Impact Of Climate Change On Precipitation and Potable Water Resources In The Bahamas

A Research Paper

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ABSTRACT

The Bahamas is one of the foremost climate-vulnerable countries in the world. Small island nations' freshwater supplies are already threatened by sea-level rise and groundwater extraction; nevertheless, increased aridity from climate change adds to the burden. This research aims to see how climate change affects precipitation and drinkable water in the Bahamas. For the historical data analysis, a summary of descriptive statistics and Mann Kendall test procedures were used to indicate the existence of any possible trends. Maximum temperature, precipitation, and potential future changes are evaluated in an ensemble of the 6^{th} Phase Coupled Model Inter-comparison Project (CIMP6) and the available historical data collected from the Bahamas Department of Meteorology during the period 1971 to 2020. The study's key findings revealed that the maximum temperature generally grew while the minimum temperature was falling. A 50-year investigation of yearly precipitation (from 1971 to 2020) showed a coefficient of variation ranging from 31.3 to 90.6%. It was discovered that the precipitation distribution is not typical, with year-to-year variations. Over the last decades, the growing climate change and variability are most likely responsible for the observed warming temperatures and rainfall fluctuations. Models project a drop in annual mean precipitation by the end of the twenty-first century. Increasing rainfall variability could cause more frequent and protracted periods of high or low groundwater levels, as well as a saline intrusion in coastal aquifers. We were confronted with a problem regarding data availability and the information quality of the available data. We conclude that coordinating efforts is required to overcome the most difficult challenges that climate change has posed and will pose to water resource management.

Keywords: Precipitation; Temperature; Trend Analysis; CIMP6 model; Potable Water; Water Resources

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LIST OF ACRONYMS

AR5	Fifth Assessment Report
AR6	Sixth Assessment Report
BDM	The Bahamas Department of Meteorology
BEST	The Bahamas Environment, Science and Technology Commission
CARICOM	Caribbean Community
CCCCC	Caribbean Community Climate Change Centre
CERMES	Centre for Resource Management and Environmental Studies
CIMH	Caribbean Institute for Meteorology and Hydrology
CMIP5	Coupled Model Intercomparison Project Phase 5
CPACC	Caribbean Planning for Adaptation to Global Climate Change Project
DEM	Digital Elevation Model
FAO	Food and Agriculture Organisation
GBUC	Grand Bahama Utility Company
GCM	Global Climate Model
GEF-SGP	Global Environment Facility Small Grant Programme
GIS	Geographical Information System
GOB	Government of The Bahamas
GPS	Global Positioning System
IISD	International Institute for Sustainable Development
IPCC	Intergovernmental Panel on Climate Change
LULC	Land use/land cover
MOH	Ministry of Health
NOAA	National Oceanic and Atmospheric Administration

RCM	Regional Climate Model
RCP	Representative Concentration Pathways
SIDS	Small Island Developing States
SRES	Special Report on Emission Scenarios
SST	Sea Surface Temperature
UNEP	United Nations Environment Programme
UNFCCC	United Nations Framework Convention on Climate Change
USAID	United States Agency for International Development
W&SC	Water and Sewerage Corporation
WMO	World Meteorological Organization

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1 INTRODUCTION

Since the beginning of time, the Earth has experienced climate changes - sometimes over a long period of time (after volcanoes erupted) and sometimes for a much shorter interval (after a massive storm). The events all fall into the category of natural climate changes (movements of the Earth's axis, its orbit, changes in solar activity, earthquakes, and volcanoes) (Stern and Kaufmann 2014). Anthropogenic greenhouse gas emissions, changes in land cover, changes in albedo, and reflections from the surface have contributed to this increase. Climate Change (CC) will likely impact both mean and extreme temperatures in addition to precipitation patterns (IPCC 2014a).

There is evidence that climate change is already manifesting as increasing storms intensity and downpours, rising sea levels, and retreating glaciers across the globe. Several extreme climate and weather events are being influenced by climate change, including heatwaves, floods, and droughts, occurring in some regions at an increased rate (Ebi, et al. 2021). As the Earth's surface temperature rises, it will change the circulation of the atmosphere, create a more active hydrological cycle, and hold more water (IPCC 2001).

Climate change drives precipitation fluctuations on the Earth's surface, influencing the planet's water balance. Consequently, these fluctuations have profound implications for hydrology and the availability of water (IPCC 2001, IPCC 2021a). Global water resources are affected by CC in various ways, including complex spatial and temporal patterns, feedback effects on physical and human systems, and interactions between these systems (Bates, et al. 2008). As a result, long-term management of water resources will be much more challenging, especially in regions where water resources are already stressed due to severely declining resources (Jobbins, Langdown and Bernard 2018). Adapting to climate change and mitigating its effects through water management is essential for long-term development and achieving the 2030 Agenda for Sustainable Development (Jobbins, Langdown and Bernard 2018).

According to the latest IPCC report (AR6), global warming already has significant effects. Even though the degree and direction of the impact vary by region, global CC has a huge impact. According to the IPCC's Fifth and Sixth Assessment Reports (AR5 and AR6), human-induced climate change has already disrupted weather patterns and increased extreme weather in every region of the world, particularly in Small Island Developing States (SIDS). Extreme weather has become more intense and frequent, and this trend is expected to continue. It has been predicted that more people will experience water stress in the future due to drought, one of the most extreme events in recent history.

According to IPCC 2021a, sea-level rise is the significant impact of climate change on coastal aquifers. However, many other factors, including coastal erosion, precipitation, and temperature, negatively affect evapotranspiration and groundwater recharge (Moeck, Brunner and Hunkeler 2016). The contribution of these individual consequences is unknown, and it is unclear if they will have a cumulative effect or cancel each other out. The climate change trends in many countries have been forecast using scenarios to develop appropriate action and adjustment measures.

1.1 BACKGROUND

An essential human right is to have access to safe and affordable water. Water is a fundamental and essential requirement for the existence and subsistence of life because plants, animals and people depend on these invaluable natural resources. The social and economic development of any nation depends upon the availability of water. Human activities such as drinking, agriculture, and producing electricity require water in significant amounts. The Bahamas' economy has always been based on mass tourism (Roebuck, Pochatila and Ortiz 2004). The tourism industry has a long history of wreaking havoc on the environment. Tourism can put pressure on scarce natural resources in a given location, including increased demand for power and water, which can strain local resources (Roebuck, Pochatila and Ortiz 2004). However, water availability in a sustainable quality and quantity is scarce for many reasons, including the most complex challenges of twenty-first-century climate change (CC).

It is impossible to live if you lack access to adequate and safe drinking water. Even though vast amounts of water are available globally, freshwater only represents 1% of it (Jackson, et al. 2001). According to UN criteria, water availability is so limited that it is classified as "scarce". According to Roebuck, Pochatila and Ortiz (2004), New Providence alone requires eleven million gallons a day out of the nine million gallons a day available, excluding the tourism industry, which puts a substantial demand on water resources (FAO 2015).

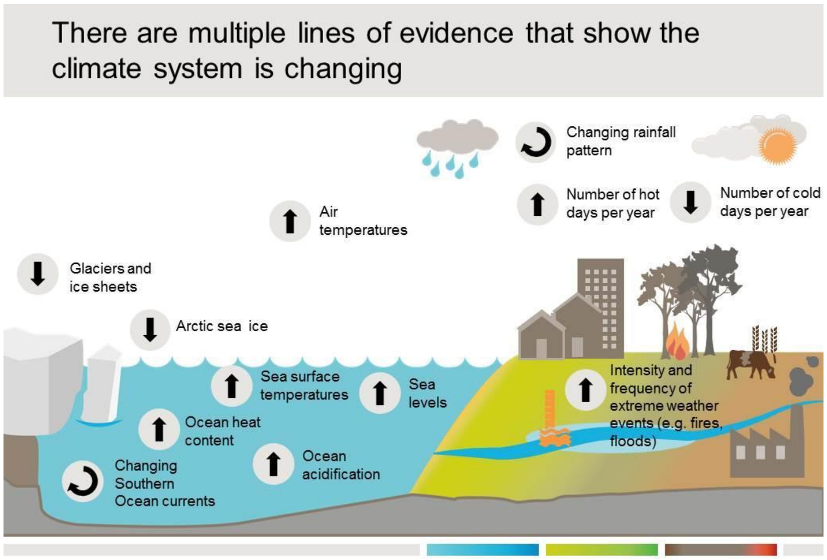
Global Climate Model (GCM) studies predict significant regional and global fluctuations in average precipitation and air temperature. It is almost certain that these changes will affect the recharge of groundwater. (Kurylyk and MacQuarrie 2013). According to the IPCC report (2008), climate change will influence rainfall patterns and sea levels around the planet over the next century. Because groundwater supplies are the principal source of potable water for human consumption in The Bahamas, with over 90% of all freshwater resources located within 1.5 meters of the surface (Roebuck, Pochatila and Ortiz 2004), water managers and governments are apprehensive about its possible decline and quality. We are experiencing an unprecedented climate change that undoubtedly poses significant threats to the planet as a whole. Understanding the science and mechanism behind this concept is vital before moving on to its implications.

1.1.1 WHAT ARE THE SIGNS THAT THE CLIMATE IS CHANGING?

Although land and sea temperatures vary considerably yearly, a distinct trend is underlying them. In the IPCC AR4 report, climate scientists noted that global temperatures increased by 0.74°C between 1906 and 2005. The IPCC AR5 report, however, indicated that temperatures increased by 0.85°C between 1880 and 2012 (IPCC 2021a). Over the past several decades, land temperatures have risen more rapidly than ocean temperatures. There has been global-mean warming in the mid-troposphere, roughly 5 km above the surface. Despite the lack of data in tropical areas, there appears to have been a slight shift in temperature in the tropical mid-troposphere over the previous two centuries (Steiner, et al. 2020), which contradicts models (Thompson, et al. 2012).

Precipitations may change due to climate change, including their amount, intensity, frequency, and types. The oceans and atmospheric circulation patterns substantially impact these changes, which show many natural variabilities (Trenberth 1995) (Mueller and Roeckner 2006). These changes already affect ecosystems, biodiversity, humans and economic activities (O'Brien and Leichenko 2000) (Sumaila, et al. 2011) (Franco, et al. 2020).

Figure 1-1: Observed changes in our climate system



According to Obeta (2009), the predicted change in mean climatic conditions is expected to be a long-term process that will take decades to complete. The climate variability is seen through seasonal fluctuations, inter-annual variability, and severe weather events. The consequences of CC are felt across the globe, and no government can take unilateral action that will have global impacts without facing the consequences. The precipitation regime shifts simultaneously as the world warms, and extreme events such as tropical cyclones, floods and droughts are becoming more commonplace (Trenberth 2011).

Freshwater resources are significantly affected by the weather and climate change. The availability of freshwater and the frequency of floods and droughts will be influenced by global climate change induced by the build-up of greenhouse gases in the atmosphere (IPCC 2021a). A changing climate will affect the availability and quality of water in numerous industries, including energy production, infrastructure, human health, agriculture, and ecosystems (Rodell, et al. 2018). In locations where rainfall is increasing, water quality may decrease (Hatfield and Prueger 2004). All water cycle components are in a delicate balance, including precipitation, evaporation, and other water cycle activities. The hydrologic cycle and water resources are crucial links in the climate change chain.

Water resources worldwide have both positive and negative effects due to changes in hydrological regimes, but there is an overall net negative impact on the availability of usable water resources. The world's water supplies are under pressure due to demographic, economic, and social concerns. Growth, gender, and age distributions affect population dynamics, and migration has strained freshwater resources (WWAP 2012). In many countries worldwide, particularly in developing countries, the increase in human population and environmental degradation have reduced human access to safe drinking water over the last few decades (McMichael 2000).

Groundwater accounts for approximately 30% of the world's fresh water (Pimentel, et al. 2004), which is 70% of the freshwater on the planet. Groundwater is the planetary most extensive freshwater reservoir, accounting for nearly 70 times the amount of surface water (Fetter 2001). The possible decline and quality of groundwater supplies is the primary concern of water managers and governments. As underground aquifers are recharged primarily by precipitation and surface water interaction, climate change is likely to have an effect on these two factors (precipitation and surface water). Changes in surface water levels and quality may be the most noticeable effects of climate change. As the principal source of drinking water for most people, surface water levels and quality are likely to vary significantly due to climate change (Bear, et al. 1999).

Considering precipitation requires consideration of the rainfall pattern. Research has not been conducted on the spatial pattern of seasonal precipitation in the Bahamas. Several statistical tools were employed to look for patterns in historical climatic evidence in the Caribbean. Detecting differences in rainfall patterns might be possible in the Bahamas by investigating the trend and homogeneity of the rainfall series in the current study.

1.2 PURPOSE AND OBJECTIVES OF THE STUDY

Climate change is examined primarily in this paper as it pertains to precipitation effects. Additionally, it will investigate how changes in precipitation and temperature may affect the availability of potable water in The Bahamas. The investigation of the climate characteristics utilises Department of Meteorology data from 1971 to 2020 and the 6th Phase Coupled Model Inter-comparison Project (CIMP6) model data for the detention of future maximum, minimum, and precipitation tends and changes using three periods.

The primary source of sustainable potable water supply for the population is groundwater aquifers lying in limestone bedrock on the islands (Rossing 2010). The possible repercussions of climate change, on the other hand, could jeopardise the groundwater's long-term viability. Since the development on the islands has soared in recent years (both permanent and temporary residences during peak tourist seasons), future climate change trends must be studied to determine how they can affect groundwater systems. The findings of such an investigation could help the islands manage their water resources more efficiently and take preventative measures to avert future water shortages.

The present study analysed the past and future precipitation variability across the Bahamas. The study was conducted using observed and downscaled climate data from the Bahamas Department of Meteorology and potable water supply data from Water and Sewage.

Main objectives

The study's main objective is to evaluate the effects of climate change on precipitation and portable water supplies in The Bahamas.

Specific objectives

The following specific objectives will help reach the primary objective:

- Examine and analyse the historical climate data (precipitation and temperature) in the research area.
- To describe the wet and dry season rainfall patterns during the last five decades.
- Analyse climatic trends over the last five decades and develop future climate scenarios based on those trends until the mid-twentieth century (the 2050s).
- Analyze the impact of extreme events on the availability and quality of water supplies using models such as Global Climate Models (GCMs) and Regional Climate Models (RCMs).
- To investigate alternate adaptation possibilities in The Bahamas (water trading, desalination, and water recycling/reuse).

Research questions

In general, the study questions will be divided into four categories:

- What temperature and precipitation trends have been observed over the Bahamas?
  - What are the features of precipitation in terms of quantity, frequency, and intensity?
- In the mid-twentieth century (the 2050s), what conditions (precipitation, temperature, sea-level rise, and saltwater intrusion) can be predicted in The Bahamas due to CC?
- What are the likely and the expected consequences for water resources?
- What climate-resilient adaptation methods exist or need to be developed in The Bahamas to reduce the detrimental impact of climate change on water resources?

