work of Gray (1979), and the Genesis Potential Index (GPI; Emanuel and Nolan 2004), the latter which will also be used in this thesis and discussed in greater detail later in section 2.3.3.

2.3.2 Tropical Cyclone Potential Intensity

Another TC index which is used heavily in this thesis is potential intensity (PI; Emanuel 1988, Blister and Emanuel 2002). While the TCGI is purely a statistical estimate of TC genesis, PI is based upon physics and relates vertical profiles of temperature, pressure, and specific humidity to the maximum intensity that a TC could physically obtain. The maximum intensity can be expressed as either the lowest attainable central pressure of a TC (in Pa) or by the maximum horizontal winds that can be generated by the storm (in m s\(^{-1}\)).

Prior to discussing how the PI index is computed, it is first helpful to understand the basic energy cycle of a TC. A tropical storm basically acts like a natural heat engine, which runs between the warm heat reservoir at the surface of the ocean (at a temperature of around 300 K) and the cold reservoir of the upper troposphere (at around 200K). Theoretically, the maximum work (energy) that can be done (obtained) by a heat engine is the difference between the amount of heat put into the system minus the heat extracted. This can be written as, \( E = Q_H - Q_C \), where \( E \) is the energy derived, \( Q_H \) is the heat added to the system and \( Q_C \) is the heat extracted. In practice, heat engines are not 100% efficient, with the efficiency of a heat engine given as 1 –
Q_C/Q_H, where Q_H is the heat added to the system and Q_C is the heat extracted. In the case of an idealized Carnot cycle, the efficiency reduces to 1 – T_C/T_H, where T_C the temperature of the cold reservoir (upper troposphere in the case of a TC) and T_H is the temperature of the relatively hot reservoir (ocean surface). In a TC, the work generated by the heat engine is proportional to the square of the maximum windspeed, or v^2. If the efficiency of the TC heat engine is given by \( \epsilon \), then \( v^2 \propto \epsilon Q \), where \( Q \) is the heat energy added to the TC.

What is the source of the heat energy that is provided to a TC? The ultimate source of energy in TC development derives from the so-called thermodynamic disequilibrium between the lower tropical atmosphere and the underlying ocean surface (Kleinschmidt 1951 and Emanuel 1988). This disequilibrium is not simply due to the temperature difference between the tropical low-level atmosphere and the ocean surface, which is typically 1°C or less, but is instead the result of the sub-saturation of the overlying tropical air (Emanuel 1991). This situation allows for latent heat to be transferred from the ocean to the atmosphere, the former having a significantly higher heat capacity than the overlying near-surface air, resulting in only a small decrease in SST as water evaporates from the surface (Emanuel 1991). The transfer of heat from the ocean is a function of surface wind speed, with increasing wind speed resulting in greater heat exchange, which then potentially allows for further strengthening of a TC. Frictional dissipation of energy, entrainment of drier air into the TC and interactions of the storm with vertical wind shear and wind induced ocean mixing (among other factors) prohibit TCs from intensifying indefinitely (Emanuel 1991). In fact, the potential intensity of a TC may be derived by equating the generation and dissipation of energy in a mature storm.

As stated above, a mature TC behaves like a heat engine that is fueled by the thermodynamic disequilibrium between the lower tropical atmosphere and underlying ocean
surface (Kleinschmidt 1951 and Emanuel 1988). The energy cycle for a developed TC has also been idealized as a Carnot cycle in a heat engine (Emanuel 1986, 1991). The Carnot cycle can be described as a closed thermodynamic cycle in which the system experiences four different processes within a closed loop. Figure 4 from Emanuel (2006) shows a schematic view of a mature hurricane viewed as a Carnot cycle. In this figure, $T_o$ represents the outflow temperature of a mature TC in the upper troposphere and $T_s$ represents the SST. The lower leg of the cycle, between points A and B, represents an isothermal expansion, as pressure decreases from A to B but temperature (when including the influence of moisture) remains constant due to a transfer of heat from the ocean (moistening of the air from the ocean surface). The next leg (B-C) represents adiabatic expansion as air parcels ascend and pressure and temperature decrease, leading to condensation (latent heating), clouds and rainfall. Air parcels undergo an isothermal compression from C-D as they lose heat by electromagnetic radiation to space, which is offset by adiabatic warming by descent towards higher pressure. Lastly, the leg D-A represents adiabatic compression and negligible heat exchange between the parcel and its environment, with temperature increasing as the parcel moves towards higher pressure.
Figure 4: Schematic view of a mature hurricane as viewed as a Carnot Cycle. The first leg (A-B) represents isothermal expansion, second leg (B-C) represents adiabatic expansion, third leg (C-D) represents isothermal compression, and fourth leg (D-A) represents adiabatic compression. From Emanuel (2006).

The derivation of potential intensity involves equating the generation of energy within a mature TC with the frictional dissipation of energy near the surface. The calculation of PI can be interpreted as combining effects of the efficiency of a Carnot Cycle with the amount of heat energy that is input to the TC. In this case, the thermodynamic efficiency of the TC can be written as

$$\varepsilon = \frac{(T_s - T_o)}{T_s}$$

Where $T_s$ represents the sea surface air temperature and $T_o$ represents the mean outflow temperature at the top of the TC. The outflow temperature can be described as the air temperature at the level of neutral buoyancy of a parcel that is lifted from saturation at the sea surface temperature (Wing et al. 2015). Mathematically it can be seen that the lower the outflow temperature (for a given sea surface temperature), the greater the thermodynamic efficiency is for a developed TC. The mean efficiency of an idealized Carnot Cycle is about $\frac{1}{3}$, or a little over 30%.

The second contributor to PI is the heat input to the TC resulting from thermodynamic disequilibrium. This term may be written as the difference between the saturation moist static energy at the sea surface and the saturation moist static energy of the free troposphere (Wing et al. 2015). The disequilibrium term used to calculate PI can thus be written as:

$$h_o^* - h^*$$

Here $h_o^*$ is the saturation moist static energy at the sea surface and $h^*$ is the saturation moist static energy of the free troposphere. Saturation moist static energy itself can be computed as:
\[ h_0^* = C_p T + gz + L_v r_{sat}, \]

where \( z \) is the geometric height above the surface, \( g \) is acceleration through gravity, \( T \) is the absolute temperature, \( C_p \) is the specific heat at constant pressure, \( L_v \) is the latent heat of vaporization, and \( r_{sat} \) is the saturation mixing ratio (at temperature \( T \) and pressure \( p \)). Combining the efficiency term with the thermodynamic disequilibrium term, PI can be expressed as the square of the maximum windspeed and written as the product of three terms:

\[ V_p^2 = C_k / C_D \times \left( (T_s - T_o) / T_s \right) \times (h_0^* - h^*) \]

In the above, \( V_p \) is the maximum potential surface windspeed (in m s\(^{-1}\)), \( C_k \) is the surface enthalpy exchange coefficient (unitless), \( C_D \) is the drag coefficient (unitless), \( T_s \) is the sea surface temperature (in degrees Kelvin), \( T_o \) is the outflow temperature (in degrees Kelvin), \( h_0^* \) is the saturation moist static energy at the sea surface (in J kg\(^{-1}\)), and \( h^* \) is the saturation moist static energy of the free troposphere (in J kg\(^{-1}\)). The first term, \( C_k / C_D \) is considered to be approximately constant, with the ratio here set equal to 0.9, as is often done in other studies (Bister and Emanuel 2002). The calculation of PI requires the use of SST and vertical profiles of temperature, pressure, and the mixing ratio (Bister and Emanuel 2002). The mixing ratio is closely related to specific humidity, with the latter variable being more readily available in reanalysis data as well as in the ECHAM5 and CAM5 model outputs. Therefore, specific humidity is utilized when calculating PI in this thesis. PI was calculated using Matlab code provided by Dr. Kerry Emanuel of MIT, which was downloaded at:

http://texmex.mit.edu/pub/emanuel/TCMAX.

2.3.3 The Genesis Potential Index
The third index used is the Genesis Potential Index (GPI; Emanuel and Nolan, 2004; Emanuel 2010). Similar to TCGI, GPI was formulated as a statistical fit between the frequency of TCs and various environmental conditions known to influence TC behavior. Gray’s (1979) work showed that TCs are dependent upon a number of environmental factors other than SST, including the magnitude of the vertical wind shear, mid-tropospheric relative humidity, and low-level vorticity. The development of the GPI expanded upon the earlier work of Gray (1979) by including the potential intensity (PI) in the product of four non-linear quantities. The numerical expression of the GPI can be written as:

\[
\text{GPI} = |10^5 \eta|^{3/2} \times (\frac{H}{50})^3 \times (\frac{V_p}{70})^3 \times (1 + 0.1 V_{\text{shear}})^2,
\]

where GPI has units of TC genesis events per unit area, \(\eta\) is the 850 hPa absolute vorticity in s\(^{-1}\), \(H\) is the relative humidity at 700 hPa in percent, \(V_p\) is the potential intensity in m s\(^{-1}\), and \(V_{\text{shear}}\) is the magnitude of the horizontal vector shear between 850 and 200 hPa in m s\(^{-1}\). This index is unique from the earlier work of Gray (1979) in that instead of relying on the absolute value of SST (Gray used 26°C) this new index is dependent upon PI, which is believed to be more representative of the overall environmental conditions (Emanuel 2010). One disadvantage of the GPI compared to the TCGI is that the calculation of GPI is far more complex due to the inclusion of the PI term.

2.4 Ability of AGCMs to Capture observed TC Characteristics

2.4.1. Evaluation of Tropical Cyclone Genesis Index (TCGI)

In order to test the robustness of the AGCM’s ability to capture observed TC statistics, I compare values of the three previously discussed TC indices computed from output from the ECHAM5 and CAM5 control runs (where the AGCMs are forced with observed SSTs) to those
obtained using observed SST and atmospheric reanalysis (“observed”) data. Reanalysis data is created by assimilating climate observations and then interpolating between observational points using a model in order to obtain a full picture of atmospheric conditions. This is different from actual observations where there is no interpolation and modeling method used. It will be shown that the results obtained when calculating TCGI using ECHAM5 and CAM5 model output are very similar. Therefore, only ECHAM5 model data will be used to compare with results from reanalysis for when examining the PI and GPI.