1.3 RESEARCH RATIONALE

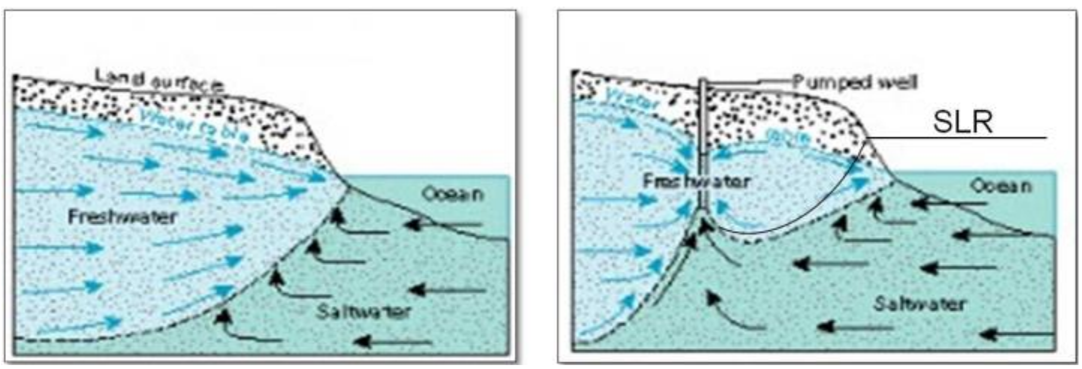
Anthropogenic activities are increasingly responsible for changing our environment. A growing number of studies have shown that Earth's temperature will rise in the twenty-first century, raising the fundamental question of what impact global warming will have on humans and the environment (IPCC 2021a). Climate change poses a severe threat to The Bahamas’ water sector because projections show that temperatures will likely rise, rainfall will decrease, storms will intensify, and sea levels will rise. The water sector is already vulnerable and is expected to become even more susceptible as sea levels rise and storm intensity increases.

According to the latest climate impact projections, climate change is expected to widen the gap between supply and demand in fresh drinking water. In the Bahamas, freshwater resources are scarce, and it is vulnerable to flooding and contamination, among others (Rossing 2010). Freshwater lakes are found only in shallow sedimentary limestone aquifers with extremely delicate freshwater “lenses” (Rossing 2010) (Cashman 2014). Due to their flat nature, there is limited surface water drainage and no freshwater rivers on the islands. The most harmful to the health of the Bahamas’ freshwater reserves is a significant increase in tropical cyclone activity since 1995 (Taylor, et al. 2020). Extreme storms result in more substantial storm surges combined with the acceleration of sea-level rise (raising the risk of saline water in very shallow aquifers (FAO 2015)).

Climate change is likely to hamper human development due to a combination of all of these factors. Climate change and predicted changes should be incorporated into each of the development plans for the country, as The Bahamas is one of the lowest-lying countries in the region. A high level of risk exposure and inadequate adaptation resources make the Bahamas one of the most vulnerable countries to climate change. As a result, the expected changes in precipitation for the country must be considered to create plans for the country's development agenda.

Seawater is an inherent component of coastal settlements in The Bahamas and can potentially seep into freshwater aquifers, making it difficult for them to maintain a sustainable groundwater supply for settlements along the coastal line. Those living on islands face a complicated issue because sea level rise has many long-term effects on coastal regions, including increased coastal erosion and saltwater intrusion.

Figure 1-2: Movement of the saltwater interface under normal conditions, and in case of saltwater intrusion due to over pumping and sea-level rise (SLR)



Current potable water harvesting practices may become unsustainable due to altering rainfall patterns or temperature changes that impair the viability of resources due to expected climate change. An over-abstraction of groundwater can also cause or exaggerate salinity intrusion (IPCC 2007). Assessing the capacity for catchments to provide potable water under the consequences of climate change requires understanding future seasonal changes in rainfall patterns and hydrological regimes (Sohoulande Djebou and Singh 2016).

Almost 400 thousand people live throughout the Bahamas, putting a heavy demand on the national water supply. International visitors amount to nearly 4 million annually, compounding the problem. Climate change, rising sea levels and increased demand for drinking water due to population growth will exacerbate the current water supply challenge. Of keen importance will be to take proactive, immediate decisions to ensure adequate supplies. Despite the unique needs of groundwater, relatively few studies have investigated the impacts of climate change on the country's aquifers.

1.4 THESIS STRUCTURE

This paper is divided into six broad parts. Starting with a brief introduction, Section 1 elucidated the general description of the problem and its components. The first section of the report examines the background, the research questions, and hypotheses and objectives.

The next section (Chapter 2) consists of a review, synthesis and discussion of studies undertaken by numerous authors. This section provides the theoretical background and important principles related to the issue in question. Climate change science, precipitation, and climate-related impacts on precipitation and potable water are the main theoretical concepts presented in this chapter. The research mentioned is focused chiefly on mechanisms for rainfall modification.

In the Methodology section (Chapter 3), the research design, data collection, data preparation, and analysis methods are outlined following the literature review. This section also discusses data scarcity in the Bahamas and outlines various data sets used for climate research. This section also gives a general overview regarding the study area, including physical characteristics.

The results and discussion from the temperature and precipitation datasets analyses using the methods specified in Section 3 are presented in Sections 4 and 5.

Finally, Section 6 summarises the research reported in earlier chapters and the thesis' findings, conclusions, and research recommendations for future studies.

2 LITERATURE REVIEW

Climate change (CC) is unequivocal (Charron 2016), and has been designated as one of the twenty-first century's major global issues, impacting natural and human systems, increasing their susceptibility in various scales and with differing degrees of intensity (IPCC 2013). Unfortunately, the problem has reached such a scale that its consequences pose serious dangers in the future (Barnett and Adger 2003) (Grove 2010). Understanding the science and mechanism is crucial to comprehend its implications fully.

2.1 WEATHER VS CLIMATE

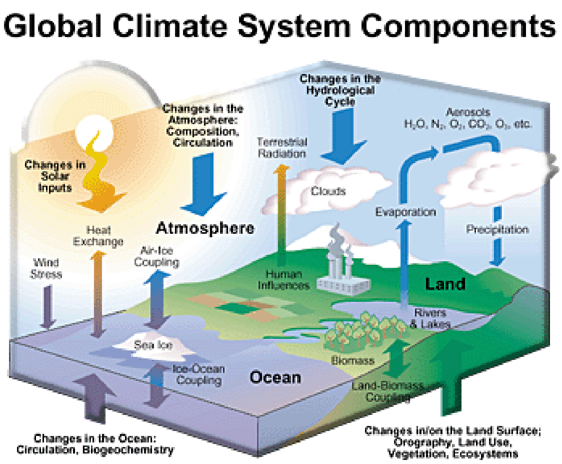
What is the Weather?

There is a great deal of variation in weather and climate on different scales, both spatial and temporal. The proof for this is evident in our present observations and simulations of climate and from documents relating to previous climates and glaciations (Bradley 2014) (Saltzman 2002) (Ahrens and Henson 2021). The conditions in the atmosphere above a specific location at a specific time are described as weather. The world experience weather every day as temperature, rain, snow, hail, and wind. These may change throughout the day. The weather forecast can be quite specific ("it will be cloudy and cool tomorrow morning, warming in the afternoon with thunderstorms, becoming fair and mild by nightfall") but remains meaningless beyond a few days (Ahrens and Henson 2021).

What is Climate?

In contrast, the climate analyses how the weather changes over time, usually over a long period of time, typically over 30 years (Armstrong, Krasny and Schuldt 2018). Short-term weather refers to the state of the atmosphere, whereas climate refers to a long-term weather pattern in a specific location (Armstrong, Krasny and Schuldt 2018) (Ahrens and Henson 2021). According to the World Meteorological Organization (WMO), the canonical time for describing a climate is 30 years. Interestingly, climate predictions are more concerned with expected changes in average conditions while acknowledging that individual days, weeks, months, or even years will always defy the overall trend. Scientists have delineated climate zones throughout the world (Belda, et al. 2014) (Beck, et al. 2018). As scientists study the atmosphere's interactions with the oceans, ice sheets, land, and vegetation, they must examine how these systems interrelate. The entire planetary climate system can be described using a five-part approach. Climate is affected by both the daily weather and the long-term averages of the interacting components of the geosphere and biosphere (Rohli and Vega 2017).

Figure 2-1: Major components of the global climate system and their main interactions



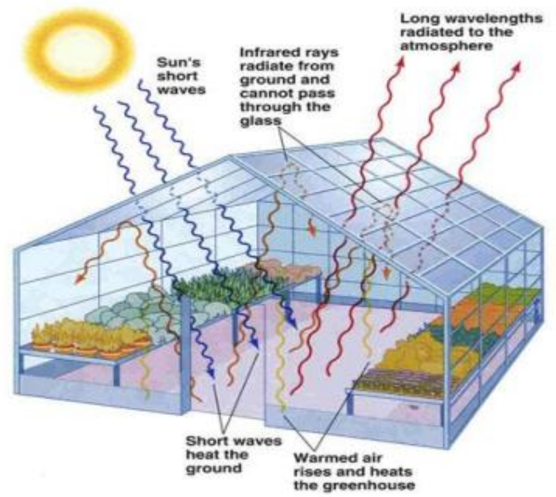
The sun significantly influences climate (Beer, Mende and Stellmacher 2000). The sun provides the energy required to warm the Earth. If the Earth's atmosphere and some gases were absent, the climate would very certainly not be the same. The atmosphere acts as a barrier to prevent heat from escaping into space (Ahrens and Henson 2021). The planet would turn into a frigid place without this mechanism. The balance of the two factors determines the Earth's average temperature as a result of the sun's energy coming in and the radiant heat made through the atmosphere (Ahrens and Henson 2021).

The equatorial location of the sun and the poles is crucial to the climate system since the sun has an uneven energy distribution. The climate of the polar regions and the warm tropical tropics is influenced by this unequal energy distribution, which the climate of the atmosphere and ocean can modify. Ocean currents, atmospheric circulation, evaporation, precipitation, and weather result from non-uniform heating or the consequent heat transport (Ahrens and Henson 2021) (Oke 2002).

The atmosphere contains gases that allow the sun's energy to pass through but prevent it from escaping into space. The greenhouse effect is the name given to this phenomenon (**Error! Not a**

valid bookmark self-reference.). The gases that cause this are called GHGs. Examples include carbon dioxide, methane, and water vapour. More than a century and a half years ago, scientists began examining the effects of GHGs. According to their findings, the Earth would be 30 °C colder without the greenhouse effect, rendering it uninhabitable (Ahrens and Henson 2021). Due to the effectiveness of GHGs in keeping the Earth warm, any temperature change will result in feedback.

Figure 2-2: The greenhouse effect



2.2 WHAT IS CLIMATE CHANGE

There is a common misconception among the general public, mainstream media, and policymakers that climate change is the same as global warming (Liu, Vedlitz and Alston 2008) (Whitmarsh 2009). It is unsurprising since the documented rise in mean temperatures near the Earth's surface presents society with the most obvious proof that our climate is changing (Hansen, Sato and Ruedy 2012) (Thomas, et al. 2020). Globally, human activity has significantly affected the climate as billions of tonnes of GHGs have been released into the atmosphere (Skripnuk and Samylovskaya 2018). Historically, these changes have been caused by things like solar and volcanic activity and minor shifts in Earth's orbit. Projections from the Intergovernmental Panel on Climate Change (IPCC) experiment and other highly known Global Climate Models (GCMs) predict significant global warming and changes in precipitation frequency and amount from 2000 to 2100 (IPCC 2001). IPCC (2019) found that extreme events have become more common, intense, and prolonged since 1850-1900.

According to the IPCC, the climate is "average weather over a specific period and area, taking into account its variability". The IPCC defines climate changes as a change in climate observable (e.g., using statistical tests) by changes in the mean and/or variability of its characteristics over time, generally decades or more (IPCC 2012). Furthermore, the IPCC stated any change in climate over time, regardless of whether it is caused by human activity or natural variability, is climate change.

Contrary to this, the UNFCC defines climate change (CC) as a change in the climate caused by human activities and natural climate fluctuations observed across comparable periods (UN 1992). A change in the mean and variability of meteorological variables is associated with it. Scientists often refer to natural climate change as climate change in a broader sense. The term "climate change" refers to statistically significant variations in climate state or variability lasting for an extended period, typically decades or longer (IPCC 2001, 2013, 2014a, 2021a).

When analysing CC, it is critical to look at the long-term record of climatic factors rather than the short-term. Despite their similarities, climate change and climatic variability refer to fundamentally different processes, despite their sometimes confused meanings. Climate variability is a short-term fluctuation in the mean temperature or climatic conditions, whereas CC is a statistically significant long-term shift (G. C. Hegerl, F. Zwiers, et al. 2007).

The atmosphere, water cycle, and socioeconomic systems have all been affected by CC, and the consequences are likely to worsen in the twenty-first century (IPCC 2013). Global temperatures have risen by about one degree Celcius since the pre-industrial period because of CC (Dibike and Coulibaly 2005). CC can influence local climatic conditions, thereby accelerating hydrological processes (Kim, Kim and Kwon 2011). The management of water resources must consider such likely hydrologic changes. Effective adaptation measures necessitate incorporating CC into long-term infrastructure investments on which society relies (IPCC 2021a).

The concept of climate change is more critical and riskier than other factors, such as climate variability and weather, since its effects last longer. It will be more challenging to change the state of the phenomenon once its threshold has been surpassed. A comprehensive study of the regional and seasonal effects of CC is required. The extent to which future climate change will influence regional shifts is unknown and varies by region. Various factors influence the global climate, and the outcome is usually a net positive or negative result.

2.3 GLOBAL CLIMATE CHANGE

As the earth heats, oceanic heat content, atmospheric humidity, sea levels, and upper atmospheric temperatures are predicted to rise, while sea ice, snow cover, and glaciers are expected to decline. (Arndt, Baringer and Johnson 2010). There is now a wealth of data that our planet has warmed in the last 200 years (Mann and Jones 2003). Global change researchers cite the current epoch as the Anthropocene because human activity has altered the composition of the Earth’s atmosphere (Comer-Warner, et al. 2021) (Steffen, et al. 2011). GHGs, in particular methane, carbon dioxide, and nitrous oxide, have all increased due to human activities during the industrial era (Marescaux, Thieu and Garnier 2018).