Figure 5 shows annual average values of the TCGI based on monthly climatological values of the output from the control runs of ECHAM5 for the years 1979 to 2004. Climatological values were generated by using monthly average values of the input variables and then computing a 1979-2004 mean by calculating TCGI for each calendar month. These TCGI values were then summed across all 12 months and averaged across all 16 ensemble members in the control runs. The ensemble averaging minimizes the influence of “noise” from random weather events in individual model runs on the overall TCGI results.
Figure 5 indicates very low values near the equator (as expected) and several areas of high TC activity around the global tropics, including the tropical eastern North Pacific, tropical western Pacific, Indian Ocean and the Gulf of Mexico and tropical North Atlantic. Substantial TC activity (high TCGI values) is seen across the western Pacific Warm Pool region (WP), an area where SSTs often exceed 29° Celsius and where weak trade winds and weak vertical wind shear allow for the development of deep convection that is inherently associated with the development of a TC (Cravatte et al. 2009). There is another area of enhanced tropical cyclone activity off the west coast of Mexico, with values locally exceeding 20 events on an annual mean basis. High values of the TCGI extend eastward from the Pacific warm pool region towards the central Pacific, with another maxima in the southern hemisphere to the east of Papua New Guinea. Figure 5 shows no TC activity off either coast of South America. Off the northwest coast of the South American continent, prevailing wind patterns and oceanic circulations are known to cause significant upwelling of cold, (nutrient rich) oceanic water to the surface and thus inhibiting TC formation. The causes for the lack in TC formation off the east coast of South America include cooler SSTs, climatologically higher wind shear, and a lack of pre-existing vorticity (Evans & Braun, 2012). Figure 6 shows the annual average, ensemble mean value of TCGI based on monthly average inputs for 1979-2004 computed from the control runs of CAM5. In this figure we see the main areas of enhanced TC activity identified for ECHAM5, including in the western Pacific WP region, the northern Indian Ocean, west-central Indian Ocean, eastern North Pacific, and the southern Gulf of Mexico. Similar to ECHAM5, the CAM5 control runs extend the area of enhanced TC activity in the west Pacific warm pool region.
towards the central Pacific. TCGI values also increase across a band running from the west coast of Africa towards the Caribbean. In general, CAM5 appears to extend the area of enhanced tropical cyclone activity further across the tropical central Pacific than seen in ECHAM5.

Figure 6: Annual average, ensemble mean TCGI (TC genesis events/time) based on average monthly values for CAM5 control runs (1979-2004).

In order to determine mathematically how similar the control run values of the TCGI are between ECHAM5 and CAM5, differences in annual average values were computed for each ensemble member for the two models and a student t-test was used to identify statistically significant differences (p <0.05) in the ensemble means. The statistically significant differences are shown in Figure 7.
The figure shows that statistically significant differences in annual average values of the TCGI for ECHAM5 and CAM5 control runs are generally modest in magnitude, with the largest differences typically of a very localized nature. ECHAM5 control runs are seen to have more tropical cyclones (higher TCGI values) compared to CAM5 across portions of the Gulf of Mexico, along the west coast of Mexico, across portions of the tropical western Pacific, and in the extreme northern and western Indian Ocean. On the other hand, ECHAM5 has a lower number of tropical cyclones compared to CAM5 across much of the central tropical Pacific, southern Indian Ocean, and portions of the Caribbean. The areas of underestimation by ECHAM5 are generally < 5 events or so while the areas of overestimation are typically < 5 events, with the exception of locally higher differences along the immediate west coast of Mexico. In order to quantify how similar the overall pattern of the annual average TCGI is between CAM5 and ECHAM5, a pattern correlation coefficient was calculated across the global
domain. The pattern correlation indicates the linear relationship between two separate variables across a given spatial domain. A pattern correlation of 1 indicates an identical spatial pattern (the magnitudes of the TCGI fields need not be identical, but the overall spatial pattern is the same). A pattern correlation of zero would indicate there is no overall spatial relationship between values for the two models. The pattern correlation of the TCGI between annual average values in the CAM5 and ECHAM5 control runs has a value of 0.585. While this value is far from a perfect correlation, it does indicate a general similarity in the spatial patterns of the TCGI, thus providing some support for using only one AGCM for the remainder of this study. Given this result and the fact that the format of the CAM5 data was far more cumbersome to work with, it was decided that only ECHAM5 will be used in the subsequent calculation of PI and GPI.

In order to determine how realistic the ECHAM5 values of the TCGI are relative to observations, the TCGI was next computed based on observed monthly average values (1979-2004) using ERSSTv4 for SST and NCEP reanalysis data for atmospheric variable inputs (i.e., “observations”). It is important to remember that reanalysis data is not the same as observations as it is created by assimilating climate observations and then interpolating between observational points using a model in order to obtain a full picture of atmospheric conditions. The annual average TCGI based on these observed inputs is shown in Figure 8. Similar to that of the control runs from both ECHAM5 and CAM5, in reanalysis “observations” there are again several areas across the global tropics of enhanced TC activity including the eastern North Pacific, western tropical Pacific, northern and central Indian Ocean, and in the Gulf of Mexico and western tropical North Atlantic. High values of the TCGI are clearly identifiable in the West Pacific WP, where the annual average TCGI exceeds 15 events per year. The observed TCGI pattern is also quite similar to the AGCM results across the eastern North Pacific. In observations, TCGI values
show an extension of TC activity stretching from northwestern coast of Africa to the southeastern U.S. coastline, which is a favorable track for some of the strongest TCs that impact the U.S. (Gray 1990). There is also an area of enhanced TC activity across the Gulf of Mexico where TCs often form in the warm and relatively shallow waters, especially when there is light wind shear. In addition, in observations there is essentially no TC activity across either coast of South America, similar to the ECHAM5 and CAM5 control run results previously described.

Figure 8: Annual average TCGI (events/time) based on average monthly values from observations (ERSSTv4 for SST and NCEP atmospheric data 1979-2004).

Following the calculation of TCGI using observed data, differences with the ECHAM5 control run results were made. Figure 9 shows the statistically significant differences (p<0.05) between ECHAM5 control run values of the annual average TCGI and those obtained using observations, both based on monthly average inputs computed over the period January 1979 to December 2004. The greatest differences are located across portions of the tropical western
Pacific, northern Indian Ocean, and extreme eastern tropical Pacific along the coast of Mexico, where ECHAM5 control runs are producing too many tropical cyclones relative to observations. On the other hand, the ECHAM5 model is slightly underestimating the number of tropical cyclones relative to observations across portions of the southern Indian Ocean and the Gulf of Mexico (as indicated by cool colors in the figure).

![Figure 9](image)

Figure 9: Statistically significant differences (p <0.05) in TCGI between ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) based on monthly average inputs averaged over 1979-2004.

Despite the differences shown in Figure 9, the overall spatial variations in TCGI computed from the ECHAM5 control runs and from observational data (Figures 6 and 9) are quite similar. In order to mathematically show how similar the patterns are, a pattern correlation was calculated using Matlab’s Corr2 function. This function returns a 2-D correlation coefficient between two arrays. The pattern correlation coefficient between TCGI values computed for ECHAM5 and observations has a value of 0.98, indicating a very good agreement of the TCGI
patterns. This result further increases confidence that the ECHAM5 control runs are doing a good job at capturing the observed pattern of the TCGI despite the model tendency to generally generate too many tropical cyclones relative to observations.

2.4.2. Potential Intensity (PI)

The next TC index considered is the Potential Intensity (PI; Emanuel 1988, Blister and Emanuel 2002), indicating the theoretical upper bound to a TC strength (as measured by maximum wind speed) given the atmospheric and SST conditions at a given location. PI was first calculated using the ensemble mean of the control runs of ECHAM5 for each month from January of 1982 through December of 1990. The average across all monthly values was then taken to obtain the average PI for the entire period. This shorter time period (1982-1990) was utilized due to the large computational expense of calculating PI as compared to the TCGI. The period of January of 1982 through December of 1990 was chosen randomly. In order to ensure that this period is representative of the overall study period, PI was also calculated from January of 1990 through December of 1998, with an overall average of monthly values obtained. A pattern correlation coefficient was then calculated between PI calculated for the two periods. A value of 0.999 was obtained, which signifies a very strong spatial correlation, which adds confidence in the results using this shorter time period.

Figure 10 shows the ensemble mean, average PI value (in m s\(^{-1}\)) computed over the period January 1982 through December of 1990. The figure shows several interesting features, including an area of high PI extending from the West Pacific WP region out into the central Pacific where values approach, and in some cases exceed, 90 m s\(^{-1}\) as indicated by the dark red shading. This area of high PI also extends into the central Indian Ocean as well as over a small
portion of the extreme eastern Pacific. Across the Gulf of Mexico and Caribbean the control runs of ECHAM5 show PI values between 70-80 m s\(^{-1}\) as well as across a narrow band extending from the west coast of Africa and extending into the central tropical North Atlantic. PI values are low (~20 m s\(^{-1}\)) off the west coast of South America where upwelling often prevents the formation of TCs. Figure 10 also shows evidence of the Eastern Equatorial Pacific Cold Tongue, where low PI values are seen, and decreasing values of PI with increasing latitude, which is expected due to decreasing SSTs with latitude.

![Figure 10: Ensemble mean monthly average PI (m s\(^{-1}\)) from ECHAM5 control runs (averaged from Jan. 1982-Dec. 1990).](image)

In order to help determine how well ECHAM5 is handling the calculation of PI, the index was computed using observational data (NCEP reanalysis atmospheric data). It is once again important to remember that reanalysis data is not the same as observations as it is created by assimilating climate observations and then interpolating between observational points using a model in order to obtain a full picture of atmospheric conditions. These data were re-gridded to 2.0° by 2.0° latitude/longitude resolution so that they would have the same spatial domain as the
ECHAM5 results. Similar to the calculation performed to generate Figure 10, PI values from observations were calculated for each month from January 1982 through December of 1990 and then averaged across all months, with the results shown in Figure 11. The figure shows several similar characteristics to those seen based on the control runs of ECHAM5, including an area of high PI across the western Pacific Warm Pool region, the central and northern Indian Ocean, and across the extreme eastern tropical Pacific. The order of magnitude of PI is similar to that calculated using ECHAM5, with observed PI values again approaching, and in some cases exceeding, 90 m s$^{-1}$ across these regions. The influence of the eastern Pacific cold tongue is again seen, with a strong meridional gradient in PI across this region. Similar to the ECHAM5 control runs, observed PI values are comparatively higher across the Gulf of Mexico and Caribbean, with maximum wind speeds between 60 and 80 m s$^{-1}$. This area of enhanced PI values extends eastward into the central tropical Atlantic. Despite the fairly coarse resolution of the data, Figure 10 also indicates the possible influence of the Gulf Stream on PI, with a narrow band of enhanced values of around 50 m s$^{-1}$ extending across portions of the southeast coast of the United States. In addition, the influence of coastal upwelling and thus lower SST off the west coast of South America are again seen, with PI values of generally 20 m s$^{-1}$ or less across this region.
The similarity of the PI based on the ECHAM5 control runs and in observations was examined in more detail by taking the difference between the two fields. A one sample student t-test was used in order to identify only statistically significant (P<0.05) differences in PI. The first step in performing this calculation was to calculate PI for all 16 ensemble members of the ECHAM5 control runs and across all months from January of 1982 through December of 1990. The next step was to calculate PI using monthly observations for the same time period. The t-test was then applied to identify the statistically significant differences that are shown in Figure 12. From this figure it can be seen that the ECHAM5 control runs are generally overestimating PI across much of the Pacific Ocean away from the immediate coastlines, with another area of slightly enhanced overestimation occurring near the equator of the tropical Pacific. This could be due to the model not adequately responding to lower SSTs associated with equatorial upwelling of cooler deep ocean water in this location. Overestimation of the PI is also occurring across much of the Indian Ocean, and western Pacific. On the other hand, ECHAM5 is underestimating