The Intergovernmental Panel on Climate Change (IPCC) fifth assessment report (AR5) asserts unequivocally that current concentration levels are unprecedented in at least the last 800,000 years (IPCC 2014a), with concentrations having risen above 300ppm and currently well over 400ppm (Ritchie and Roser, CO_2 and Greenhouse Gas Emissions 2020). An increase in the greenhouse effect has the potential to drastically alter the global climate, with far-reaching regional implications (IPCC 1997). Despite the fact that the world's population is expected to exceed 10 billion by the end of the century (There is a great deal of variation in weather and climate on different scales, both spatial and temporal. The proof for this is evident in our present observations and simulations of climate and from documents relating to previous climates and glaciations. The conditions in the atmosphere above a specific location at a specific time are described as weather. The world experience weather every day as temperature, rain, snow, hail, and wind. These may change throughout the day. The weather forecast can be quite specific ("it will be cloudy and cool tomorrow morning, warming in the afternoon with thunderstorms, becoming fair and mild by nightfall") but remains meaningless beyond a few days.

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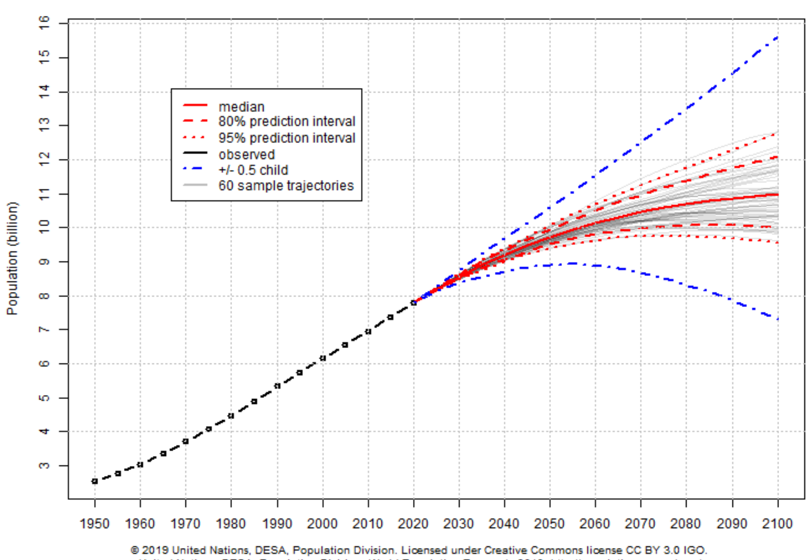
Figure 2-1), and per capita, energy consumption is projected to rise, without intervention, GHG concentrations will continue to increase, exacerbating a current radiative imbalance on the planet (IAEA 2021).

Figure 2-3: World: Total Population



As a result of the GHGs, the Earth's temperature remains at an appropriate level for habitation (King 2005). If the GHGs reach levels above normal, energy is trapped, causing additional warming of the atmosphere, oceans, and land surfaces (Armstrong, Krasny and Schuldt 2018). Scientists acknowledge that human-induced activities have led to the accumulation of GHGs like carbon dioxide, methane, and nitrous oxide (e.g. (Armstrong, Krasny and Schuldt 2018)).

Since 1958, the Mauna Loa Observatory has been taking carbon dioxide (CO_2) readings in the atmosphere (Elnar, et al. 2021). For the first time, the station measured above 400 ppm in May 2013, while the weekly average reading was above 408 ppm in May 2016 and 414 ppm in August 2021 (gml.noaa.gov). GHG concentrations will continue to rise unless action is taken, aggravating the current radiative imbalance on Earth.

Figure 2-4: Monthly CO2 concentrations at Mauna Loa Observatory since 2016. Source: https://gml.noaa.gov/ccgg/trends/

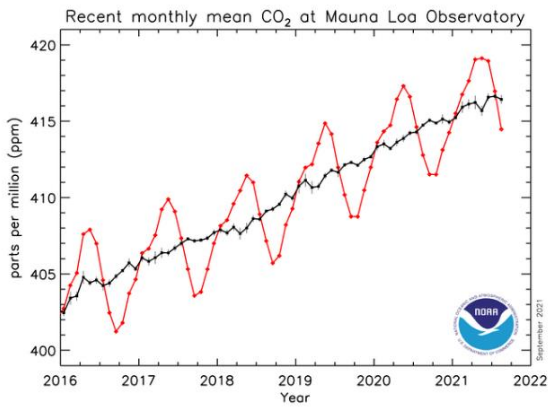
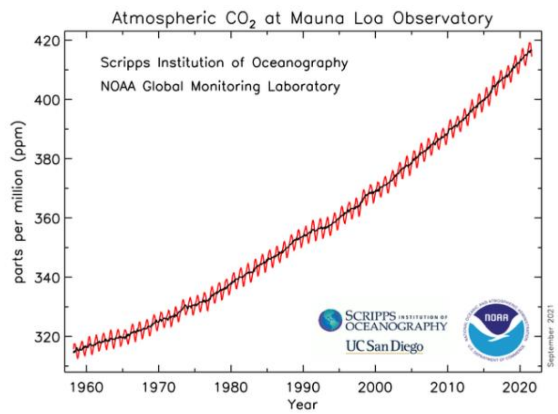


Figure 2-5: Growth of CO2 concentrations at Mauna Loa Observatory since 1960. Source: https://gml.noaa.gov/ccgg/trends/



2.3.1 GLOBAL WARMING FEEDBACKS

Several positive feedbacks result from warming. The reason why temperatures are rising cannot be explained entirely by GHGs. Atmospheric CO_2 contributes to global warming (Scheffer, Brovkin and Cox 2006). Increasing anthropogenic emission of CO_2 causes more heat to be trapped at the surface and in the lower atmosphere since carbon dioxide absorbs heat (Boer and Arora 2013). A major source of global warming is the combustion of fossil fuels, with CO_2 emissions responsible for almost half of the atmospheric greenhouse gas emissions (Ritchie and Roser 2020). CO_2 levels in the atmosphere may increase due to global warming due to the loss of carbon from terrestrial ecosystems (Zeng, et al. 2004). Through several climate models, it has been suggested that the terrestrial carbon cycle may accelerate such warming (Cox, et al. 2000).

Kirehl and Trenberth (1997) have identified water vapour as the major GHG in the greenhouse effect under clear skies (approximately 60%). Warm temperatures tend to increase water vapour levels in an atmosphere (Houghton 2005). Because water vapour is a GHG, increasing its amount causes the environment to warm even more (Hall and Manabe 1999). As a result, the greenhouse effect is substantially more significant than that caused only by CO_2 (Held and Soden 2000). In general, this positive feedback is referred to as "water vapour feedback" in the climate literature.

Climate sensitivity is significantly higher than the previously stated theoretical figure of 0.25 degrees for every 1 watt of radiant energy increase per square metre (Hall and Manabe 1999), (IPCC 2001), (Stephens and Ellis 2008), (Rafferty 2010).

The concept of cloud feedback describes the relationship between atmospheric circulations, cloudiness, radiative, latent heating of the atmosphere and surface air temperature (G. Stephens 2005) (Erfani and Burls 2019) (Yue, et al. 2019). Clouds absorb emitted infrared radiation from the planet's surface, which provides warmth to the surface (Houghton 2005). Yue et al. (2019) found a substantial correlation between intermodel differences in climate sensitivity and cloud feedback in response to long-term climate change. Cloud types and distribution are expected to change as a result of global warming (Sun, Yu and Zhang 2009). Climate models differ in their representations of cloud cover, and even small changes in cloud cover can have a significant impact. According to satellite data, the increasing temperature is associated with increasing cloud optical thickness (Yue, et al. 2019).

2.3.2 TEMPERATURE

The global average surface temperature is a significant indicator of global climate change. Mean global surface temperature is linked to the global energy balance and rises in a quasi-linear relationship with cumulative GHGs emissions (IPCC 2013). In the scientific community and general society, mean global surface temperature evolution is equally fascinating (Boykoff 2014) (Lewandowsky, et al. 2015). Between 1906 and 2005, mean global surface temperatures increased by 0.5°C to 0.9°C, with a pace of warming that has nearly doubled in the latter 50 years compared to the first 50 years (Trenberth et al., 2007).

Increasing greenhouse gases contribute to higher temperatures. According to the IPCC (2013), the global average surface temperature has risen nearly every three decades since 1850, with the exception of the decade from 1901 to 2012. Meanwhile, the IPCC's 2018 report places global warming at 1.0 degrees Celsius above pre-industrial levels, with 1.5 degrees Celsius predicted by 2030-2050 if temperatures continue to rise at their current rates. The current warming rate is approximately ten times faster than during the Ice Age, according to researchers Armstrong et al. (2018).

2.3.3 PRECIPITATION SHIFTS

Precipitation is an even more important indicator of climate change than temperature (Houghton 2005). Climate change will increase atmospheric water vapour content as the air gets warmer and, therefore, on average, increase precipitation, according to Houghton (2005). The can lead to more intense rainstorms. According to the general theory, a changing climate has caused wet areas to become wetter, while the drier ones become drier (Dore 2005). However, a later study challenges that widely accepted theory (Ljungqvist, et al. 2016) High latitudes and near the equator will see an increase in precipitation (Trenberth 2011) (Gimeno, et al. 2012), whereas subtropical subsidence regions will see decreases (Allen and Ingram 2002). The regional water budget may be influenced by changes in circulation patterns as well as thermodynamic effects. It is critical to consider both the dynamic (circulation) and thermodynamic influences of a region's moisture sources.

A link exists between precipitation and surface temperature, according to the Clausius-Clapeyron equations (Skliris, et al. 2016) (Fujita and Sato 2017). In accordance with the Clausius-Clapeyron equations, temperature increases lead to increases in saturation vapour pressure and rate (Held and Soden 2006). Because water vapour is a gas, it is sensitive to changes in temperature, which results in water vapour feedback. As a result of this interaction, many researchers believe the water cycle has been accelerated or intensified (Berg, Moseley and Haerter 2013).

A climate model simulation under global warming examines the range of annual precipitation, which is the difference between maximum and minimum precipitations along a year. As an immediate consequence of CO2 warming in the atmosphere, Yang et al. (2003) demonstrate a decrease in precipitation rate. According to a numerical simulation done by Douville et al. (2002), the global cycling rate appears to decrease when evaporation, total precipitable water (TPW), and precipitation increase. Climate change tends to increase precipitation variability on average over the globe. Generally speaking, this is a global phenomenon, except for a few bands along 30°S and 30°N. In addition to changes in intensity, changes in precipitation frequency are also correlated with changes in mean precipitation (Sun, et al. 2007) (Liu, et al. 2009) (R. Allan, et al. 2010).

2.3.4 IMPACTS OF GLOBAL CLIMATE CHANGE

The impact of global climate change is likely to lead to more extreme weather patterns, which will likely worsen and become more frequent in the future (Coumou and Rahmstorf 2012). There has been an increase in drought events with the rise of extreme events (IPCC 2018). As a result, more people worldwide will experience water stress (IPCC 2018). This may be particularly true in tropical areas (Dore 2005) and regions dominated by snowmelt, such as the Colorado River Basin in the Northwest United States.

The implications highlighted by Armstrong et al. (2018) are rising ocean temperatures and acidity, rising sea levels, melting ice, and changing local and regional weather. The rising sea levels and disruption of the hydrological cycle (primarily changes in precipitation amounts and patterns) result from this climate phenomenon, which has ramifications for ecosystems. Besides increasing air temperature, climate change can also cause a variety of other phenomena. Due to climate change, extreme weather events such as heatwaves, cold spells, floods, and droughts can also occur. Can also expect fluctuations in agricultural outputs, ecosystems deterioration, and species to become extinct in response to temperature changes (Grotjahn 2020) (IPCC 2021a).

2.4 CLIMATE CHANGE IN THE CARIBBEAN

Climate conditions in the Caribbean are influenced by the Pacific and Atlantic Oceans as well as North and South America (Jury 2009c). The climate in the Caribbean region is also expected to change significantly due to global warming. The Caribbean will most likely suffer severe climate change impacts over the course of this century (Pulwarty, Nurse and Trotz 2010) (Nurse, et al. 2014). Small Island Developing States (SIDS) and maritime borders are more prevalent in the Caribbean than anywhere else in the world (Pulwarty, Nurse and Trotz 2010). There has been less research done on Caribbean climatology than on northern climates. Various early analyses used monthly temperature and precipitation series from individual islands (Singh 1997) or made comparisons with other tropical regions.

Climate change science has made great strides in the region (Karmalkar, et al. 2013) (Hall, et al. 2013). By contrast, regional impact analysis focusing on socio-economic systems has not increased in a comparable way. The complex and diverse nature of the exposure of Caribbean countries and their vulnerability to the impacts of climate change is better understood. However, it is urgently necessary to carry out a more comprehensive study of the underlying reasons behind and the factors driving its social and economic vulnerability (Shah, et al. 2013).

Vulnerability

Vulnerability is frequently described or framed in terms of a social or ecological system's sensitivity or exposure to shocks, stresses, or disturbances (Adger 2006). According to the IPCC AR5 Report, vulnerability is defined as “the propensity or predisposition to be adversely affected”. It is generally accepted that vulnerability has external and internal components, particularly within disaster literature.

Several factors make Caribbean small island states vulnerable to climate change. Research has well documented the region’s vulnerability to a changing climate (Hall, et al. 2013) (Pulwarty, Nurse and Trotz 2010). Low-lying locations and the storm surges generated by sea-level rise are among the geographical vulnerabilities. Other vulnerabilities include coastal areas heavily affected by tropical storms and hurricanes, high temperatures, few land resources, and increased dependence on fresh groundwater (Benjamin 2010).

The vulnerability and resilience of Caribbean communities to climate change threats also depend on other factors such as population, an overreliance on climate-sensitive economic activities, and massive public debt, multiple impact studies have confirmed. The conditions confronting Caribbean countries are typically exacerbated by their colonial history and underlying historical legacies (Cardona 2011) (Wisner, et al. 2004). Global economic change has long created additional vulnerabilities in the Caribbean, primarily because of the damage caused by imperialism over many centuries.

Temperature and Precipitation

The tropical Caribbean has experienced an average temperature increase of 1°C since pre-industrial times (IPCC 2018). The IPCC (2018) estimates that warming occurs in the Caribbean at a rate of 0.2°C every decade. By 2030, it is predicted that the Caribbean will reach 1.5°C of warming, based on current trends and IPCC estimates (2018). Precipitation is higher in May and October and lowers in July when air pressure and trade winds increase in the Caribbean (Gamble and Curtis, Caribbean precipitation: review, model and prospect 2008) (Gamble, Parnell and Curtis 2008).

2.5 CLIMATE CHANGE IN THE BAHAMAS

Vulnerability

A small island nation like the Bahamas brings many challenges. In the Bahamas, sea levels rise, erosion of sandy beaches, and droughts are occuring due to climate change. Several hurricanes and other damaging storms have previously struck the country, as have others in the Caribbean. Hurricanes Irma and Maria, both Category 5 storms, devastated the Bahamas in 2017 (ACAPS; OCHA; UNDP; 2017). Their combined damages triggered the evacuation of many of the islands. The Bahamas were devastated by Hurricanes Joaquin (2015) and Matthew (2016) only a short time earlier. Approximately USD 3 billion was estimated to have been lost in damage from Hurricane Dorian, a Category 5 storm that happened in 2019. These effects have negatively affected economic development in the Bahamas, and they will likely become worse going forward.

2.6 WATER USE

Water scarcity is the world's most serious problem (Jury and Vaux 2006). Water use patterns may change as a result of population growth, economic development, and shifting perspectives on the value of water. Water for irrigation, for example, maybe prioritized over water for domestic use. Rising population, urbanisation, and climate change in developing countries may restrict urban water availability (O'Hara and Georgakakos 2008). UNEP has identified the Bahamas as one of the SIDS countries where water scarcity or stress will be a problem by 2025 (UNEP 2014).

Table 2-1: Water Use (Source: FAO (2015), Country profile – Bahamas)

Water withdrawal:				
Total water withdrawal		-	-	million m^3 /year
	- Agriculture (Irrigation + Livestock + Aquaculture)	-	-	million m^3 /year
	- Municipalities	2013	31	million m^3 /year
	- Industry	-	-	million m^3 /year
	Per inhabitant	-	-	m^3 /year
Surface water and groundwater withdrawal (primary and secondary)		-	-	million m^3 /year
	As % of total actual renewable water resources	-	-	%
Non-conventional sources of water:				
Produced municipal wastewater		-	-	million m^3 /year
Treated municipal wastewater		-	-	million m^3 /year
Direct use of treated municipal wastewater		-	-	million m^3 /year
Direct use of agricultural drainage water		-	-	million m^3 /year
Desalinated water produced		2000	7.4	million m^3 /year

Figure 2-6: Households' Access To Water. Source: 2010 Census

Type of access	Households (2010)	Percentage
Public piped into dwelling	63438	62%
Public piped into yard	1749	2%
Private piped into dwelling	31763	31%
Private not piped	2920	3%
Public standpipe	1036	1%
Public well or tank	93	0%
Rainwater system	1111	1%
Other	648	1%
Total	102758	100%

Alternative sources need to be explored to compensate for the decline in groundwater resources, especially in New Providence. According to FAO (2015), desalination is becoming more popular, and it will most certainly continue to do so. The availability of fresh groundwater is decreasing, while water demands are increasing. FAO (2015) further explained that rainwater catchment is infrequently employed, providing only 3% or less of the total water supply. The depletion of resources and quality deterioration are two separate but interrelated problems (Jury and Vaux Jr 2007). A decline in groundwater quality can be caused by pollution and excessive extraction.

Table 2-2: Freshwater resources in The Bahamas. Source: IWRM Plan Bahamas Report (Final Report Feb 07)

Island	Size (Acres)	Freshwater Lens (Acres)	Lens Area/Size	Max. Daily Abstraction (MIG)	Water Available (IG/D) Person 1990 Census	Total Population 1990 Census
Abaco	415360	116280	0.28	79.1	7.906	10003
Acklins	96000	15783	0.16	4.36	10765	405
Andros	1472000	338585	0.23	209.92	25672	8177
Bimini	7040	395	0.06	0.17	104	1639
Cat Island	96000	14774	0.15	6.8	4005	1698
Crooked Is.	58900	5923	0.1	1.74	4223	412
Eleuthera	128000	16599	0.13	8.13	768	10584
Exumas	71680	6586	0.09	2.9	816	3556
Grand Bahama	339200	147884	0.44	93.17	2278	40898
Gt, Inagua	383360	3571	0.01	0.86	873	985
Long Island	147200	9301	0.06	2.88	977	2949
Mayaguana	70400		0.03	0.65	2083	312
New Providence	51200	2340	0.34	9.63	60	172196

TOTAL	3336340	695524	0.208	420.31	60530	253814

2.7 RESEARCH ON CLIMATE MODELS

Climate models were used to predict how the climate changes and evolves. The fact that climate projections can differ is due to the fact that different climate models use different plausible representations of climate systems. Models of climate change can be used to calculate the amount that climate change will affect temperature and precipitation under different climate scenarios. Many aspects, such as emission circumstances and historical data, are taken into account by climate models. This study's section on climate scenarios includes a discussion of possible emission scenarios.

Using multiple numerical models, scientists study the climate system and its behaviour across a wide range of spatial and temporal scales (IPCC 2021a). The increasing availability of inexpensive computational resources has enabled many scientific institutions to use global circulation models (GCMs) and regional climate models (RCMs) to simulate climate. Our understanding of past and present climate is advanced by using climate models (IPCC 2021a). These models help understand climate processes, simulate historical climates, and predict future climates (e.g., future GHG concentrations and land use).

Various climate models are employed in this study to avoid uncertainty because one model may raise the result's uncertainty. This paper's models incorporate historical climate simulations as well as future climate change scenarios. Changes in temperature and precipitation are analysed for the historical projection from 1991 to 2016 and the future prediction from 2020 to 2100.

2.7.1 GLOBAL CLIMATE MODELS (GCM)

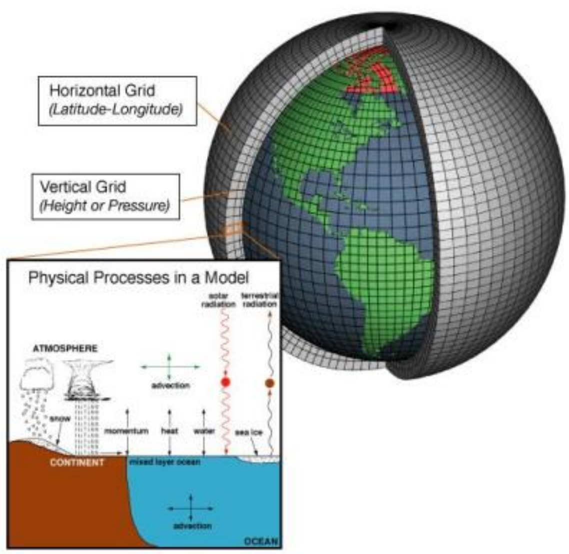
The GCM is a three-dimensional model that represents the climate system mathematically (Basher et al., 2000) (Asch, et al. 2016). The modelling tool helps reproduce a complex ensemble of processes that impact climate evolution (G. C. Hegerl, F. Zwiers, et al. 2007) (Kiktev, et al. 2007) (Min, et al. 2009). As a result, derived differential equations reproduce the whole climate evolution by combining the fundamental laws of physics, fluid mechanics, and chemical reactions (Trzaska and Schnarr 2014). Grids are created, both horizontal and vertically, for the Earth, oceans, and atmosphere in order to make this possible (There is a great deal of variation in weather and climate on different scales, both spatial and temporal. The proof for this is evident in our present observations and simulations of climate and from documents relating to previous climates and glaciations. The conditions in the atmosphere above a specific location at a specific time are described as weather. The world experience weather every day as temperature, rain, snow, hail, and wind. These may change throughout the day. The weather forecast can be quite specific ("it will be cloudy and cool tomorrow morning, warming in the afternoon with thunderstorms, becoming fair and mild by nightfall") but remains meaningless beyond a few days.

What is Climate?

In contrast, the climate analyses how the weather changes over time, usually over a long period of time, typically over 30 years. Short-term weather refers to the state of the atmosphere, whereas climate refers to a long-term weather pattern in a specific location. According to the World Meteorological Organization (WMO), the canonical time for describing a climate is 30 years. Interestingly, climate predictions are more concerned with expected changes in average conditions while acknowledging that individual days, weeks, months, or even years will always defy the overall trend. Scientists have delineated climate zones throughout the world. As scientists study the atmosphere's interactions with the oceans, ice sheets, land, and vegetation, they must examine how these systems interrelate. The entire planetary climate system can be described using a five-part approach. Climate is affected by both the daily weather and the long-term averages of the interacting components of the geosphere and biosphere.

Figure 2-1). Pressure, wind, temperature, humidity, and rainfall data are just a few variables that are calculated at each grid point throughout time to anticipate their future values (Wilby, Troni, et al. 2009). As the grid size increases, the time step (the time between each solution) also decreases. The finer the grid resolution, the shorter the time between computations (Schneider, et al. 2017).

Figure 2-7: Conceptual Structure of a GCM.
Source: NOAA, 2012



2.7.2 EARTH SYSTEM MODELS (ESM)

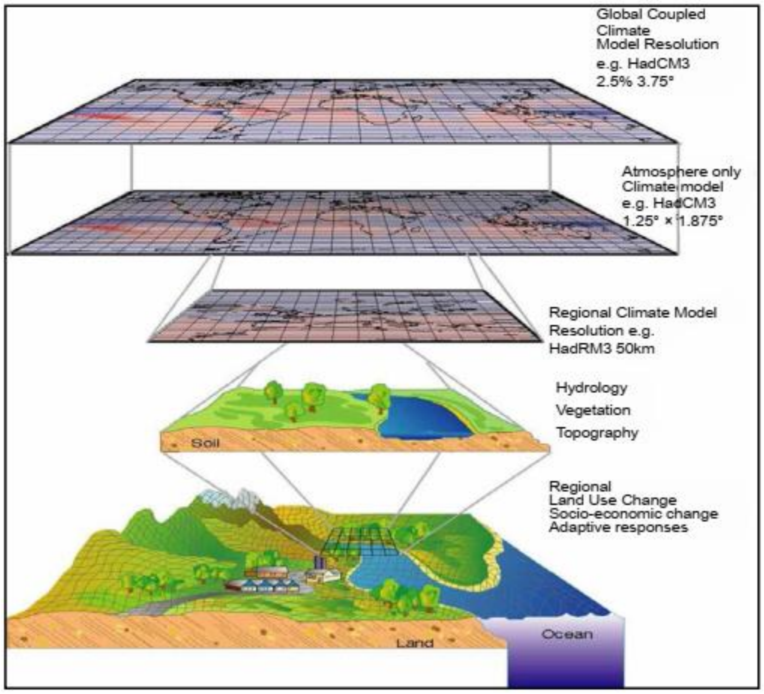
Simulating all relevant aspects of the earth system is the aim of Earth System Models (ESMs). In addition to modelling the carbon cycle, dynamics of flora, atmospheric chemistry, and biogeochemical processes, the ESM, an expansion and more complex than their predecessors, the GCM (Foley, et al. 2013), also explores the interactions between cryospheric processes and climate (Heavens and Ward 2013) (Sueyoshi, et al. 2013) (Asch, et al. 2016). As such, it can dynamically adjust its response to other driving factors such as GHGs emissions. By including the global carbon cycle, we can show how climate regulates itself via feedbacks from the ocean and the land that takes up some of the emitted CO_2 and helps reduce global warming (Tjiputra, et al. 2010) (Anav, et al. 2013) (Schneider, et al. 2017).

In addition, the sulphur cycle contributes to the formation of sulphate aerosols, which directly absorb sunlight (direct cooling effect) and indirectly modify the properties of clouds (indirect cooling effect) (Murphy, et al. 2014). ESMs may include other components, such as ozone (Sueyoshi, et al. 2013). A gap in global observational data makes it difficult to assess the biogeochemical component of an ESM (Ng, et al. 2016). As a result, the evaluation of the physical component is becoming increasingly complete and sophisticated. Although these models provide valuable information on future climate change, human activities, and potential mitigation actions, they also provide valuable information on climate variability and change trends (Sueyoshi, et al. 2013) (Kawamiya, et al. 2020).

2.7.3 REGIONAL CLIMATE MODEL (RCM)

RCM can integrate with a global model to provide more information about specific locations (Trzaska and Schnarr 2014) and simulate climate for selected regions at high resolution up to a hundred years in the future (Leung, et al. 2004) (Wang, et al. 2004). RCMs cover only a portion of the globe (**Error! Not a valid bookmark self-reference.**). Therefore, the model equations can be solved at a finer horizontal resolution (45 km or less) within a reasonable timeframe (Charron 2016). No doubt, local topography influences local climate change significantly (Centella-Artola, et al. 2015). According to Charron (2016), as GCMs use a relatively coarse spatial resolution, they cannot account for these local topographies. In order to avert a dangerous deterioration in the global climate, social and economic policies must be justified by assessing what the impact really will be in different countries. Moreover, a better understanding of regional processes is crucial to global research (IPCC 2007).

Figure 2-8: Dynamical downscaling of GCM data (coarse scale) to RCM data (fine scale).



2.7.4 CLIMATE DOWNSCALING

Global Climate Models, also known as Global Circulation Models (GCMs), are commonly used to generate climate data for future and past scenarios. Data or information at relatively coarse spatial and temporal scales can be classified as downscaled if it has been transformed into products at smaller scales (Maraun, et al. 2010) (Wilby and Fowler 2011) (Ng, et al. 2016). With the help of downscaling, these interactions can be modelled and relationships between the present-day climate and atmospheric conditions established. When evaluating climate change projections, it is crucial to consider seasonal fluctuations in precipitation because there may be more changes than annual averages can reflect (Sohoulande Djebou and Singh 2016). The vast majority of GCMs do not incorporate or provide information for scales smaller than a few hundred kilometres or two. GCMs have a low resolution of 150 to 30 kilometres by 150 to 300 kilometres in most cases (Vavrus, et al. 2011) (UNFCCC 2018). RCMs simulate the climate features dynamically at a high resolution of 10 to 50 km in the context of varying atmospheric conditions at a domain boundary (Wilby, Troni, et al. 2009) (Teutschbein and Seibert 2012). Wilby and Fowler (2011) pointed out that the procedures for downscaling have been examined previously.

GCMs are downscaled to examine local seasonal impacts. Downscaling GCMs can also be done in a variety of ways (PIRCA 2016, UNFCCC 2018).

- The statistical downscaling predict how the future will change due to observed local climate and GCM data. Future variables of GCM projections are used for constructing statistical correlations and estimating future local climates (Maraun, et al. 2010).

Statistics downscaling utilises the statistical link between large-scale climate models and local observations (Xu, Han and Yang 2019).

- Dynamical downscaling employs atmospheric physics in RCMs to make GCM projections more regionally relevant (Tang, et al. 2016). It necessitates the use of high-performance computing resources to simulate how the climate responds to increased GHG concentrations using a limited-area high-resolution model driven by GCM boundary conditions (Tang, et al. 2016).