Figure 11: Monthly mean PI (m s\(^{-1}\)) from observations (ERSSTv4 for SST and NCEP atmospheric data) averaged over Jan. 1982 to Dec. 1990.
PI off the west coast of North Africa, the Gulf of Mexico, off the southeast U.S. coast, and across the extreme eastern tropical Pacific off the west coast of Mexico. The magnitude of the differences in PI is generally modest, typically ranging between 10-15 m s\(^{-1}\). The pattern correlation coefficient between the ensemble mean, annual average value of PI from the ECHAM5 control runs and the observed annual average value was 0.86. This result provides further confidence that the ECHAM5 control runs are able to reasonably capture observed conditions. Overall, the magnitude and spatial pattern of PI obtained using the control runs of ECHAM5 and observations (ERSSTv4 for SST and NCEP reanalysis atmospheric data) have been shown to be very similar. This similarity increases confidence in the ability of ECHAM5 to properly simulate TC potential intensity.

Figure 12: Statistically significant (P<0.05) differences in PI (m s\(^{-1}\)) between ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) averaged over the period Jan. 1982 to Dec. 1990.
2.4.3. Genesis Potential Index (GPI)

The last TC index that this thesis will examine is the Genesis Potential Index (GPI; Camargo et al., 2007, Emanuel and Nolan 2004; Emanuel 2010), which is a measure of the frequency of TC genesis within a particular region based on both PI and a number of environmental conditions. Similar to the PI analysis, GPI is first calculated monthly from January of 1982 through December 1990 using the control runs of ECHAM5 and then based on observations (NCEP reanalysis and observed SST). Following the separate evaluation of calculated GPI from ECHAM5 control runs and reanalysis data, a one sample student t-test will again be used to determine statistically significant differences between the two.

Figure 13 shows the annual average ensemble-mean value of the GPI (units of average number of events per year). This figure was obtained by first calculating the GPI for all months from January of 1982 through December of 1990 across all 16 ensemble members and then averaging the results. In this figure it can be seen that there is an area of enhanced TC genesis frequency across the extreme eastern Pacific as well as across the Western Pacific Warm Pool and north-central Indian Ocean. There is also a weak, narrow strip of enhanced GPI stretching across the central Pacific south of Hawaii. Across the Gulf of Mexico, and Caribbean there is also elevated values of GPI, although of comparatively smaller magnitudes, ranging from about 1 to 4 events. These relatively small magnitudes are not too surprising given that this figure is for the annual average and there typically are not any TCs across the Gulf of Mexico and tropical Atlantic for about half of the year. There is also a comparatively weak area of TC activity stretching from the west coast of Africa where tropical waves often come off the coast and drift westward towards the Caribbean islands and continental United States. These results are very similar to TCGI obtained using observations and the control runs of ECHAM5. Both TCGI and GPI control run
simulations show enhanced areas of TC activity across the western tropical Pacific, eastern tropical Pacific, northeastern and southern Indian ocean, and Gulf of Mexico. Although there are some differences in the number of TC events between the two, the overall spatial patterns are quite similar.

![Figure 13: Ensemble mean monthly average GPI from ECHAM5 control runs averaged over Jan. 1982 to Dec. 1990.](image)

Following the completion of calculating GPI index using the control runs of ECHAM5 the same calculation was performed again but this time using observations (reanalysis atmospheric data and observed SST). Once again it is important to remember that reanalysis data is not the same as observations as it is created by assimilating climate observations and then interpolating between observational points using a model in order to obtain a full picture of atmospheric conditions. As was done for ECHAM5, the GPI was computed from monthly
observations from January 1982 through December of 1990 and then averaged across all months to obtain an annual average. The results are shown in Figure 14, which shows several areas of similarly enhanced GPI values, including across the eastern North Pacific, western Pacific Warm Pool region, north-central Indian Ocean, and the Gulf of Mexico and Caribbean. The observed values of the GPI across the eastern and western Pacific are generally lower than those obtained from the ECHAM5 control runs, although across the Gulf of Mexico and Caribbean they are slightly higher. Another difference between observations and the ECHAM5 is that the GPI from the ECHAM5 has a larger spatial coverage (that is, non-zero values cover a greater area in the model than in observations).

![GPI Map](image)

Figure 14: Annual average GPI from observations (ERSSTv4 for SST and NCEP atmospheric data) averaged over Jan. 1982 to Dec. 1990.

As a final step in comparing annual average values of the GPI calculated from the ECHAM5 control runs and observations, a student t-test was used to determine statistically significant differences between the two. The results are shown in Figure 15. In regions of warm colors, such as across the eastern and western tropical Pacific, north-central Indian Ocean, and
extreme southern Gulf of Mexico and Caribbean the sign of the difference is positive, indicating that the GPI based on the ECHAM5 control runs is higher than observed. In some instances, such as in the extreme eastern tropical North Pacific, there are differences approaching 10 events, but on average the differences between ECHAM5 and observations are between 1 to 4 events. On the other hand, areas of cool colors, such as across portions of the extreme northwestern North Pacific and northern Gulf of Mexico, indicate areas where computed GPI using ECHAM5 control runs is lower than observed. Similar to the regions of overestimation, the differences are on average rather small, typically less than 5 events. Similar to the results for TCGI, ECHAM5 in general produces too many storms compared to observational data. The pattern correlation coefficient between the annual average values of GPI in ECHAM5 and observations is 0.56, indicating that although ECHAM5 control runs produce on average too many TC genesis events, the model generally captures the overall observed spatial pattern of the GPI.

Figure 15: Statistically significant GPI differences (P<0.05) between ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) for the period Jan. 1982 to Dec. 1990.
2.4.4. Seasonal Analysis of Potential Intensity and the Genesis Potential Index

In order to provide greater detail of the spatial variations in PI and GPI than is provided in annual average values, each index was also evaluated by season. As previously stated, TCGI and GPI are both a statistical fit between the frequency of TCs and various environmental conditions known to influence TC behavior. Given the earlier results which showed significant similarity between TCGI and GPI only GPI was evaluated seasonally in order to reduce redundancy. The examination of seasonal differences across various ocean basins is also paramount given the climatological differences in the seasonal timing of peak TC activity across different parts of the globe. The first season which was evaluated was Northern Hemisphere Spring, which for the purposes of this study were the months of March, April, and May (MAM). Figure 16 shows statistically significant differences (P<0.05) between calculated PI using ECHAM5 control runs and reanalysis data. The figure shows areas of model overestimation (indicated by warm colors) occurring across much of the central and southern tropical Pacific, central tropical Atlantic Ocean, and the southern Indian Ocean. There are areas of weak overestimation also present across the northern Pacific as well as across the Caribbean and off the New England coastline. One area of particularly large overestimation by the model is in the east-central Pacific, where observed equatorial upwelling is prevalent. On the other hand, underestimation (indicated by cool colors) is present across the extreme western Pacific, off the northwest coast of Africa, extreme eastern Pacific, and in parts of the Gulf of Mexico as well as in the vicinity of the southeast U.S. coastline. There is also some weak underestimation present in the central Indian Ocean and off the east coast of Asia. The magnitude of the underestimation and overestimation within the control runs of ECHAM5 compared to observations is modest, typically < 10 m s⁻¹.
The same calculation described above was also performed for Northern Hemisphere Summer, which for the purpose of this study includes the months of June, July, and August (JJA), with results shown in Figure 17. The figure shows underestimation in the ECHAM5 control runs is present off the west coast of Africa and extending into the tropical Atlantic and off the southeast U.S. coastline. In some instances, these differences are 15 m s\(^{-1}\) or greater, especially in the vicinity of western Africa. There is also underestimation by the model present across the Gulf of Mexico and eastern tropical Pacific. Finally, small underestimations are present off the west coast of South America and southern Indian Ocean, although these differenced are generally only 5-10 m s\(^{-1}\). Overestimation of PI calculated from ECHAM5
control runs is present across the western Pacific in the vicinity of the Western Pacific Warm Pool region, north-central Indian Ocean, central Pacific, and across much of the southern Atlantic and Pacific. Similar to MAM, there is overestimation located near the equator.

![Image](image_url)

Figure 17: Statistically significant JJA PI (m s\(^{-1}\)) differences (P<0.05) between ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) for the period Jan. 1982 to Dec. 1990.

Results for the months of September, October, and November (SON) are shown in Figure 18. During SON there is an overestimation (indicated by warm colors) of PI in ECHAM5 throughout much of the northern Atlantic and Pacific, including within the West Pacific WP region as well as along the east coast of the U.S., much of the Indian Ocean, and across portions of the central Pacific, including in the vicinity of the equator. The magnitudes of the overestimation are generally less than 15 m s\(^{-1}\) with the largest differences located across north of Hawaii as well as off the northeast U.S. coast. There is underestimation (indicated by cool colors) located across the extreme eastern Pacific near the coast of Mexico, southern Indian Ocean, extreme western Pacific, Gulf of Mexico, eastern tropical Atlantic off the west coast of Africa. The magnitude of these underestimations is generally the same as the overestimation.
areas, with the largest differences located directly along the west coast of Mexico where in some cases, they exceed 15 m s\(^{-1}\).

![Map showing statistically significant SON PI differences (P<0.05) between ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) for the period Jan. 1982 to Dec. 1990.]

Finally, during the Northern Hemisphere Winter months of December, January, and February (DJF; Figure 19) ECHAM5 generally overestimates PI across much of the globe, including across the tropical central Pacific, Indian Ocean, tropical eastern Pacific, Caribbean, and tropical Atlantic. The magnitude of these overestimations is generally 5-10 m s\(^{-1}\), which is of a similar magnitude to the previous seasons that were examined. Areas of underestimation (indicated by cool colors in Figure 19) are present in the extreme western Pacific, along the west coast of Australia, along a portion the central South America west coast, along the southeast U.S. coast, and in a small region off the west coast of Africa. The magnitude of these underestimations is generally 5 m s\(^{-1}\) or less, with locally higher values.

In summary, it was shown that ECHAM5 control runs tend to overestimate PI across the east-central Pacific within a region of observed equatorial upwelling. This was observed during
all seasons but especially during MAM, JJA, and DJF where in some instances it approached 10 m s\(^{-1}\). Upwelling is often troublesome for many coupled models and based on these results it appears ECHAM5 is no exception to this. In addition, ECHAM5 was shown to overestimate PI across the western Pacific in the vicinity of the Western Pacific Warm Pool, especially during the summer season. During the winter it was found that on a global scale ECHAM5 tends to overestimate PI across most areas. On the other hand, it was found that ECHAM5 underestimates PI near the west coast of Africa during all seasons, but especially during the summer. Overall, the season with the least significant differences between the control runs and observations was SON, with differences of generally less than or equal to 5 m s\(^{-1}\) observed.

Figure 19: Statistically significant DJF PI (m s\(^{-1}\)) differences (P<0.05) between ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) for the period Jan. 1982 to Dec. 1990.

The seasonal analysis of differences in the GPI between the ECHAM5 control runs and observations data were conducted next, with the results for MAM shown in Figure 20. The figure shows areas where ECHAM5 overestimates GPI (indicated by warm colors), including portions of the tropical eastern and western Pacific, western Indian Ocean, northern Indian Ocean, and
portions of the tropical Atlantic. The only statistically significant area of underestimation (indicated by cool colors) is present across a small portion of the central Indian Ocean, where differences of generally less than 2 events. In areas of overestimation, such as off the northern coast of Australia, the differences between GPI calculated using ECHAM5 control runs and reanalysis data approach 6-10 events.

Results for JJA are shown in Figure 21. Areas where ECHAM5 underestimates the GPI (indicated by cool colors) are present in the Gulf of Mexico, Caribbean, as well as the extreme western Pacific. There are areas of overestimated GPI present in the eastern and western tropical Pacific, and the north-central Indian Ocean. An area of weak overestimation is present along a narrow band stretching across the central Pacific, with areas of larger overestimation are present off the west coast of Mexico and within the West Pacific WP. The magnitude of the underestimated GPI within the Gulf of Mexico is generally between 2 and 4 events, although along the immediate coast of the Gulf Coast they approach 6 events. On the other hand, the

Figure 20: Statistically significant MAM GPI (TC genesis events/time) differences (P<0.05) for ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) for the period Jan. 1982-Dec. 1990.
magnitude of the overestimation in GPI along the west coast of Mexico and across portions of the western tropical Pacific and northern Indian Ocean locally approach 10 events, but on average the differences are between 2 and 6 events.

![Image](image.png)

Figure 21: Statistically significant JJA GPI (TC genesis events/time) differences (P<0.05) for ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) for the period Jan. 1982-Dec. 1990.

Results for SON are shown in Figure 22. During boreal Fall ECHAM5 overestimates the GPI (indicated by warm colors) in the extreme eastern tropical Pacific as well as the northern Indian Ocean and tropical western Pacific. During boreal fall there appears to be essentially no underestimation in GPI occurring within the control runs of ECHAM5 with only very locally negative differences (represented by cool colors) present in the south-central Indian Ocean and along the east coast of Honduras. The magnitude of the differences where overestimation in GPI is occurring is typically 6 events per year or less, but there are again some locally higher differences in the extreme eastern tropical Pacific.
Lastly, Figure 23 shows seasonal GPI difference results for DJF. There are generally very few instances where ECHAM5 control runs underestimate GPI with the only region occurring between Africa and Australia. On the other hand, ECHAM5 control runs are overestimating GPI across portions of the western tropical Pacific along the north coast of Australia as well as across portions of the Philippine sea as well as along the southeast coast of Africa. The greatest overestimation in GPI during boreal winter occurs north of Australia and in parts of the western Indian Ocean where in some instances there are locally greater than 10 events of difference. In summary, it was shown that ECHAM5 control runs tend to overestimate GPI rather than underestimate it. The regions of overestimated GPI were found to be in generally similar locations to that of PI, including across the east-central tropical Pacific where equatorial upwelling is observed. This region of overestimated GPI across the east-central Pacific was particularly prevalent during JJA and SON, where it locally approached 10 events. Another region with relatively high overestimated GPI is across the western Pacific, in the vicinity of the
Western Pacific Warm Pool. It was found that during the winter season, the regions of overestimated GPI generally shifted south of the equator. Only during JJA was there underestimated GPI, and this was located in the Gulf of Mexico but with generally low magnitudes.

![Statistically significant DJF GPI (TC genesis events/time) differences (P<0.05) for ECHAM5 control runs and observations (ERSSTv4 for SST and NCEP atmospheric data) for the period Jan. 1982-Dec. 1990.](image)

2.5 Discussion and Conclusions

This chapter investigated the ability of two AGCMs run with observed SSTs to properly simulate observed climate conditions that relate to tropical cyclones when they are run (or forced) with observed sea surface temperatures.Confirming such an ability is a vital step before the examination of the potential influence of coupled model SST biases on AGCM simulations. Initially two AGCMs were used, the ECHAM5 and CAM5, but the results obtained from the two were found to be generally similar and therefore to avoid repetition only the ECHAM5 was subsequently used. Observational data from the NCEP reanalysis was utilized for atmospheric
variables, with the Extended Reconstructed Sea Surface Temperature, Version 4 (ERSSTv.4) used for SSTs. The ERSST data was also used to specify sea surface temperatures in the ECHAM5 and CAM5 AGCM control runs. Three tropical cyclone indices were used to compare AGCM results with observations: the Tropical Cyclone Genesis Index (TCGI), the Genesis Potential index (GPI) and the Potential Intensity (PI). Based on the TCGI, it was found that on average, the two AGCMs produce too many TCs relative to observations across portions of the eastern and western tropical Pacific, northern Indian Ocean, and Gulf of Mexico. In some very localized areas these differences are greater than 10 events, but generally much lower. On the other hand, the models underestimate the number of TCs relative to observations across portions of the tropical Atlantic, southern tropical Pacific, and southern Indian Ocean. The areas of underestimation were found to be of lower magnitude compared to the regions of overestimation. Overall, the models did a very good job in capturing the observed pattern of TC genesis. The pattern correlation between the annual average TCGI obtained using the ECHAM5 control runs and observations was 0.98, indicating an excellent correlation between the two. As the results obtained using CAM5 and ECHAM5 output were found to be very similar, only the ECHAM5 model was used in subsequent analyses.

Comparing results for the PI index calculated using the ECHAM5 control runs and observations (NCEP reanalysis, observed SSTs) showed that, on average, the ECHAM5 overestimated PI when considering annual average values. In particular, the ECHAM5 control runs tend to overestimate PI throughout much of the central tropical Pacific, Indian Ocean, and central/southern tropical Atlantic. On the other hand, ECHAM5 tends to underestimate PI along the west coast of Africa, Gulf of Mexico, Caribbean, extreme western Pacific, and off the west coasts of South America and Australia. The magnitude for regions of overestimation and
underestimation are generally 10 m s\(^{-1}\) or less. Similar to what was done for TCGI, a pattern correlation coefficient was calculated between PI calculated from ECHAM5 control runs and reanalysis data and a value of 0.86 was obtained. This value further increases confidence that ECHAM5 control runs are doing a good job at capturing the overall pattern of the TC indices.

The effect of seasonality on the results was also examined, with PI calculated for each season and statistically significant differences with observations analyzed. This was done in order to examine how well the model captures observed conditions during specific times of the year owing to the fact that TC activity is seasonally dependent across ocean basins. In general, the largest differences between the ECHAM model and observations were found to occur during Northern Hemisphere spring (MAM), summer (JJA), and winter (DJF), with the smallest differences occurring during the fall season (SON). In some circumstances, such as during JJA the magnitude of the differences in PI exceeded 15 m s\(^{-1}\) but these were only for a few localized areas. Overall, seasonality testing showed that while there were differences between ECHAM5 control runs and observational data, the model did a good job at capturing the spatial patterns of observed TC activity with mostly small differences observed.

Results obtained for the GPI were found to be very similar to those of TCGI, which is expected given that the two indices are related. On average, the ECHAM5 control runs produce too many TCs compared to observations when considering annual average values. This tendency is particularly prevalent across the eastern and western tropical Pacific, north-central Indian Ocean, and along the southeast coast of Africa. In some instances, the magnitudes of the overestimations approach 10 events, but again, these large differences tend to be in localized areas. There are very few areas where the ECHAM5 control runs underestimate GPI, the only regions in this case being across the northern Gulf of Mexico and along a small area off the east
coast of China. The magnitudes of the underestimations were found to be between 2 to 4 events. The pattern correlation between annual average GPI values for ECHAM5 and observations was found to be 0.56 which, although lower than pattern correlations for TCGI and PI, still indicates the model is generally capturing the overall observed pattern. Seasonally testing identical to that completed for PI was also performed. In general, during most seasons ECHAM5 had a tendency to overestimate GPI values relative to observations. Interestingly, during JJA the control runs were shown to underestimate GPI throughout the Gulf of Mexico, which is the season when TC activity is often frequent across this basin. The magnitude of this underestimation was found to be between 4-6 events, with local differences up to 8 events identified along the Gulf Coast. On the other hand, during this same season the control runs overestimate GPI by 10 events or greater in the eastern and western tropical Pacific. It was shown that the remaining three seasons generally experiences less significant differences in GPI. Overall ECHAM5 control runs did a good job at capturing observed TC activity but they did in some cases significantly overestimate the number of TCs, especially across the eastern and western tropical Pacific.

Based on the results presented in this chapter it was determined that although ECHAM5 shows differences in capturing the magnitude of observed values of the TC indices, it is capturing the overall observed patterns rather well. These findings provide confidence that the ECHAM5 AGCM can be subsequently used to examine the influence of coupled model SST biases on the behavior of the TC indices. A second set of runs of the ECHAM5 were used for this latter purpose, where the sea surface temperatures in the model were the same as those used in the control runs, but with the monthly multi-model mean climatological SST biases added. Changes in the TC indices were then computed by comparing results from these “bias” runs with those just described for the control runs. These results are presented in the next chapter.
3.1. Introduction

In Chapter 2, it was shown that the ECHAM5 control runs were generally able to capture observed spatial patterns of three TC indices considered throughout the global tropics. That set of analyses was a key first step in this thesis: to see if the ECHAM5 model forced with observed SST was able to provide an accurate depiction of observed conditions. In this chapter I now examine the influence of coupled model SST biases on the tropical cyclone indices using the same AGCM.