2.7.5 CLIMATE SCENARIOS

Climate scenarios are a plausible and often simplified view of future climate that explains the possible effects of anthropogenic climate change as described by the IPCC (2021). A climate scenario describes the evolution of the climate over an extended period in a logical and internally consistent manner (Charron 2016). Climate scenarios aid in climate change analysis, including climate modelling, impact assessment, adaptation, and mitigation while taking future population size, economic activity, and governance structure into account (Santoso, Idinoba and Imbach 2008) (Mote, et al. 2011).

The relationships between human choices, emissions, concentrations, and temperature change can be uncovered through the analysis of climate projections based on a range of plausible scenarios (van Vuuren, Edmonds, et al. 2011). While we may be able to achieve certain scenarios as long as we continue to consume fossil fuels, reducing emissions may lead to others. Other scenarios may merely entail an end goal or target, such as limiting cumulative carbon dioxide emissions at a certain level or stabilising global temperatures at a certain level. For example, under the Paris Agreement, GHG emissions will be drastically cut to keep annual global temperature increases to 1.5 degrees Celsius above pre-industrial levels by the end of the century, while also exploring measures to keep them below 2 degrees celsius (UNFCCC 2015).

2.7.6 FUTURE EMISSIONS PATHWAYS

The future emissions of GHG are affected by a wide range of factors (Meinshausen, Smith, et al. 2011). Adaptation to climate change will depend on how the earth system responds and how humans respond through technology, economics, lifestyles, and policy changes. A set of scenarios was developed before the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, known as Representative Concentration Pathways (RCP) (Moss, Edmonds, et al. 2010) (van Vuuren, Stehfest, et al. 2011).

Two-decade history of developing scenarios is reflected in the RCPs. There are at least four significant differences between RCPs and previous sets of standard scenarios (van Vuuren, Edmonds, et al. 2011). First and foremost, RCPs are radiative forcing scenarios, not emissions scenarios. Among the four RCPs, there is a full range of scenarios, including climate policies and without policies (IPCC 2013). Each is numbered according to how the radiative forcing will change by 2100. Secondly, each RCP encompasses a range of emission trajectories with corresponding policies and technological strategies. RCPs are also useful for climate modellers as well as land use and land cover gridded trajectories.

One of the mitigation scenarios would reduce forcing to very low levels, an aggressive action plan for mitigating greenhouse warming (RCP 2.6) (van Vuuren, Stehfest, et al. 2011). There are also two medium stabilisation scenarios. At the upper end is a scenario with very high baseline emissions, a fossil fuel-intensive scenario with little emissions reduction, with CO2 concentrations continuing to rise rapidly (RCP 8.5) (Moss, Babiker, et al. 2008). CO2 emissions in the RCP8.5 are comparable, although marginally lower than those of the highest Special Report on Emissions Scenarios (SRES) forcing scenario (A1FI) for the twenty-first century (Raper 2012). Specifically, RCP2.6, RCP4.x, RCP6.0, and RCP8.5 are named after a range of radiative forcing values in the year 2100 (Table 3-1).

Table 2-3: Overview of representative concentration pathways (RCPs) (Meinshausen, Smith, et al. 2011)

	Description	CO2 Equivalent	SRES Equivalent	Publication
RCP 8.5	Pathway towards 8.5 W/m^2 of radiative forcing by 2100. According to this scenario, there is no climate policy baseline and relatively high GHGs emissions.	1370	A1FI	(Riahi, Grübler and Nakicenovic 2007)
RCP 6.0	Stabilisation to 6 W/m^2 by 2100 without overshooting. Compared to the number of mitigation scenarios leading to 6 W/m2, the number of baseline scenarios (no climate policy) represents this forcing level.	850	B2	(Fujino, et al. 2006) (Hijioka, et al. 2008)
RCP 4.x	A stable trajectory without an overshoot of 4.x W/m^2 by 2100. Refers to the scenario in AR4 that consists of most of the assessed scenarios.	650	B1	(Smith and Wigley 2006) (Clarke, et al. 2007) (Wise, et al. 2009)
RCP 2.6	There will be a peak in radiative forcing at ~ 3 W/m^2 before 2100, followed by a decline. The objective is to limit global mean temperatures to an increase of not more than 2C above pre-industrial levels.	490	None	(van Vuuren, et al. 2007)

In comparison to the previous generation of climate models featured in the IPCC AR5, the sixth generation CMIP6 is a major improvement. The purpose of CMIP6 is to create a set of standard simulations for each model. By doing so, different models can be directly compared, so that future changes can be identified where models agree and disagree. The scenarios are a mix of Shared Socioeconomic Pathways and Representative Concentration Pathways forcing levels (RCP) (O'Neill, et al. 2017). An SSP1-1.9 scenario seeks to limit warming to below 1.5C by 2100 above pre-industrial levels. According to SSP1-2.6, emissions would decline more gradually than under RCP 2.6, and the starting point would be higher. SSP5-3.4OS is an overshoot scenario (OS) in which emissions follow a worst-case RCP5-8.5 path until 2040. With the addition of SSP3-7.0 to CMIP6, a new scenario has been added, which lies close to the middle of the range of baseline outcomes produced by energy system models (Tebaldi, et al. 2021). Climate models will now be able to explore impacts and changes at 1.5C warming under new CMIP6 scenarios. New SSP scenarios started in 2014, while the older RCP scenarios began in 2007.

3 METHODOLOGY

This chapter introduces relevant data and tests it for homogeneity. The following sections (3.1.2 and 3.1.3) demonstrate station data gathered from weather stations in The Bahamas, in addition to a gridded temperature and precipitation series reanalysed by NCEP/NCAR (Kalnay et al., 1996) for comparison. A description of the mathematical approaches used to analyze climate data appears in Section 3.3.

3.1 COUNTRY BACKGROUND

The area chosen for this study encompasses the islands of The Bahamas. Many of the islands have undergone limited development and groundwater exploitation.

3.1.1 LOCATION OF THE STUDY AREA

Unlike the volcanic islands of the Antilles, The Bahamian archipelago (Figure 3-1) comprises about 700 islands and cays formed from limestone located on two large submerged banks' northern and eastern boundaries and several smaller, more isolated banks (Young 2013). The archipelago is oriented northwest to southwest and extends about 6° of latitude (between 20.9° and 27.4°N), about 8° of longitude (between 72.5° and 79.3°W) across the Tropic of Cancer. Approximately half of the islands are located north of the Tropic of Cancer, which runs through Exuma and northern Long Island. The Bahamas stretches from about 50 miles (80 kilometres) east of Florida to about 50 miles (80 kilometres) northeast of Cuba (FAO 2015) (Buchan 2000). Between Grand Bahama Island (27.5°N) and Great Inagua Island (20°N), it runs more than 500 miles (800 kilometres) southeast-northwest.

Figure 3-1: Map of The Bahamas

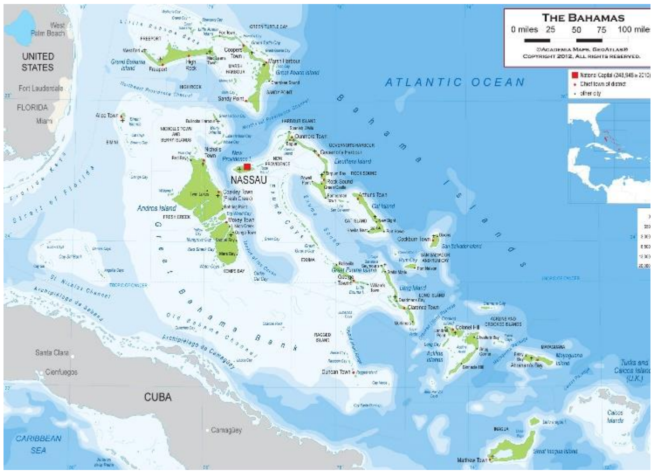
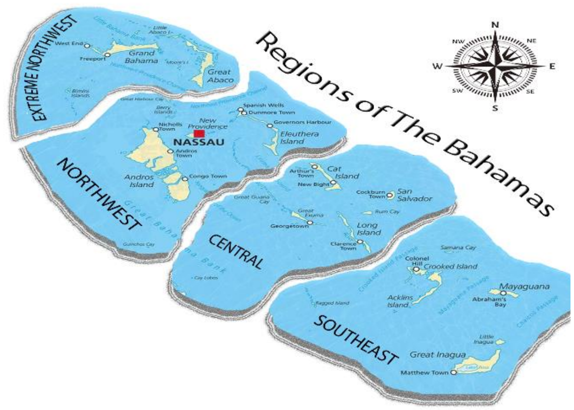


Figure 3-2: Regions of The Bahamas



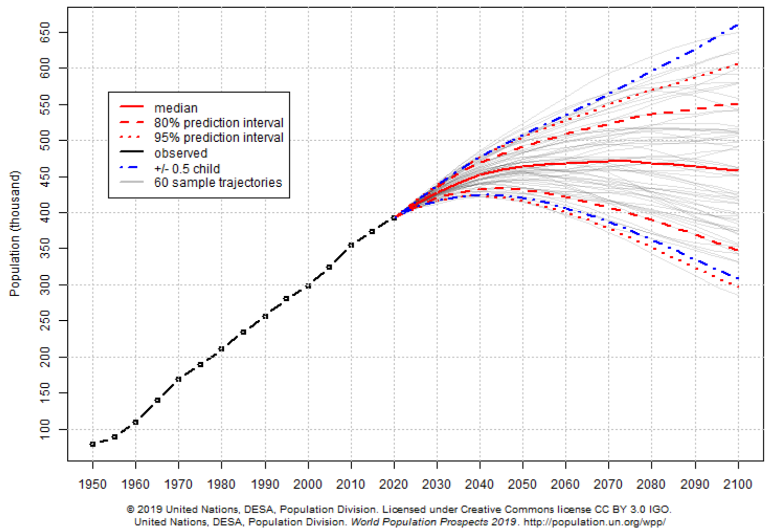
3.1.2 TOPOGRAPHY

The archipelago is low-lying, surrounded by coral reefs and vast sand flats. There are only about 30 habitable islands and about 2,000 low, desolate rock formations. The Out (Family) Islands are the islands outside of New Providence. Mount Alvernia on Cat Island is the country's highest point, rising 207 feet (63 meters) above mean sea level. New Providence Island's highest point is only 125 feet (38 meters) above sea level. The major islands' dominant physical features are large stretches of flat land with only a few feet of elevation.

3.1.3 DEMOGRAPHICS TRENDS AND PATTERNS

The total population increased from 304,913 in the 2000 census (BNSI 2009) to 351,461 in the 2010 census (Lowe, et al. 2017). The population centres are dispersed extensively on each island, with 95% living on seven islands. The islands of New Providence, Grand Bahama, and Great Abaco have seen the most internal population shift (Lowe, et al. 2017). Major communities are usually found with a natural harbour or at least shipping accessibility. The country's population growth rate is significantly higher than the Caribbean average. Also, the population has shifted dramatically from fishing and rural communities to tourist and economic hubs. According to the 2019 Revision of World Population Prospects, The Bahamas' population will increase to over 450,000.

Figure 3-3: Bahamas: Total Population



3.1.4 CLIMATE OF THE STUDY AREA

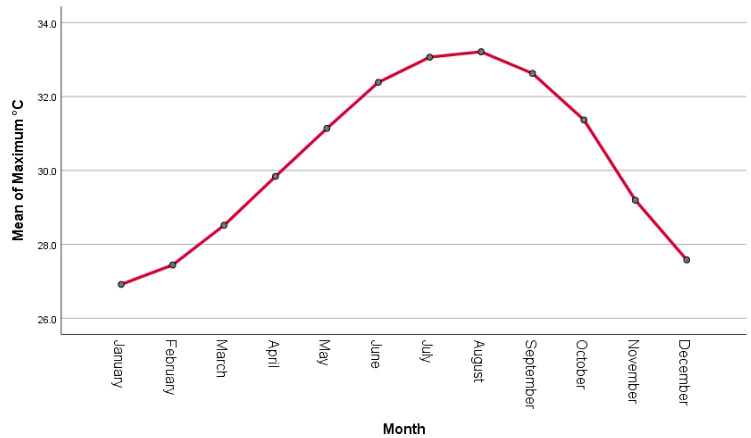
Warm Gulf Stream waters contribute to the prevailing tropical marine climate of the Bahamas. Bermuda Azores anticyclone, which spans large regions of high air pressure in the subtropical North Atlantic Ocean, is the primary climate factor influencing the Bahamas. Statistically, winds are mainly from the east and southeast from May to September (summer), but mainly from the northeast and east the rest of the year (FAO 2015). Warm, humid, and sunny conditions prevail, with regional variations due to trade winds.

The Bahamas is situated in the path of several developing weather systems. Among them are tropical waves and tropical cyclones, and migratory areas of persistent rain. The tropical cyclone season officially runs from June through November. However, the Bahamas are considered to be affected from mid-July through October. August, September, and October have the highest frequency of cyclone impacts or approaches within 100 miles of the Bahamas.

Temperatures

Winter temperatures in New Providence rarely fall below 15°C and frequently rise above 24°C in the afternoon. Summer temperatures frequently fall to 26°C or less at night and rarely rise above 32°C during the day. The northernmost islands have colder winters than New Providence. Temperatures in the Bahamas tend to be consistent during the summer.

Figure 3-4: Mean Monthly temperature pattern of The Bahamas



Precipitation

Because rainfall is the only source of freshwater for the islands, precise historical rainfall data is
Because rainfall is the only source of freshwater for the islands, precise historical rainfall data is
critical for future planning. The Department of Meteorology (BDM) has historical precipitation data for meteorological stations on a number of the larger islands in The Bahamas, including the Nassau, New Providence (LPIA) and Freeport, Grand Bahama Airports Weather Service Offices. These two stations provide the most comprehensive historical climatic data, going back to 1951 for New Providence and 1967 for Grand Bahama.

The archipelago's average rainfall totals range from 600 mm in the drier southeastern islands to over 1600 mm in the northwestern section. The rainiest months are May to October (Figure 3-5), when temperatures are at their highest (Warm Gulf Stream waters contribute to the prevailing tropical marine climate of the Bahamas. Bermuda Azores anticyclone, which spans large regions of high air pressure in the subtropical North Atlantic Ocean, is the primary climate factor influencing the Bahamas. Statistically, winds are mainly from the east and southeast from May to September (summer), but mainly from the northeast and east the rest of the year. Warm, humid, and sunny conditions prevail, with regional variations due to trade winds.