3.2. Data Used and Setup of AGCM Bias Runs

The second set of AGCM model runs utilized will be the “bias” runs, where the ECHAM5 has been forced with observed monthly SSTs plus the multi-model mean, CMIP5 monthly climatological SST bias computed over the period 1979-2004. The ECHAM5 bias runs again consist of 16 ensemble members, generated by using slightly different initial conditions in the atmosphere prior to running the model. The generation of 16 ensemble members was done for the same reasons as previously described for the control runs, which is to reduce the potential noise in the analysis resulting from random weather events in the model by using the ensemble mean values of variables in the analysis.
If the observed monthly SST is considered as the sum of a climatological monthly mean value plus a monthly anomaly, the SSTs used to force the ECHAM5 in the bias runs (\(SST_{BIAS}\)) can be expressed as:

\[
SST_{BIAS} = (\overline{SST}_{bias} + \overline{SST}_{obs}) + SST'_{obs}
\]

Where \(\overline{SST}_{bias}\) is the multi-model mean CMIP5 bias in monthly SST climatology and \(\overline{SST}_{obs}\) and \(SST'_{obs}\) are the observed monthly SST climatology (1979-2005) and monthly anomaly, respectively. Similar to the AGCM control runs, both ECHAM5 and CAM5 bias runs were generated at Columbia University, with output stored at the International Research Institute’s (IRI) Climate Data Library, which can be accessed at: https://iridl.Ideo.columbia.edu. Once again, for all model variables, both daily averages and monthly averages were archived.

3.3. Analysis of the Tropical Cyclone Indices in the ECHAM5 Bias Runs

3.3.1. Tropical Cyclone Genesis Index (TCGI) in Bias Runs

The first tropical cyclone index considered is the TCGI. Figure 24 shows the annual mean TCGI averaged over computed monthly values between January 1979 through December 2004 based on the ECHAM5 bias runs, with results based on the control runs also shown for reference. There are several areas of enhanced TC activity in Figure 24, including across the eastern Pacific along the west coast of Mexico as well as across the Western Pacific Warm Pool region. One difference is that TCGI computed from the bias runs has lower values across the western Pacific compared to the control run values. In addition, across the north-central Indian Ocean less frequent genesis events are observed when using the bias runs compared to the
control runs. Another area where the bias runs result in less tropical cyclones is across the Gulf of Mexico and Caribbean. The bias runs also produce a narrow strip of enhanced TC across the central north tropical Pacific as well as across the central north tropical Atlantic. In the tropical South Atlantic, the bias runs result in enhanced activity extending westward from the Gulf of Guinea. Lastly, the bias runs result in enhanced activity along the northern coast of Australia in a similar location to the control runs calculation.
In order to quantify the differences between the bias and control runs of computed TCGI, the latter were subtracted from the bias run values and a student t-test was then calculated in order to only retain statistically significant differences at a 95% confidence level. The results are shown in Figure 25. The figure shows that, compared to the control run values, the bias runs result in an overestimation in TCGI across the extreme eastern Pacific, with differences in localized areas approaching 15 events or greater. There is an additional region of overestimation stretching across the central tropical Pacific, but the magnitude of the difference in this region is generally only between 2-6 events. There are locally overestimations in TCGI present across the south-central Indian Ocean, southern tropical Pacific in the vicinity of northern Australia as well as across the extreme eastern Atlantic along the west coast of Africa. On the other hand, the SST biases result in ECHAM5 underestimating TCGI across the western Pacific in the vicinity of the western Pacific Warm Pool. These differences locally approach 5 to 10 events on average. There is also underestimation of the TCGI present across the northern Indian Ocean, with localized differences approaching 6 events. A broad area of underestimation is present across the Gulf of Mexico and Caribbean, with differences on average ranging from 4 to 8 events. Increased TC genesis activity relative to the control runs is seen by the elongated region of positive difference values in the tropical South Atlantic Ocean extending westward from the Gulf of Guinea. The regions of overestimated and underestimated TCGI between ECHAM5 bias and control runs are within the same regions of positive and negative SST biases, which were shown in Figure 3.
As an additional step, an analysis was undertaken to determine the sensitivity of each of the four input variables to the calculation of TCGI in the bias runs. This was accomplished by setting only one of the four inputs in the TCGI calculation to the “bias” run values while the control run values were used for the remaining three inputs. For example, the contribution of relative humidity to changes in TCGI for the bias runs was determined by using the bias run values of relative humidity while using the control runs for the other input variables (relative SST, vertical wind shear, and low-level vorticity). A student t-test was then computed to determine statistically significant differences in the associated TCGI index. The first input which was analyzed for sensitivity was the relative SST with the results shown below in Figure 26. It can be seen that the change in relative SST in the bias runs result in an underestimation in TCGI across the extreme eastern tropical Pacific along the west coast of Mexico. In some locations,

Figure 25: Statistically significant differences (P <0.05) in TCGI (TCs/month) between ECHAM5 bias and control runs (1979-2004).
these differences approach 10 events per year. There are also underestimations, but of much smaller magnitude, near the north coast of Australia and off the west coast of Africa. On the other hand, overestimations in TCGI from relative SST changes are present across the Gulf of Mexico, Caribbean, and the northern Indian Ocean, with differences locally approaching 6 events per year. On average, there appears to be more overestimated areas compared to underestimated when examining the influence of relative SST changes alone in the bias runs.

![Figure 26: Statistically significant differences (p <0.05) in TCGI (TCs/month) between ECHAM5 bias and control runs based only on changes in relative SST from the bias runs (1979-2004).](image)

The next input variable which was examined for sensitivity was relative humidity, with results shown below in Figure 27. In this figure it can be seen that RH changes in the bias runs result in underestimated TCGI across a portion of the east-central tropical Pacific, along the northern coast of Australia, near the east coast of Africa, and in a narrow strip offshore of
western Africa. These differences are on average 4 events or less per year. Overestimated TCGI is present across much of the eastern tropical Pacific, western tropical Pacific, Gulf of Mexico, Caribbean, and northern Indian Ocean. The magnitude of overestimated TCGI is up to 10 events, with locally higher values located across the far eastern tropical Pacific. Similar to the SST biases, on average the contribution from RH changes in the bias runs appears to result in more areas of overestimated TCGI versus underestimated.

Figure 27: Statistically significant differences (p <0.05) in TCGI (TCs/month) between ECHAM5 bias and control runs based only on RH from the bias runs (1979-2004).

The third input variable examined for TCGI sensitivity testing was the magnitude of the vertical wind shear, with results shown below in Figure 28. In this figure it can be shown that the change in shear in the bias runs result in underestimated TCGI throughout the much of the northern Indian Ocean, tropical western Pacific, central tropical Pacific, and offshore from Mexico. On average the magnitude of the underestimated TCGI are 6 events per year or less,
with the exception of the tropical eastern Pacific where at some grid points they exceed 10 events per year. On the other hand, overestimated TCGI is located across the extreme northern Indian Ocean, north western tropical Pacific, directly along the west coast of Mexico and the extreme southern Gulf of Mexico. The magnitude of the overestimated TCGI is on average less than 4 events, but in some cases exceed 6 events per year. Unlike the relative SST and RH changes, the changes in wind shear in the bias runs results in more underestimated regions of TCGI compared to overestimated values relative to the control runs.

![Figure 28: Statistically significant differences (p <0.05) in TCGI (TCs/month) between ECHAM5 bias and control runs based on wind shear from the bias runs (1979-2004).](image)

The last input variable for TCGI which was examined for sensitivity was the 850 hPa vorticity, with results shown below in Figure 29. In the figure it can be shown that the change in vorticity in the bias runs results in areas of overestimated TCGI across the western Tropical
Pacific, northern Indian Ocean, and along the west coast of Mexico. On average these differences are 6 events per year or less, with locally higher values located north of Australia and along the west coast of Mexico. Areas of underestimated TCGI are extremely scattered across the tropics in this case, with only minor patches located across the eastern tropical Atlantic, central tropical Pacific, near the east coast of Africa with differences generally 2 events per year or less. These results are similar to those obtained when examining the SST and RH impacts where more areas experienced overestimated TCGI compared to underestimated.

Figure 29: Statistically significant differences (p <0.05) in TCGI (TCs/month) between ECHAM5 bias and control runs based only on absolute vorticity from the bias runs (1979-2004).

Summarizing the above results, it was found that when looking at an annual timescale, the SST bias runs from ECHAM5 resulted in an extension of TC activity across the central Pacific and Indian oceans relative to the control runs. This amplification of TC activity overall
correlated well with the regions of positive SST biases, which were shown in Figure 3. In addition, there were generally less TCs compared to the control runs across the western Pacific, Gulf of Mexico, western Indian ocean, and the Caribbean. On the other hand, there were more storms across the eastern and central Pacific in the bias runs. The areas of over and underestimated TC activity were found to be well correlated with the SST bias patterns, which were shown in Figure 3. More specifically, regions of overestimated TC activity such as across the eastern Pacific and underestimated activity such as across the Caribbean were found to be correlated with positive and negative SST biases. These results are very similar to those found in Hsu et al. 2018, which found that overall the SST biases resulted in overestimated TC activity across portions of the eastern tropical Pacific while much of the Gulf of Mexico experienced underestimated activity. Results shown above and from Hsu et al. 2018 indicate an extension of increased activity across the central tropical Pacific and a decrease in activity across the western tropical Pacific.

When examining the contributions to each of the four input variables to TCGI, it was shown that the relative SST biases resulted in less storms across the eastern Pacific and more storms across the western Pacific, Gulf of Mexico, and the northern Indian ocean. The results showed that this term overall had the largest impact on TCGI as compared to the other 3 terms. In some cases, such as across the eastern Pacific, the SST biases resulted in an underestimation of 10 or more storms with a similar magnitude across the western Pacific but of overestimated storms. When comparing regions of higher and lower TCGI (relative to control run values) to positive and negative SST biases, a few interesting features are observed. The first is that across the eastern tropical Pacific, the positive SST biases resulted in less storms but across the western Pacific, the positive SST biases resulted in more storms. This is an interesting result since this
indicates that the response to the coupled model SST biases is basin-dependent and not uniform globally. The RH biases resulted in more storms across the eastern tropical Pacific, Gulf of Mexico, western Pacific, and the northern Indian ocean. There was less TC activity though across the western Indian and central Pacific oceans. Results showed that this was the second most important term in the calculation of TCGI between the bias and control runs, with only slightly lower magnitudes as compared to the relative SST term. The shear biases resulted in less TC activity across most locations including the northern Indian ocean as well as the eastern and western tropical Pacific. Some increased activity was observed along the east coast of South America. The magnitude of these differences was generally more modest as compared to those found when looking at the SST and RH bias terms. The final term which was examined was vorticity, which was found to have the least impact on TC activity as compared to the previous 3 terms.