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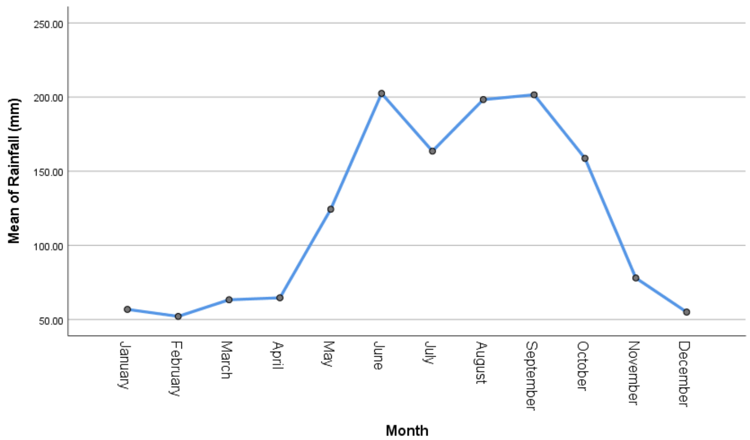
Figure 3-4). The cooler months of November to April experience limited rainfall as a result of the passing of northern winter frontal systems. Due to the influence of tropical storms, annual rainfall totals differ significantly from the norm.

Climate variables such as seasonal and annual precipitation, mean sea level, and the occurrence of tropical cyclones all significantly impact the health and availability of resources on the islands. Climate change is expected to change these conditions.

Figure 3-5: Mean Monthly rainfall pattern of The Bahamas



3.2 DATA TYPES AND SOURCES

The information needed for this research study was gathered from several sources, including international, regional and local hydrologists, government agencies, and online databases for retrieving both remote sensing data and peer-reviewed academic papers.

The subsection discusses the data collection procedure, quality control measures, challenges faced in obtaining the data, the analysis method used, and finally, characteristics specific variables.

A reliable assessment of the trends, temporal and spatial patterns of climate over the Bahamas requires data that cover decades. The data series must also contain a comprehensive or essentially comprehensive set of high-quality values (Manton et al., 2001). Several decades ago, the Bahamas possessed an extensive network of weather stations that measured various meteorological variables, including temperature, precipitation, and pressure. However, the majority of these stations are no longer operational.

Table 3-1: Required Data Types and Sources

No	Data types	Description	Sources
1	Monthly rainfall	Monthly observed rainfall data for the period from 1951-2021 was collected.	BDM

2	Monthly Tmax and Tmin temperature	Monthly observed Tmax and Tmin temperature data was collected for the period from 1951-2021.	BDM
3	DEM (30m spatial resolution)	Is the main input for spatial data	https://gadm.org/data.html
4	Herrera and Ault	High-resolution precipitation and temperature products	https://ecommons.cornell.edu/handle/1813/58763
5	CMIP6		https://cds.climate.copernicus.eu/cdsapp#!/dataset/projections-cmip6?tab=form

3.2.1 STATION DATA

3.2.1.1 NATIONAL OCEANIC AND ATMOSPHERIC ADMINISTRATION (NOAA).

From the NOAA Climate Prediction Centre's Caribbean Desk, it is possible to access the global data sets of all NOAA meteorological stations, including those in The Bahamas. Temperature measurements in degrees Celsius and precipitation measurements in millimetres are included in the climate dataset. The temperature data are the minimum and maximum monthly temperatures, while the precipitation data are monthly precipitation observations.

3.2.1.2 BAHAMAS DEPARTMENT OF METEOROLOGY (BDM) STATION DATA

Two weather stations within a few kilometres of the sea were chosen for this investigation, as shown in Table 2-1 because they have a considerable amount of historical meteorological data that is accurate and consistent. The BDM provided monthly rainfall data for New Providence (from January 1951 to August 2021) and Grand Bahama (from January 1970 to August 2021). The BDM also provided monthly temperature data for New Providence (January 1951 to September 2021) and Grand Bahama (January 1967 to September 2021). Climate data, such as temperature and rainfall, is scale data. Certain studies require categorical independent variables apart from correlations and regressions.

3.2.1.3 HIGH-RESOLUTION CLIMATE DATA

As reference observations, Ault and Herrera's high-resolution temperature and precipitation products were compared to CMIP6 models. The data ranges from 1950 to 2015, with a horizontal resolution of 4 km. Ault and Herrera describe the downscaling techniques used to create these high-resolution gridded products in detail, including the statistical approach used to downscale each climatic variable and its validation. The scaled products are used because the typical resolution of the currently available observed gridded climate data for The Bahamas, and the Caribbean Islands is relatively coarse.

3.2.2 DATA QUALITY AND SCREENING

It is possible to find data in many formats, resolutions, and quality levels. Additionally, collected data may contain errors due to faulty measuring devices, errors in recording devices, or errors on the part of observers. So, data must be checked and errors removed using various tools before storing. Consequently, temporal data is preprocessed and filtered with EXCEL's and IBM SPSS Statistics sophisticated capabilities in this study. The study used the Environmental Systems Research Institute's (ESRI) ArcMap 10.8 software and Google Earth for all GIS-related tasks. Complete-time series is a requirement to study climate. Meteorological and hydrological time series are incomplete for a variety of reasons. A solution to this incongruence can be found by imputing missing values based on measurements from nearby climatic and hydrologic stations.

The observation data sets from most climate stations are not completely accurate or complete. Often, data is lost or not available for a variety of reasons. Consequently, handling the data before starting the main process is essential. There were gaps in the data for several months and years, but they were not filled for the Mann-Kendall trend analysis since that particular trend analysis enables gaps in the data record to not affect the outcome. Quality control procedures from CLIMSoft was used on the data supplied from the Bahamas Department of Meteorology. The primary goal of this quality control technique was to discover mistakes in data processing, such as manual keying errors.

The negative precipitation values are removed, and the daily maximum temperature is set to missing values if the maximum temperature is less than the minimum temperature. The daily maximum and minimum temperatures are also examined for outliers. These are values outside the user-defined range. Statistical tests, local knowledge, a study of station histories, and comparisons with nearby stations were all used to determine if an outlying precipitation measurement in New Providence was incorrect.

Missing Data

The initial check for missing values revealed two types of missing values in the data. The first problem encountered was incomplete precipitation and temperature measurements on previously recorded dates. It is likely that observations were missing because of human error, misplaced data, or incorrect transfer. Blocks of missing record dates with their respective measurements were the second type of missing value. Precipitation and temperature records and entire blocks of consecutive years were missing from several sites.

3.2.3 CMIP6 MODEL DATA SET

The World Climate Research Program (WCRP) and the ClimateData Store provided monthly observational and CMIP6 model products for temperature and precipitation over the Bahamas. CMIP6 data were obtained for the country's future climate forecast and trend analysis under low forcing (sustainable development) scenario (SSP1-2.6), medium forcing (middle-of-the-road development) scenario (SSP2-4.5), medium to high forcing (regional rivalry) scenario (SSP3-7.0), and strong forcing (fossil fuel-driven development) scenario (SSP5-8.5). **Error! Not a**

valid bookmark self-reference. summarizes CMIP6 products, including acronyms, resolution, and sources.

For the near and long term, climate projections have been conducted using monthly mean temperatures and precipitation measurements over 30-year intervals for the baseline period derived from historical simulation (1985–2014). The non-parametric Mann-Kendall (MK) trend test method was used to determine their significance after examining the trend in temperature and precipitation.

The Z-value determines whether or not a statistically significant trend exists. The statistics serve to assess the null hypothesis for no trend to the alternative hypothesis for a trend. A positive Z value indicates that the time series displays an upward trend, while a negative Z value suggests that the time series displays a downward trend. The analysis used three significance levels for each time series, namely low (0.1), medium (0.05), and high (0.01). A p-value for each significant level was then calculated.

Table 3-2: Climate models used in the analysis and projection of the Bahamas climate from CMIP6.

No.	CMIP6 Model Name	Modelling group and Country	Horizontal Resolution	Variant Label
1	BCC-CSM2-MR	Beijing Climate Center (China)	1.1° * 1.1°	r1i1p1f1
2	CNRM-CM6-1	France	1.4° * 1.4°	r1i1p1f2
3	CNRM-ESM2-1	France	1.4° * 1.4°	r1i1p1f2
4	CanESM5	Canadian Centre for Climate Modelling and Analysis (Canada)	2.8° * 2.8°	r1i1p1f1
5	GFDL-ESM4	Geophysical Fluid Dynamics Laboratory (USA)	1.3° * 1°	r1i1p1f1
6	IPSL-CM6A-LR	Institut Pierre Simon Laplace (France)	2.5° * 1.3°	r1i1p1f1
7	MIROC-ES2L	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (Japan)	2.8° * 2.8°	r1i1p1f2
8	MIROC6	Japan	1.4° * 1.4°	r1i1p1f1
9	MRI-ESM2-0	Meteorological Research Institute (Japan)	1° * 1°	r1i1p1f1

3.3 DATA ANALYSIS

This study attempts to determine trends in temperature and precipitation over The Bahamas in the second half of the twentieth century and precipitation patterns over the country.

Meteorological data for 1980-2010 were analysed for any significant trends. The data collected were tabulated in MS-Excel and SPSS 26 and was used for data processing, data analysis and interpretation of the information collected. The results were also analysed for years with extreme precipitation and temperature in the same time frame. A series of graphs were developed with IBM SPSS software, and ArcGIS spatial analyst was used to create the maps presented in this study.

Climatic trends detection

Rather than relying on spatial correlation alone, the Kriging approach incorporates spatial correlation into the interpolation equation, whereas other interpolation techniques do not. The analytical method used is properly defined below.

Linear regression

Decision-makers can use regression to develop quantitative relationships between variables and assess the strength of those relationships. The relationship between an unknown variable and a known quantity is computed using regression analysis. The coefficient of determination (r2) represents the strength of the relationship between X and Y. For trends, time-series data were analyzed using simple linear regression analysis. When x is increased, y increases proportionally (slope). To determine a line, it must be measured above the origin (intercept), and the amount y increases when x is increased by the unit (slope). Temperature and rainfall trends were examined using regression analysis.

Significance and stability testing

Throughout this study, the significance of each trend is analyzed. Statistics defines an important finding as one that cannot have resulted from chance. A probability level of significance is a measure of how likely it is that a statistic would be observed, assuming the null hypothesis holds. Consequently, the significance level relates to the likelihood of a false positive or Type I error occurring when a null hypothesis is rejected. The null hypothesis is supported or rejected using a p-value. It provides evidence that poses a challenge to the null hypothesis. It is generally better to have a lower p-value.

3.3.1 STATISTICAL SIGNIFICANCE TESTS

The Statistical Package for the Social Sciences (SPSS), version 26.0 (IBM Corporation 2019), and MAKESENS 1.0 were used to analyze the statistical data. The independent and dependent variables must be categorical for the Chi-Square, Cramer's V, and Phi tests. On the other hand, other tests require scale data as a dependent variable.

Trend analysis forecasts future outcomes by analyzing historical data. Statistical analysis was conducted in two phases to determine whether all independent meteorological factors increased or decreased over time (such as yearly and seasonal temperature, rainfall, etc.). The nonparametric Mann-Kendall test and the nonparametric Sens slope estimator are among the first two options. To determine whether the trend was rising or decreasing, we used normalized test statistics (Z) values. Trends are considered to be increasing when Z is positive and declining when Z is negative. The slope of the trend determines the annual pace and direction of change (Salmi, et al. 2002) (Helsel and Hirsch 2002).

The Mann-Kendall Test

Hydrological data are rarely independent or have a normal distribution. Following consideration of various studies that focus on trend analysis of hydrological and climatic data series, the rank-based non-parametric Mann-Kendall trend test was chosen for this study. Mann (1945) is known for his findings of trends, whereas Kendall (1975) is known for his discoveries of statistical distributions. The Mann-Kendall test has several advantages, including the fact that no specific distribution for the data is necessary, which allows for data gaps (Wilks 2019). Extreme data points do not affect the result due to the rank-based characteristic. The null hypothesis (H_0) in this test was that there was no trend in precipitation over time, while the alternate hypothesis (H_1) was that there was a trend (increasing or decreasing) over time. The Mann-Kendall statistic is expressed as follows:

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1} \operatorname{sign}\left(x_j - x_k\right)$$

$$\operatorname{sign}\left(x_j - x_k\right) = \begin{cases} 1 \text{ if } x_j - x_k > 0 \\ 0 \text{ if } x_j - x_k = 0 \\ -1 \text{ if } x_j - x_k < 0 \end{cases}$$

Spearman's rho Test

The Spearman's rho test is a rank-based nonparametric trend analysis tool that was used to compare the Mann-Kendall test (Lehmann and D'Abrera 1975) (Sneyers 1990). The null hypothesis (H_0) implies that there is no trend over time in this test, which assumes that time series data are independent and uniformly distributed; the alternate hypothesis (H_1) indicates that there is a trend and that values rise or decrease with *i* (Yue, Pilon and Cavadias 2002). To calculate the Spearman rank correlation, use the following formula:

$$R_{sp} = 1 - \frac{6\sum_{i=1}^{n}(D_i)^2}{n\,(n^2-1)},$$

$$Z_{sp} = R_{sp}\sqrt{\frac{n-2}{1-\ {R_{sp}}^2}}$$

D_i is the difference in paired ranks, n is the entire length of the time series data, and Z_{sp} is the Student's t-distribution with (n-2) degrees of freedom in these equations. Positive Z_{sp} values indicate that the hydrologic time series trend is increasing, while negative values indicate decreasing. The critical value of t in the Student's t-distribution table at a 0.05 significance level is t(n-2, 1 - a/2). If $|Z_{sp}|$ > t(n-2, 1 - a/2), (H0) is rejected, and the hydrologic time series shows a significant trend.

Sen's Slope Estimator

A nonparametric technique developed by Sen was used to estimate the size of trends in the time series data (Sen 1968):

$$Qi = \frac{x_j - x_k}{j - k}$$

Data values at time j and k are represented by x_j and x_k in this equation.

$$\mathrm{B}i = \begin{cases} Q_{(N+1)/2} & N \text{ is odd} \\ \frac{1}{2}\left(Q_{\frac{N}{2}} + Q_{\frac{N+2}{2}}\right) & N \text{ is even} \end{cases}$$

N is the number of calculated slopes. An upward trend is indicated by a positive B_i value, whereas a negative Bi value indicates a downward trend.

3.4 LIMITATIONS

Data availability is a significant limitation in most research, and The Bahamas' inadequate data coverage is no exception. The lack of variety among meteorological stations (only synoptic stations) from the Department of Meteorology was the fundamental limitation in data collection. This constraint can be solved by utilising the online remotely sensed climatic time series. This investigation has no notable restrictions because data from remotely sensed climatic time series is often easy to access, and similar analyses have already been undertaken using the same datasets. Due to the high uncertainties associated with long-term predictions and computer resource constraints, climate projections appear to be limited in their ability to project into the future beyond a given time.

The impact of climate change on freshwater availability, precipitation and potable water is a long-term study that will necessitate a considerable investment of time, resources, and scientific instruments and techniques. Because observations are rarely perfect, choosing the most dependable dataset is essential. Although radar analysis is the most reliable, it has only been available since the mid-2000s. Due to the minimal number of data points collected, various assumptions must be made to extract the most information from the time series.

A variety of factors constrained this study, including lack of funds, the timing for the studies, and insufficient prior research training. Access to fully functional software was another limiting factor in this study. Several restricted trial software versions were utilized to conduct comparative analysis on the datasets. Although this study on precipitation and potable water included essential aspects of climate change impacts, it could not capture them all. Unfortunately, some factual information was not available. This study's conclusions related to generalisation are limited without detailed and disaggregated data.

3.5 DEFINITION OF SPECIFIC PERIODS

The time spans for analysing historical data from The Department of Meteorology were from 1971 to 2020. The CMIP6 model analysis time spans are divided into three future periods: near-term (2015 - 2040), mid-term (2041 - 2070), and long-term (2071 - 2100). Four seasons from four forcing scenarios were analyzed for future changes using measurements from the reference period (1995–2014). According to O'Neill et al. (2016) and Gidden, Riahi et al. (2019), the four seasons is winter (December–January–February; DJF), spring (March–April–May; MAM), summer (June–July–August; JJA), and autumn (September–October–November; SON).

4 RESULTS AND ANALYSES

Based on BDM data for The Bahamas, daily maximum temperature and rainfall records for the past 50 years (1971-2020) have been studied. This section presents the trend analysis results for two meteorological stations' monthly, annual, and seasonal mean precipitation and temperature series.

4.1 TEMPERATURE

4.1.1 CHARACTERISTICS OF TEMPERATURES

Maximum and minimum temperature data were found to show significant trends for both the annual and monthly observations from 1971 to 2020 (Figure 4-2 and Figure 4-3). During the period 1971-2020, the total annual and New Providence maximum temperature trend showed a warming trend; however, in Grand Bahama (Figure 4-4), the minimum temperature trend showed a cooling trend, and all results are statistically significant at 95% confidence limit. The increase in yearly temperature in the study area is due to an increase in the summer and autumn months, which offsets a minor reduction in other seasons, particularly the winter months.

Table 4-1: Statistical parameters of monthly, seasonal and annual maximum temperature time series for the two synoptic stations during 1971–2020.

	N	Mean	S. E. Mean	Range	Std. Dev	CV (%)	Skewness	Kurtosis	Minimum	Maximum
January	46	26.691	0.1309	3.5	0.8878	3.3%	-0.536	-0.411	24.7	28.2
February	46	27.194	0.1479	4.4	1.0030	3.7%	-0.114	-0.287	24.8	29.2
March	48	28.229	0.1325	4.5	0.9178	3.3%	0.351	0.811	26.6	31.1
April	48	29.649	0.1264	4.3	0.8757	3.0%	0.080	0.633	27.7	32.0
May	48	31.049	0.1173	3.3	0.8123	2.6%	0.442	-0.361	29.7	33.0
June	48	32.343	0.1011	3.9	0.7002	2.2%	-0.033	0.836	30.3	34.1
July	48	33.065	0.0923	2.8	0.6397	1.9%	-0.412	-0.065	31.4	34.2
August	48	33.135	0.0875	2.4	0.6062	1.8%	-0.432	-0.579	31.9	34.2
September	47	32.553	0.0807	2.3	0.5533	1.7%	-0.037	-0.567	31.4	33.7
October	47	31.270	0.0990	2.8	0.6788	2.2%	-0.213	-0.439	29.7	32.5
November	47	29.018	0.1172	3.7	0.8034	2.8%	-0.090	-0.047	26.8	30.5
December	47	27.444	0.1148	3.3	0.7871	2.9%	0.083	-0.378	25.9	29.3
Annual	48	30.169	0.0685	1.9	0.4745	1.6%	0.113	-0.923	29.2	31.1
Total Annual	50	342.613	10.2604	373.1	72.5523	21.2%	-4.478	19.774	0.0	373.1
Winter (DJF)	45	27.089	0.0894	2.6	0.5994	2.2%	-0.124	-0.587	25.8	28.4
Spring (MAM)	48	29.642	0.0961	3.2	0.6656	2.2%	0.163	0.108	28.1	31.3
Summer (JJA)	48	32.848	0.0776	2.4	0.5379	1.6%	-0.351	-0.452	31.6	34.0
Autumn (SON)	46	30.946	0.0777	2.2	0.5272	1.7%	0.225	-0.221	30.0	32.1
Wet Season	50	29.636	1.2502	33.4	8.8404	29.8%	-3.177	8.470	0.0	33.4
Dry Season	45	28.036	0.0805	2.3	0.5398	1.9%	0.219	-0.413	26.9	29.2

Table 4-2: Statistical parameters of monthly, seasonal and annual minimum temperature time series for the two synoptic stations during 1971–2020.

	N	Mean	S. E. Mean	Range	Std. Dev	CV (%)	Skewness	Kurtosis	Minimum	Maximum
January	46	13.797	0.2902	8.6	1.9680	14.3%	-0.479	-0.357	8.3	16.9
February	46	14.126	0.3142	8.4	2.1310	15.1%	0.361	-0.706	10.4	18.8
March	48	15.178	0.2579	7.3	1.7870	11.8%	0.381	-0.494	11.9	19.2
April	48	17.192	0.2283	6.6	1.5815	9.2%	-0.530	-0.198	13.2	19.8
May	48	19.435	0.1827	4.8	1.2661	6.5%	-0.477	-0.775	16.6	21.4
June	48	21.791	0.1961	7.1	1.3584	6.2%	-0.492	1.303	18.3	25.4
July	48	22.808	0.1227	4.3	0.8503	3.7%	0.377	0.586	20.9	25.2
August	48	22.866	0.1308	4.1	0.9064	4.0%	0.149	-0.366	20.8	24.9
September	47	22.385	0.1359	5.6	0.9315	4.2%	-0.576	2.262	19.3	24.9
October	47	20.470	0.1958	5.2	1.3424	6.6%	0.015	-0.965	17.5	22.7
November	47	17.701	0.1973	6.3	1.3529	7.6%	-0.180	0.220	13.9	20.2
December	47	15.343	0.2657	8.5	1.8215	11.9%	0.622	0.358	12.1	20.7
Annual	48	18.636	0.1378	4.1	0.9548	5.1%	-0.124	-0.715	16.5	20.5
Total Annual	50	211.534	6.4431	242.3	45.5599	21.5%	-4.223	18.291	0.0	242.3
Winter (DJF)	45	14.391	0.2318	7.1	1.5550	10.8%	0.090	-0.574	11.0	18.1
Spring (MAM)	48	17.268	0.1821	5.0	1.2616	7.3%	-0.239	-0.535	14.7	19.7
Summer (JJA)	48	22.489	0.1253	4.0	0.8679	3.9%	-0.019	-0.103	20.5	24.5
Autumn (SON)	46	20.183	0.1262	4.3	0.8559	4.2%	-0.052	0.648	17.8	22.1
Wet Season	50	19.881	0.8450	23.3	5.9753	30.1%	-3.093	8.133	0.0	23.3
Dry Season	45	15.538	0.1743	5.4	1.1691	7.5%	-0.187	-0.372	12.4	17.8

Figure 4-1: Bahamas Average Monthly Temperature and Rainfall (1971-2020)

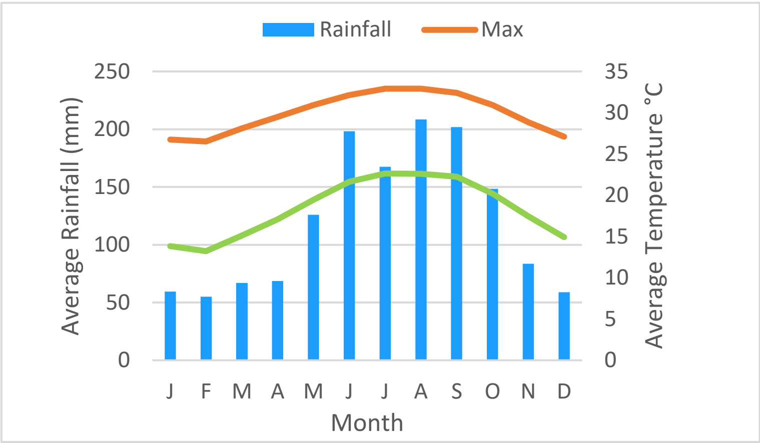


Figure 4-2: Trend of annual maximum in The Bahamas (1971 – 2020)

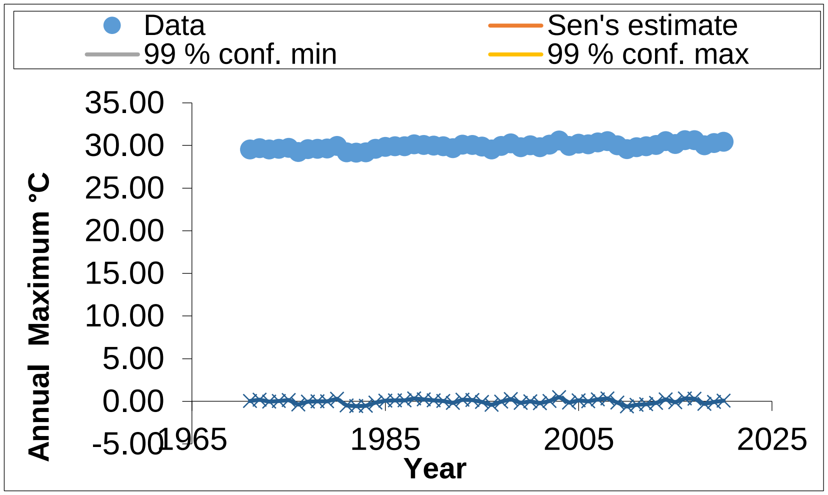


Figure 4-3: Trend of annual minimum in The Bahamas (1971 – 2020).

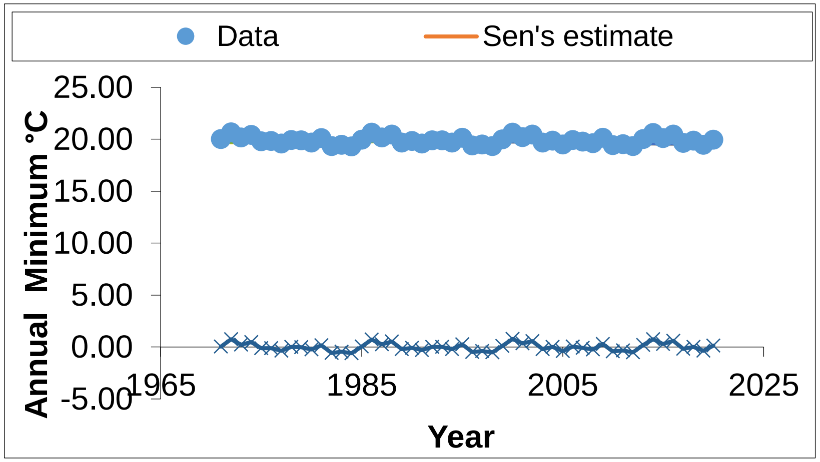
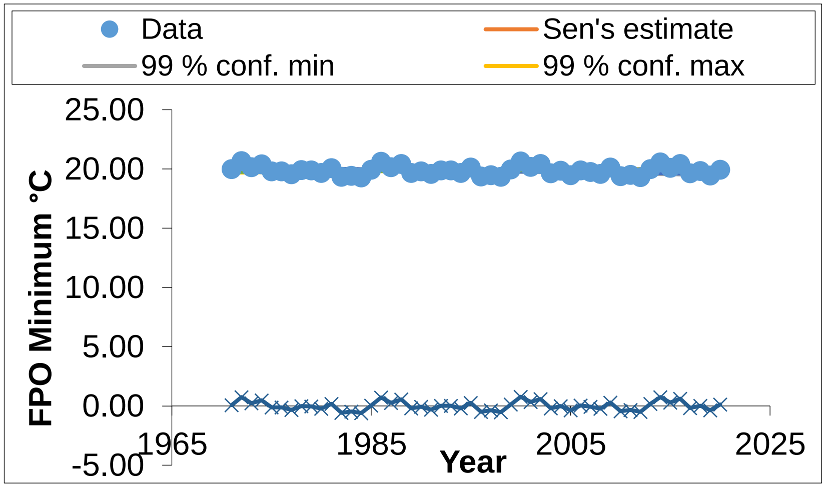


Figure 4-4: Trend of annual minimum in Freeport, Grand Bahama (1971 – 2020)



Projected mean temperature changes

Time series	First year	Last Year	n	Test Z	Q	B
January	*2021*	*2040*	*20*	1.46	0.032	24.64
February	*2021*	*2040*	*20*	1.01	0.022	24.22
March	*2021*	*2040*	*20*	-0.75	-0.015	24.93
April	*2021*	*2040*	*20*	-0.42	-0.007	25.54
May	*2021*	*2040*	*20*	-0.29	-0.005	26.83
June	*2021*	*2040*	*20*	1.20	0.026	28.17
July	*2021*	*2040*	*20*	1.14	0.017	29.19
August	*2021*	*2040*	*20*	1.46	0.016	29.67
September	*2021*	*2040*	*20*	1.78	0.023	29.49
October	*2021*	*2040*	*20*	1.07	0.015	28.54
November	*2021*	*2040*	*20*	0.88	0.015	27.093
December	*2021*	*2040*	*20*	1.91	0.025	25.722
Annual	*2021*	*2040*	*20*	2.63	0.016	27.122
Winter (DJF)	*2021*	*2040*	*20*	1.52	0.026	24.412
Spring (MAM)	*2021*	*2040*	*20*	-0.36	-0.005	25.755
Summer (JJA)	*2021*	*2040*	*20*	1.14	0.021	28.963
Autumn (SON)	*2021*	*2040*	*20*	1.07	0.013	28.401
Wet Season	*2021*	*2040*	*20*	1.52	0.013	28.653
Dry Season	*2021*	*2040*	*20*	0.36	0.006	24.89

4.1.2 PROJECTED TEMPERATURE CHANGES

The annual average time series of MIROC-ES2L maximum temperature shows a rising trend for the SSP1-2.6, SSP2-4.5, SPP3-37, and SSP5-8.5 scenarios. **Error! Not a valid bookmark self-reference.** below shows that warming will continue throughout the 21st century. Under SSP1-2.6, SSP2-4.5, SPP3-3.7, and SSP5-8.5, the increasing trend in temperature across The Bahamas is anticipated to be 0.543°C, 0.86° C, and 1.2°C. Under SSP1-2.6, SSP2-4.5, SPP3-37, and SSP5-8.5, the increasing trend in temperature across The Bahamas is anticipated to be 0.087°C, 0.543°C, 0.86° C, and 1.2°C.