3.3.2. Potential Intensity (PI) in Bias Runs

As discussed previously, PI is the theoretical upper bound of near-surface wind speed that a TC could achieve based on a number of environmental conditions. Annual average values of the PI based on monthly inputs obtained from the ECHAM5 bias runs from January 1982 through December of 1990 are shown in Figure 30, where annual average PI values from the ECHAM5 control runs are also shown for comparison. Similar to the results from the control runs, there are enhanced values of PI located across much of the tropical Pacific and north-central Indian Ocean. Across portions of the west-central Pacific and Indian oceans PI values exceed 90 m s⁻¹, although on average they cover a smaller area compared to results from the control runs. There are also enhanced PI values located across the eastern tropical Pacific, but of
lower magnitude compared to results using the control runs. Comparatively high PI values are located across the tropical Atlantic, Gulf of Mexico, and Caribbean, with values locally approaching 70 m s⁻¹. These PI values are also on average lower than those obtained using ECHAM5 control runs. There is also still an indication of the Gulf Stream with comparatively higher values of PI located at higher latitudes across the western Atlantic. Finally, lower values of PI are observed across the eastern Pacific and off of the west coast of South America, where upwelling of cooler sub-surface waters typically occurs.
To quantify changes in the annual average PI based on the ECHAM5 bias runs, control run values were subtracted out, with statistically significant differences identified using a t-test. The results are shown in Figure 31 where only statistically significant (P<0.05) differences are shown. From this figure it can be seen that the bias runs overestimate PI relative to the control runs across the eastern tropical Pacific, off the northeast U.S. coastline, and in a portion of the
eastern Atlantic. In some instances, these differences exceed 15 m s\(^{-1}\). There are also weaker areas of overestimated PI located across the central and southern Indian ocean and southern tropical Pacific. On the other hand, ECHAM5 bias runs underestimate PI on an annual monthly basis (indicated by negative values) across much of the west-central tropical Pacific, northern Indian ocean, Caribbean, Gulf of Mexico, and tropical Atlantic. The area of greatest underestimation is present across the tropical Atlantic where in some locations the differences exceed 15 m s\(^{-1}\). On average, the magnitude of underestimation is between 5-10 m s\(^{-1}\) across the rest of the global tropical oceans.

Figure 31: Statistically significant (P<0.05) differences in PI (m s\(^{-1}\)) between the ECHAM5 bias and control runs averaged over the period Jan. 1982-Dec.1990.
In summary, it was found that the coupled model SST biases resulted in underestimated PI across much of the tropical Atlantic, Gulf of Mexico, Caribbean, central Pacific, western Pacific, and northern Indian ocean relative to the control run results. In some instances, the magnitude of underestimation was found to exceed 15 m s\(^{-1}\), especially across the tropical Atlantic. On the other hand, there was overestimated PI located across the eastern tropical Pacific, eastern tropical Atlantic, southern Indian ocean, and off the northeastern U.S. coastline. Similar to that of regions with underestimation, the magnitude of the differences in some cases exceeded 15 m s\(^{-1}\). When comparing regions of underestimated and overestimated PI to the SST biases themselves (Figure 3), they generally tended to coincide with cold and warm SST biases, respectively. More specifically, it was found that cold (negative) SST biases are associated with lower PI across the central tropical Pacific, northern Indian ocean and tropical Atlantic. On the other hand, warm (positive) SST biases are associated with higher PI across the eastern tropical Pacific, extreme eastern Atlantic, and western Indian ocean.

3.3.3. Genesis Potential Index (GPI) in Bias Runs

The final index relating to TCs that was evaluated to determine the influence of CMIP5 SST biases on the ECHAM5 bias runs was the Genesis Potential Index (GPI; Emanuel and Nolan, 2004; Emanuel 2010). Figure 32 shows the ensemble mean, annual average GPI (events/time) obtained using the ECHAM5 bias runs from January of 1982 through December of 1990 along with associated values from the control runs for comparison. Similar to results obtained using the control runs, there is enhanced TC genesis located across much of the eastern and tropical Pacific, Indian ocean, along the northern coast of Australia, and across the Gulf of Mexico and Caribbean. Generally speaking, the bias runs produce fewer TCs compared to the control runs across much of the tropical Pacific, although there are slightly higher GPI values
across the central Pacific portion of the basin. The bias runs also result in slightly more tropical cyclones across the extreme eastern Atlantic near and along the west coast of Africa and a zonally-elongated region of TC genesis in the tropical South Atlantic not seen in the control runs. Similar to the control run results, there is a narrow strip of increased activity stretching from the west coast of Africa and extending across the central tropical Atlantic into the southern Caribbean.
The next step was to calculate the statistically significant differences in GPI between the ECHAM5 bias and control runs, with results shown in Figure 33. From this figure it can be seen that ECHAM5 bias runs result in an overestimation (indicated by positive values) across the central tropical Pacific, eastern tropical Atlantic, central Indian Ocean, and along the northern
coast of Australia. While these differences are generally small (on average 2 events or less), they do locally approach 6 events along the northern Australia coastline. On the other hand, ECHAM5 bias runs result in underestimated GPI across the extreme eastern Pacific along the west coast of Mexico and central America, the western Gulf of Mexico, the western Pacific, and the northern Indian Ocean. These areas of underestimated GPI are generally 4 events or less but they do approach locally 8 events along the west coast of Mexico.

Figure 33: Statistically significant (P<0.05) differences in GPI (TC genesis/time) between ECHAM5 bias and control runs averaged over the period Jan. 1982-Dec.1990.

In summary, it was found that the coupled model SST biases resulted in underestimated GPI across the tropical western Pacific, extreme eastern tropical Pacific, northern Indian ocean, and in the western Gulf of Mexico. The areas of greatest underestimations were found to occur along the west coast of Honduras, where in some instances they approached 8 events. Areas of overestimated GPI were then found to be present across portions of the central tropical Pacific,
along the northern coast of Australia, the southern Indian ocean, and in a small area off the coast of Africa. The magnitude of the overestimations approached 4 events in some instances. When comparing these results to the coupled model SST biases (Figure 3) a few relationships can be identified. The first is that the overestimated GPI across the central tropical Pacific is collocated with a region of positive SST bias. This is also true along the northern coast of Australia, western Indian ocean, and extreme eastern tropical Atlantic. In addition, Figure 33 showed underestimated GPI located across the northern Indian ocean, western tropical Pacific, and western Caribbean. These regions are also approximately collocated with areas of negative SST biases in CMIP5 (Figure 3). One region where a relationship between over/underestimated GPI is not collocated with a warmer/cooler SST bias is across the eastern tropical Pacific. In this region, GPI is underestimated but SST is warmer than observed. This indicates one of the other input variables (shear, relative humidity, or vorticity) must be unfavorable for TC formation to offset the direct influence of SST.

3.4.4. Seasonal Analysis of Potential Intensity and Genesis Potential Index in Bias vs. Control Runs

Similar to what was done in Section 2.4.4, where the seasonal behavior of PI and GPI was compared between observations and output from the AGCM control runs, comparisons were made between these indices computed using the bias and control run data from the ECHAM5 AGCM. As previously stated in Section 2.4.4, since TCGI and GPI are both statistical fits between the frequency of TCs and various environmental factors known to influence TC behavior it was decided that only GPI would be evaluated on a seasonal time scale in order to
prevent being redundant. The first index considered is the PI, with the first season examined being the Northern Hemisphere Spring (MAM). Statistically significant ($p < 0.05$) differences between PI values computed using output from the bias and control runs of the ECHAM5 are shown in Figure 34. This figure shows that ECHAM5 bias runs result in a comparative underestimation in PI (indicated by negative values in the figure) across much of the tropical Atlantic, western tropical Pacific, central tropical Pacific, and western Indian ocean. In some circumstances, such as across the central tropical Atlantic and west-central Pacific, these differences approach or exceed 15 m s$^{-1}$. On the other hand, ECHAM5 bias runs result in an overestimation (indicated by positive values) throughout the eastern tropical Pacific, western Atlantic near the east coast of the U.S., off the west coast of South America, and across the extreme eastern Atlantic near the west coast of Africa. The largest of these differences are located near the west coast of South America where in some cases they exceed 15 m s$^{-1}$. This is an area where continental upwelling often occurs, which is known to be troublesome for many coupled models to properly capture.
The next season evaluated was Northern Hemisphere Summer (JJA). Statistically significant differences (p< 0.05) in JJA PI are shown in Figure 35. The figure shows that the ECHAM5 bias runs result in a comparative underestimation in PI throughout much of the central tropical Atlantic, Gulf of Mexico, central Pacific, and northern Indian ocean. The regions of greatest underestimation are present across the tropical Atlantic and Pacific where in some cases they approach and exceed 15 m s\(^{-1}\). There is also a narrow strip of underestimated PI located across the tropical central Pacific near the equator. On the other hand, ECHAM5 bias runs result in an overestimation in PI during Northern Hemisphere summer throughout the eastern tropical Pacific including along the west coasts of Mexico and South America, the southern Indian ocean, and along the northeastern U.S. coastline of the western Atlantic. There are also strong overestimations in PI present across the extreme eastern Atlantic near Africa. On average, the

Figure 34: Statistically significant (MAM; P<0.05) differences in PI (m s\(^{-1}\)) between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.
areas of overestimated PI are 10 m s\(^{-1}\) or less, but they do exceed 15 m s\(^{-1}\) across portions of the eastern tropical Pacific and western Indian ocean.

![Image of statistical differences in PI between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.](image)

Figure 35: Statistically significant (JJA; P<0.05) differences in PI (m s\(^{-1}\)) between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.

Results for SON are shown in Figure 36, which provide a similar picture to what was found during the summer season, with the ECHAM5 bias runs resulting in a comparative underestimation in PI across the central Pacific, central Atlantic, and parts of the northern Indian Ocean. One difference between fall and summer results is that the magnitude of the comparative underestimation of PI is on average less for SON compared to JJA. For example, during the summer season many areas across the tropical Atlantic approached or exceeded 15 m s\(^{-1}\) whereas during the fall season these regions of 15 m s\(^{-1}\) or greater are far more scattered in nature. Another difference is that across the Gulf of Mexico there is not a strong signal in the influence of the SST bias on PI during SON, with differences in PI being close to zero in that location.
during this season. The regions of comparative overestimation in PI during SON are generally located in the same areas, and are of similar magnitudes, to those observed during the JJA, with the eastern Pacific experiencing both the greatest spatial coverage and highest magnitude PI differences, which in some cases exceed $15 \text{ m s}^{-1}$. There is also still a local maximum in overestimated PI compared to the control runs located across the extreme western Atlantic along the eastern U.S. coast.

Figure 36: Statistically significant (SON; $P<0.05$) differences in PI ($\text{m s}^{-1}$) between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.

Finally, results for the DJF season are shown in Figure 37, which shows that the ECHAM5 bias runs result in a comparative underestimation of PI across the majority of the tropical Atlantic, northern Indian ocean, central Pacific, and extreme eastern Pacific along the west coast of Central America. There is also underestimated PI across the western Pacific in the region of the Western Pacific Warm Pool as well as across the Gulf of Mexico and Caribbean. The region of underestimated PI along the west coast of Central America is in stark contrast to
the summer and fall seasons where there was either a weak signal or it was overestimated. On the other hand, the bias runs of ECHAM5 result in a comparative overestimation of PI across the western Atlantic in the vicinity of the U.S. northeast coast, across the eastern Pacific along the west coast of South America, across the eastern Pacific along the west coast of Mexico, and across the extreme eastern Atlantic near Africa. These regions of overestimated PI are generally in the same regions as those during the SON season.

Figure 37: Statistically significant (DJF; P<0.05) differences in PI (m s\(^{-1}\)) between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.

In summary, it was shown that the impact of the coupled model SST biases across each ocean basin are seasonally dependent. While the spatial patterns and magnitude of over and underestimated PI were found to be similar during MAM, JJA, and SON, there were some notable exceptions. One such exception was that the area of underestimated PI across the
northern Indian ocean during MAM generally weakened during JJA but strengthened across the western Pacific. Another difference was that the area of underestimated PI across the Gulf of Mexico during MAM and JJA weakened during SON with very little to no relationship to model SST biases observed. This indicates that one (or more) of the other inputs to PI is dominating the calculation during this season or the net effect of the SST bias is being cancelled out. Lastly, during DJF, while the areas of overestimated PI were found to be similar to MAM, JJA, and SON there were differences across the areas of underestimated PI. One of the most significant differences was across the west coast of Central America. Across this region, PI was found to be underestimated during DJF, which was in stark contrast to JJA and SON, which both featured overestimated PI across this region. Upon comparing these results to the actual coupled model SST bias field (Figure 3), it was shown that positive and negative SST biases generally were within the same regions as over and underestimated PI. For example, across the west coast of Central America positive SST biases were found to be approximately collocated with overestimated PI during all 4 seasons.

Following the completion of seasonality testing and comparisons of the PI between the ECHAM5 bias and control runs, the next TC index that was examined was the GPI. The same approach taken for the PI was used, where GPI was calculated for each season using both the bias and control runs of ECHAM5 and then statistically significant differences were identified. In doing so, Figure 38 shows statistically significant, ensemble mean differences in calculated GPI between ECHAM5 bias and control runs during Northern Hemisphere Spring (MAM). The figure shows that ECHAM5 bias runs result in an underestimation in GPI relative to the control runs across the eastern tropical Pacific, along the east coast of Ecuador, across the western tropical Pacific, across the northern Indian ocean, as well as in the vicinity of New Guinea.
These differences are generally less than 6 events per year. On the other hand, ECHAM5 bias runs reveal an overestimation of GPI across the central Pacific and Atlantic south of the equator, along the northern coast of Australia, and across the extreme eastern tropical Pacific near the west coast of Africa. These differences are of similar magnitude to those where GPI was underestimated, on average typically less than 6 events per year. This pattern of positive GPI differences generally located in the Southern Hemisphere and negative values in the Northern Hemisphere during MAM suggest a delay in the annual cycle of SSTs, as identified in Lyon (2020).

![Statistically significant (MAM; P<0.05) differences in GPI (TC genesis/time) between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.](image)

Figure 38: Statistically significant (MAM; P<0.05) differences in GPI (TC genesis/time) between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.

Results for the JJA season are shown in Figure 39. These results show that ECHAM5 bias runs significantly underestimate the number of TC genesis events relative to the control runs.
across the extreme eastern Pacific and along the west coast of Mexico, with differences locally exceeding 10 events per year. There are also areas of underestimation, albeit of smaller magnitude, located across much of the Gulf of Mexico, Caribbean, western Pacific, north-central Indian Ocean, as well as along the east coast of New Guinea. In these regions the differences are on average 2 to 4 events. Areas where the ECHAM5 bias runs overestimate GPI (relative to control runs) during the summer season include the eastern tropical Atlantic near the west coast of Africa, the central tropical Pacific, and across a portion of the extreme western Pacific. These differences are on average between 2 to 4 events. Overall, the differences in GPI during the summer season are of larger magnitude compared to northern hemisphere spring, especially across the eastern Pacific.

Figure 39: Statistically significant (JJA; P<0.05) differences in GPI (TC genesis/time) between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.
Results for SON are shown below in Figure 40. During the fall season, ECHAM5 bias runs result in comparatively too many TC events across the central tropical Pacific, west-central Indian ocean, portions of the western Pacific, as well as in the extreme eastern Pacific surrounding the west coast of Africa. The largest differences are observed across the central tropical Pacific where in some locations they approach 6 events, but on a global average basin the overestimations are generally 3 events or less. Areas where ECHAM5 bias runs underestimate GPI relative to their control run counterparts include the extreme eastern Pacific, southern Gulf of Mexico, Caribbean, northern Indian ocean, as well as portions of the western Pacific. On average these underestimations are between 2 and 4 events but in some cases, such as along the immediate west coast of Mexico, they approach and exceed 6 events. The spatial coverage for greater than 6 events of underestimated GPI is significantly smaller during the fall season compared to that observed during the summer.
Finally, results for DJF are shown in Figure 41. During the winter season the ECHAM5 bias runs result in a comparative overestimation of GPI across portions of the southwestern Indian ocean, along the northern coast of Australia, parts of the central Indian ocean, as well as across portions of the southcentral tropical Pacific and Atlantic. The magnitude of the overestimated GPI is generally between 2 to 4 events but in some locations, such as in portions of the Pacific and Indian oceans, they approach and exceed 6 events. The regions of underestimated GPI during the winter season are relatively sparse but do include a small portion of the eastern tropical Pacific as well as the western Pacific near New Guinea, with underestimations generally between 2 and 4 events. The differences in calculated GPI between
ECHAM5 bias and control runs during the winter season are generally of lower magnitude and have a smaller areal coverage compared to the other three seasons.

Figure 41: Statistically significant (DJF; P<0.05) differences in GPI (TC genesis/time) between ECHAM5 bias and control run averages over the period Jan. 1982-Dec.1990.

3.5. Discussion and Conclusions

This chapter builds on the results of Chapter 2, where it was found that the ECHAM5 tend to capture climatological TC patterns generally similar to observations. Given this result, in this chapter the potential influence of coupled model SST biases on the TC indices was evaluated utilizing the ECHAM5 bias runs and control runs for the period 1982-1990. The impact of the
coupled model SST biases was determined by taking the difference in TC index values between the ECHAM5 bias and control runs.

The first index considered was the TCGI. It was found that there are several areas of enhanced TC activity relative to the control runs (statistically significant differences at $P < 0.05$), particularly across the eastern tropical Pacific near the west coast of Mexico, the central tropical Pacific, extreme eastern tropical Atlantic near Africa, the central Indian ocean, as well as a portion of the western Pacific near the northern coast of Australia. While the magnitude of these differences is generally between 2 and 5 events, they do locally approach and exceed 10 events, especially across the eastern Pacific. On the other hand, it was shown that the bias runs of ECHAM5 result in an underestimation of TCs across much of the Gulf of Mexico, Caribbean, northern Indian ocean, as well as the western Pacific, with differences locally exceeding 10 events on an annual basis.

Differences (bias minus control) in the TCGI index were then evaluated by considering changes in the 4 individual input variables (relative SST, RH, shear, and vorticity) to determine which input variable has the largest impact on the index. For example, to examine the influence of changes in relative SST in the bias runs on the TCGI, statistically significant differences ($P<0.05$) in TCGI from the control runs were identified using the relative SST from the bias runs while holding the RH, shear, and vorticity inputs all to their respective control run values. In doing so, it was found that the relative SST bias results in an underestimation of TC genesis across the eastern tropical Pacific while it overestimates TCs across the Gulf of Mexico, Caribbean, western tropical Pacific, and northern Indian ocean. The same procedure was completed to examine the influence of RH, shear, and vorticity in the bias runs. Results showed that the term which had the largest overall impact on the calculation of TCGI was the relative
SST. In some cases, the magnitude of over/underestimated events exceeded 10 when examining the impact of just this term. The RH bias resulted in more storms across the eastern tropical Pacific, Gulf of Mexico, western Pacific, and northern Indian ocean. It was found that this term resulted in less storms across the western Indian ocean as well as the central tropical Pacific. The magnitude of these differences were only slightly lower to those found when examining the SST bias term, and hence this is the second most influential term. The shear bias resulted in less storms across most ocean basins including the northern Indian ocean and the eastern Pacific, but overall, the magnitude of these differences was modest compared to those found when examining the SST and RH biases. In general, it was found that the vorticity bias resulted in the smallest overall difference in TCGI.

It was found that regions of positive and negative SST biases (Figure 3) where generally collocated with areas of over/underestimated TCGI (Figure 25). For example, Figure 3 showed a region of positive SST bias located across the eastern tropical Pacific and then extending westward across the central Pacific and western Indian ocean which is collocated with a region of overestimated TCGI (Figure 25). In addition, negative SST biases were found to be located across portions of the Gulf of Mexico, which are collocated with underestimated TCGI. These findings support the hypothesis that SST biases can substantially influence TC environmental conditions.

The next step was to examine how coupled model SST biases result in changes in PI, the theoretical upper bound of surface wind speed that a TC could have based on a number of environmental factors. It was found that the bias runs resulted in overestimated PI relative to the control runs across the eastern Pacific, western and southern Indian ocean, across the western
Atlantic near the U.S. east coast, and across a portion of the extreme eastern Atlantic near Africa. In some regions these differences approach and exceed 15 m s\(^{-1}\). On the other hand, the ECHAM5 bias runs resulted in underestimated PI across the central tropical Atlantic, Gulf of Mexico, central tropical Pacific, northern Indian Ocean, and the Caribbean with again differences approaching 10-15 m s\(^{-1}\). Similar to the results obtained when examining TCGI, the regions of underestimated (overestimated) PI were approximately collocated with regions of negative (positive) SST biases. For example, Figure 31 shows a region of overestimated PI across the eastern tropical Pacific and along the west coast of South America near Honduras. This is in the same region of positive SST biases, shown in Figure 3. In addition, Figure 3 showed a region of negative SST bias across the central tropical Atlantic, which was found to be collocated with an area of underestimated PI (Figure 31).

Seasonality testing was performed to determine the influence that the SST biases have on PI through four seasons of the year. This was an important step given the different climatological seasons for ocean basin for TC activity. It was found that across all seasons, PI was overestimated in the bias runs across the eastern tropical Pacific and along the west coast of South America. These regions coincided with positive SST biases, which was shown in Figure 3. Upwelling of cooler, deep ocean water is typical across the west coast of South America and this is something that coupled models often have trouble simulating. It was found that the seasons which had the largest overall differences between the bias and control runs were MAM and JJA. During both of these seasons, PI was significantly overestimated across the eastern tropical Pacific, off the west coast of South America, across the western Atlantic near the northeast U.S. coastline, and across the extreme eastern Atlantic near Africa. During these same two seasons, PI was underestimated across the central Pacific, central Atlantic, and northern Indian ocean. The
magnitude of the over/underestimations in many cases exceeded 15 m s\(^{-1}\). The spatial extent and magnitude of PI differences between bias and control runs were generally found to be more modest during both SON and DJF.

The final index evaluated was the GPI, where statistically significant differences (P<0.05) were evaluated between the bias and control runs of ECHAM5. Again, seasonality testing was performed for the GPI analysis. Across all four seasons, the ECHAM5 bias runs resulted in underestimated GPI across portions of the eastern tropical Pacific. The magnitude of this underestimation was found to be greatest during JJA, where it locally exceeded 10 events. GPI was also generally underestimated in all seasons across the western Pacific, but the magnitude of these differences were generally more modest. It was also found that GPI was overestimated in all four seasons across portions of the central tropical Pacific, with some fluctuations in latitude observed between each season. This region of overestimated GPI was generally greatest in SON, where it approached 10 events. When comparing these results to the actual SST bias patterns (Figure 3), a few interesting relationships were found. The first is that across all seasons except for DJF, GPI was underestimated across portions of the Gulf of Mexico and western Caribbean, which coincided with negative SST biases. In addition, the region of positive SST biases across the central tropical Pacific was found to be in the same general area as overestimated GPI during all four seasons. One region where the SST bias does not correlate with changes in GPI was across the eastern tropical Pacific and off the west coast of South America. Across both of these regions, despite strongly positive SST biases and overestimated PI, GPI was found to be underestimated, which was a surprising result. The cause of this underestimation must be due to one of the other 3 terms in the calculation of GPI cancelling out the contribution of the SST bias to the calculation of PI. For example, GPI may not show a
strong relationship to the SST bias field because its impacts are more indirect since it uses PI rather than relative SST.
CHAPTER 4

CONCLUSIONS

Global sea surface temperatures (SSTs) play a fundamental role in determining regional climate conditions, especially in the tropics. Coupled climate models are often used to increase our understanding of the climate system yet, despite constant improvements, these models still exhibit several biases, including in the spatial distribution of SSTs. The main motivation for this study was to determine the potential influence these coupled model SST biases have on environmental conditions that affect tropical cyclones. Emphasis here was on TC development and intensity.

The first goal in this thesis was to assess the ability of two AGCMs to properly simulate observed climate conditions that relate to TCs when they are run (or “forced”) with observed SSTs. Confirming such an ability was a vital step before the examination of the potential influence of coupled model SST biases on AGCM simulations. In order to evaluate this I utilized the output from the AGCMs where the models were run with observed monthly SSTs from 1979-2005. A set of 16 ensemble members were generated for each model by using slightly different initial atmospheric conditions for each ensemble run. Ensemble means were then calculated in order to reduce the potential “noise” that results from random weather events generated by the models. These runs constituted a set of “control” runs for each model. The output from the AGCMs were then used to calculate three TC indices, two of which were statistically-based and one was physically-based. The TCGI and GPI are statistical fits to estimate the frequency of TCs and the PI is a physically-based index that indicates the potential intensity of a TC given specified SST and atmospheric conditions.
It was determined that results obtained from ECHAM5 and CAM5 were very similar and therefore only output from ECHAM5 was used for the majority of this thesis in order to prevent redundancy. Results between the AGCMs control runs and observations from NCEP reanalysis data indicated that the models tended to produce too many TCs compared to observations, except across portions of the Gulf of Mexico, Caribbean, and extreme western Pacific where the control runs did not produce enough TCs compared to observations. Generally, the models performed best across the Atlantic and Indian ocean and worst across the eastern and western tropical Pacific. Despite this, the models did a very good job in capturing the observed pattern of TC genesis, with a pattern correlation for the TCGI of 0.98 obtained between ECHAM5 and observations, indicating an excellent agreement between the two. Results for the PI index indicated that, when considering an annual average, ECHAM5 control runs tended to overestimate PI compared to observations. Some exceptions to this were across the eastern tropical Atlantic near the coast of Africa, in the Gulf of Mexico and Caribbean, and across the extreme eastern and western tropical Pacific. Across these regions, PI was generally underestimated compared to observations. Generally, the modeled performed best across the Indian ocean, where differences between ECHAM5 control runs and observations were on average less than 5 m s\(^{-1}\). The global pattern correlation of PI computed between the ECHAM5 control runs and observations had a value of 0.86. This further increased confidence that ECHAM5 control runs were doing a good job at capturing the overall pattern of the observed values of the TC indices. Results for GPI were found to be generally similar to those of TCGI, which was expected given that the two indices are related. The pattern correlation between annual average GPI values for ECHAM5 and observations was found to be 0.56, which although is lower than TCGI and PI it still indicated that the model was generally capturing the observed
pattern. Seasonality testing was also performed, with each index calculated for each season. This was done in order to examine how well the model captured the observed conditions during specific times of the year owing to the fact that TC activity is seasonally dependent across each ocean basin. Overall, this seasonality testing showed that while there were differences between ECHAM5 control runs and observational data, the model did a good job at capturing the spatial patterns of observed TC activity.

Once it was determined that the control runs of ECHAM5 were doing a good job at capturing the observed climatological TC conditions the next step was to investigate the impact that the coupled model SST biases have on the TC indices previously evaluated. In the second set of runs (the “bias” runs) the monthly climatological CMIP5 multi-model (31) mean SST biases were added to the observed SSTs prior to running the ECHAM5, with 16 ensemble members once again generated. It was found that, over the period 1982-1990, differences in atmospheric conditions between the bias and control runs resulted in statistically significant changes in the three TC indices from their control run values. The results indicated that regions of coupled model positive and negative SST biases were generally collocated with areas of over/underestimated TCGI in the bias runs. One exception to this is across the western Gulf of Mexico, where despite positive SST biases, TCGI was actually underestimated across this region. This implies that there is a more indirect relationship between SST biases and TC activity across this region. As an additional step, sensitivity testing was performed, where each of the 4 inputs to the TCGI (relative SST, relative humidity, vertical wind shear, and vorticity) were set to the “control” run values individually in order to determine the contribution that each “bias” term has on the total TCGI. Statistically significant differences (P<0.05) were identified for each term but overall, it was found that the relative SST had the largest impact and the
vorticity bias resulted in the smallest. This result further showed that changes in SST both regionally and globally can have a significant impact on TC environmental conditions.

Statistically significant differences in PI were identified within each ocean basin and overall it was found that, similar to the results obtained when examining TCGI, the regions of underestimated (overestimated) PI in the ECHAM5 bias runs were approximately collocated with regions of negative (positive) SST biases. One exception to this is across portions of the western Indian ocean, where despite positive SST biases, there is a region of underestimated PI. This implies that there is a more indirect relationship within this region between SST biases and TC behavior. It is also possible that other atmospheric conditions may be unfavorable for TC development. Seasonality testing was then performed to determine the influence that the SST biases have on PI during MAM, JJA, SON, and DJF. While statistically significant differences were found during all seasons, it was found that overall, the largest differences occurred during the Northern Hemisphere spring and summer. These are important seasons for TCs, as spring is generally when the storm season begins across the western Pacific and Indian ocean whereas the eastern tropical Pacific, Gulf of Mexico, and western Atlantic typically begins to become more active by mid to late northern hemisphere summer.

The last index evaluated to see the influence of coupled model SST biases was the GPI, with seasonality testing once again performed. Unlike TCGI and PI, GPI did not show as strong of a relationship to the positive SST biases located across the eastern tropical Pacific. Results between ECHAM5 bias and control runs showed a region of underestimated GPI across portions of the eastern tropical Pacific along the coast of Mexico and South America, which is approximately in the same region as positive SST biases. As stated earlier, this must be due to a more indirect relationship between GPI and SST biases. That is, since GPI uses PI rather than
relative SST it is possible that the SST biases are impacting other atmospheric conditions which is limiting TC development. In addition, there is also a region of underestimated GPI located across portions of the tropical western Pacific, which are in the vicinity of positive SST biases. Despite these mostly localized exceptions, results showed that regions of over/underestimated GPI generally were in the same locations as positive/negative SST biases. Seasonality testing was once again performed, and while statistically significant differences were again identified during all seasons, it was found that overall, the largest differences occurred during Northern Hemisphere summer and fall. Moreover, across all four seasons the SST biases resulted in underestimated GPI across portions of the eastern tropical Pacific, but this was the most significant during the summer season where it locally exceeded 10 events.

Overall, the study found that despite the coarse resolution of the ECHAM5 and CAM5 AGCMs, they were able to accurately simulate observed conditions for TCs, particularly the spatial patterns of three widely-used TC indices. This was shown by comparing three TC indices that were calculated using the output from the control runs of ECHAM5 and CAM5 to the same indices calculated using observed SSTs and NCEP reanalysis data. The next, and major, goal of the study was to determine the influence of the coupled model SST biases on AGCM simulations. It was found that the SST biases resulted in statistically significant differences in all three indices. These differences were generally collocated with the SST bias patterns although a few exceptions were found. The differences were on average the greatest across the tropical eastern and western tropical Pacific and the smallest in the Atlantic and Indian oceans. Overall, results showed that TCGI had the greatest sensitivity to the SST biases, with regions of over/underestimated TCGI generally collocated with positive/negative SST biases. This was likely due to a more direct relationship between TC behavior and SST bias patterns compared to
GPI. These findings were very similar to those found in Hsu et al. 2018, which also showed a strong relationship to SST bias patterns to TC frequency.
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BIOGRAPHY

Hunter Tubbs was born in West Milford, New Jersey and moved to Massachusetts at a young age. After living in Massachusetts for around 8 years, Hunter and his family moved back to New Jersey where he graduated from Allentown High School in 2013. Hunter then attended Millersville University for one year before transferring to Rutgers University in 2014. In 2017, he earned the degree of Bachelor of Science in Meteorology. He then moved back north to New England in 2018 when he accepted a research assistant position at the University of Maine Climate Change Institute. He is a candidate for the Master of Science Degree in Earth and Climate Sciences from the University of Maine in December 2021.