The following maps (Figure 4-6 to Figure 4-9) depicts the spatial distribution of expected increases in MIROC-ES2L mean annual maximum temperature for SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios across the Bahamas. For the medium and long term, all future climate scenarios except the low forcing scenario (SSP1-2.6) show increased warming over The Bahamas compared to the baseline (1995–2014) climate. According to both short- and long-term projections, warming is more evident in the southeastern portions of the country than in the northern parts.

Figure 4-5: MIROC-ES2L model mean maximum temperature (°C) projections under SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios.

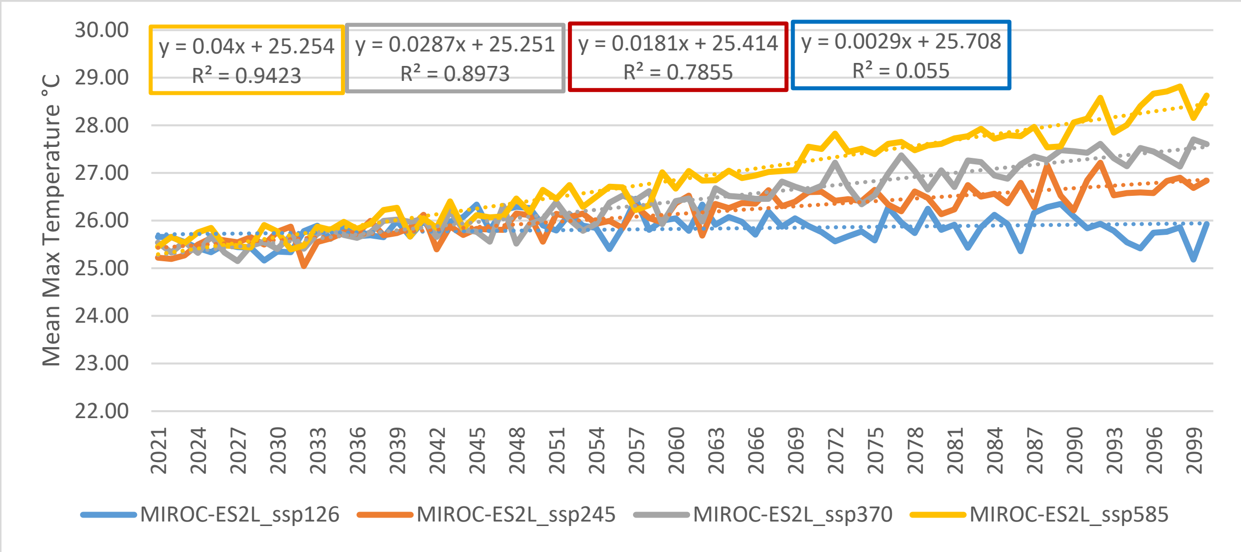
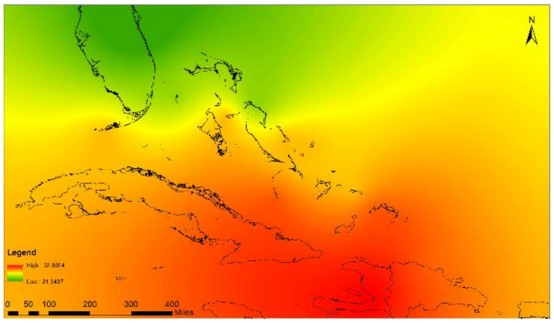
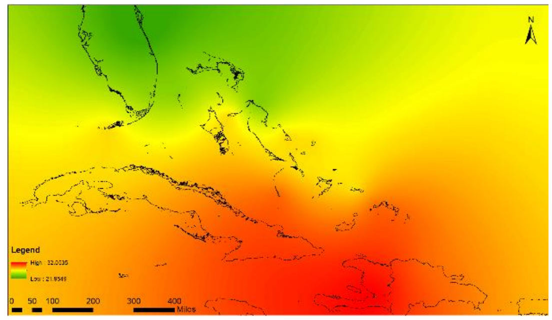


Figure 4-6: CMIP6-MIROC-ES2L SSP1-2.6 Near Term Monthly Mean Maximum Temperature (°C)



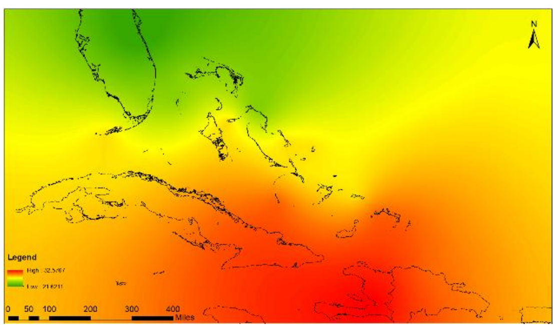
a) 21.3 - 33.0°C

Figure 4-7: CMIP6-MIROC-ES2L SSP2-4.5 Near Term Monthly Mean Maximum Temperature (°C)



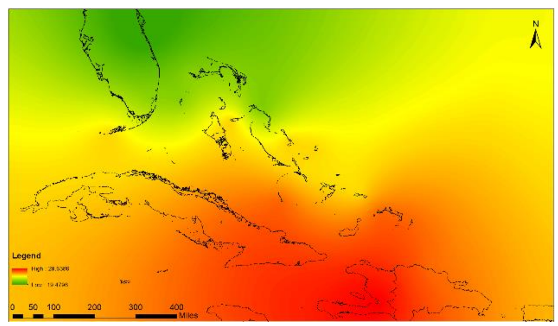
b) 21.9 - 32.1°C

Figure 4-8: CMIP6-MIROC-ES2L SSP3-7.0 Near Term Monthly Mean Maximum Temperature (°C)



c) 21.6 - 32.6°C

Figure 4-9: CMIP6-MIROC-ES2L SSP5-8.5 Near Term Monthly Mean Maximum Temperature (°C)



d) 19.5 - 29.6°C

The spatial distribution of CMIP6-MIROC-ES2L model monthly mean maximum temperature (°C) scenarios over The Bahamas for the near-term projections (2015–2040). The monthly mean maximum temperature spatial distributions for four SSP scenarios appear identical, but the range of values differ.

4.2 PRECIPITATION

4.2.1 OBSERVED CHARACTERISTICS OF PRECIPITATION

Monthly descriptive statistics were computed during the study period: total rainfall, minimum and maximum rainfall, mean, range, variance, standard deviation, skewness, kurtosis, and minimum and maximum rainfall.

The essential characteristics of the monthly precipitation time series for the two synoptic stations from 1971 to 2020 are summarized in **Error! Not a valid bookmark self-reference.**. The abnormal distribution of rainfall data series is detected by measuring skewness and kurtosis quantities. Hare (2003) defines CV as low (CV less than 20%), moderate (CV greater than 20%

and less than 30%), high (CV greater than 30%), or very high (CV greater than 40%), and CVs greater than 70% indicate exceptionally high inter-annual rainfall variability. Observations indicate that all of the months had a coefficient of variation (CV) greater than 40%, suggesting a very high degree of precipitation variability throughout the zone.

Table 4-3: Statistical parameters of monthly, seasonal and annual precipitation time series for the two synoptic stations during 1971–2020

	N	Mean	S. E. Mean	Range	Std. Dev	CV (%)	Skewness	Kurtosis	Min	Max
January	48	59.67	7.80	298.70	54.07	90.6%	2.56	8.59	3.30	302.01
February	48	55.52	5.47	230.76	37.89	68.2%	2.32	9.50	2.54	233.30
March	50	65.99	7.16	203.33	50.61	76.7%	1.23	0.89	2.54	205.87
April	50	68.77	7.49	294.51	52.99	77.1%	2.07	6.64	5.84	300.36
May	50	124.56	11.75	336.04	83.06	66.7%	1.30	1.12	30.10	366.14
June	50	195.85	12.04	373.63	85.14	43.5%	1.00	0.87	72.39	446.02
July	50	167.09	9.74	274.96	68.90	41.2%	0.35	-0.49	53.59	328.55
August	50	209.08	9.44	308.36	66.76	31.9%	0.65	0.60	83.69	392.05
September	50	203.25	9.00	322.58	63.62	31.3%	1.00	1.37	79.76	402.34
October	50	148.40	11.18	303.28	79.06	53.3%	0.36	-0.73	16.26	319.53
November	50	81.66	7.29	230.51	51.57	63.1%	0.95	0.76	3.56	234.06
December	50	58.05	5.15	177.29	36.45	62.8%	1.11	1.59	4.70	181.99
Annual	50	120.23	2.82	92.17	19.96	16.6%	0.53	0.62	82.98	175.15
Total Annual	50	1433.28	34.64	1106.04	244.94	17.1%	0.56	0.44	995.81	2101.85
Winter (DJF)	50	55.57	4.46	182.20	31.54	56.8%	1.86	5.35	3.81	186.01
Spring (MAM)	50	86.44	5.31	158.67	37.57	43.5%	0.74	0.19	25.23	183.90
Summer (JJA)	50	190.67	6.49	212.51	45.86	24.1%	1.12	1.21	121.88	334.39
Autumn (SON)	50	144.98	6.02	207.65	42.60	29.4%	1.09	1.52	76.67	284.31
Wet Season	50	174.93	4.90	165.33	34.65	19.8%	0.90	1.01	115.68	281.01
Dry Season	50	63.44	3.51	126.13	24.85	39.2%	0.44	0.90	8.28	134.41

4.2.1.1 PRECIPITATION DATA ANALYSIS

This subsection contains the findings of the trend analysis for monthly, yearly, and seasonal mean precipitation series.

Monthly Trend

The results of the MAKESENS analysis show that in January, February, March, August, October, November and December, there is a ‘decreasing trend.’ April, May, June, July, and September show an ‘increasing trend.’ There is a substantial change for April and September (95% significance level). According to Sen’s slope estimator calculation, there is a significant increasing trend in April, June, and September. There is a clear significant negative trend in November.

Annual Trend

The Bahamas' average annual rainfall was 2821.83 mm, according to statistics collected (Figure 4-11) over a five-decade period (1971-2020). During the study period, the minimum average annual rainfall of 1261.36 mm occurred in 2011, whereas the maximum of 4203.70 mm occurred in 2020. Three out of 50 years had excess precipitation (>3518 mm), while four years had deficient rainfall. Over the course of 50 years, an average amount of precipitation was observed in 43 years.

According to Figure 4-12, Sen's slope estimate is close to parallel to the x-axis, suggesting more consistency in average annual rainfall. Furthermore, the plot displays 95% and 99% confidence intervals, showing that annual rainfall is relatively consistent. For the last 50 years, there was a variability of the annual rainfall (**Error! Not a valid bookmark self-reference.**).

Figure 4-10: Annual rainfall variability pattern of The Bahamas (1971–2020).

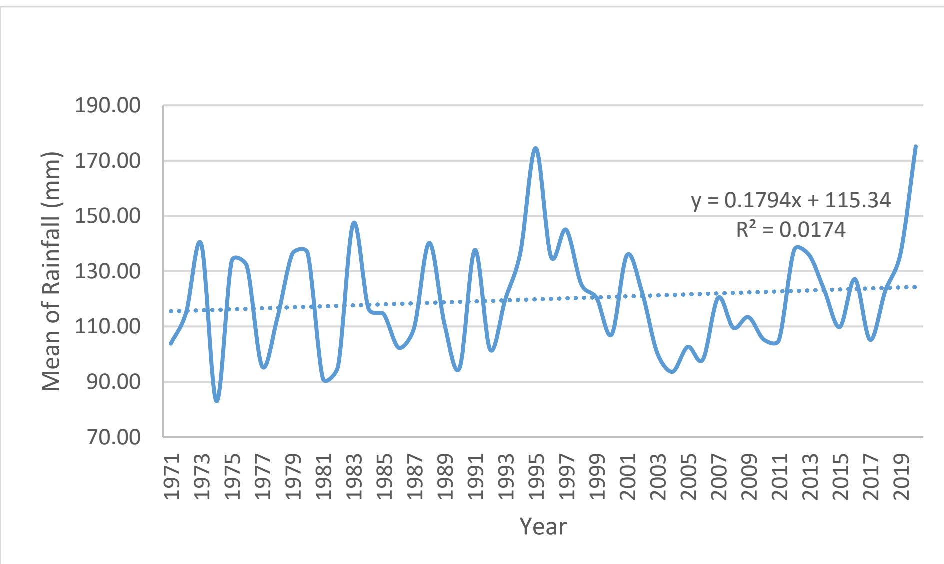


Figure 4-11: Average annual rainfall in The Bahamas (1971 – 2020)

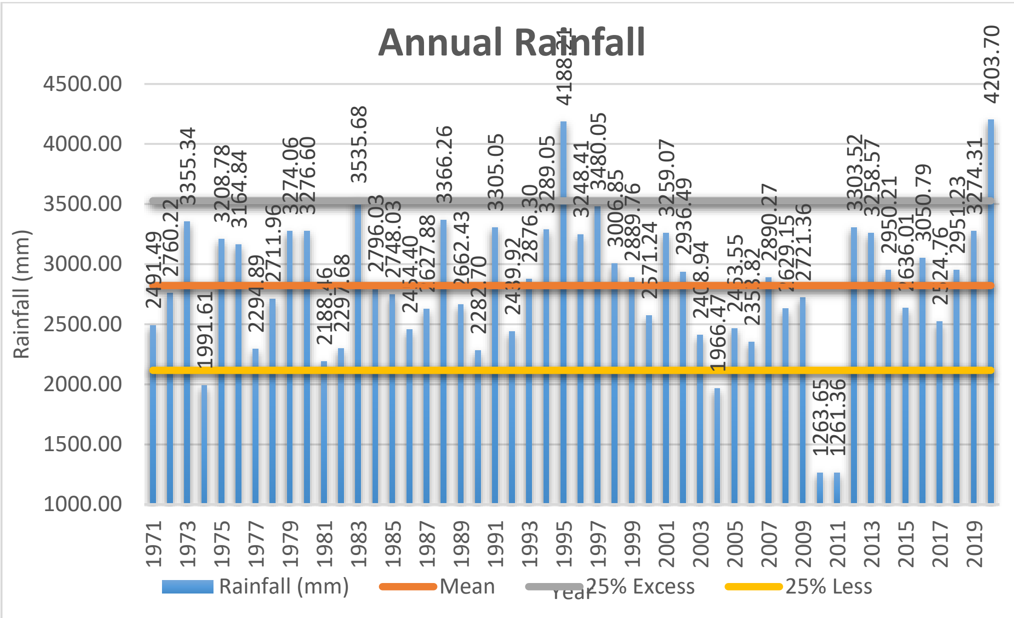


Figure 4-12: Trend of annual rainfall in The Bahamas (1971 – 2020)

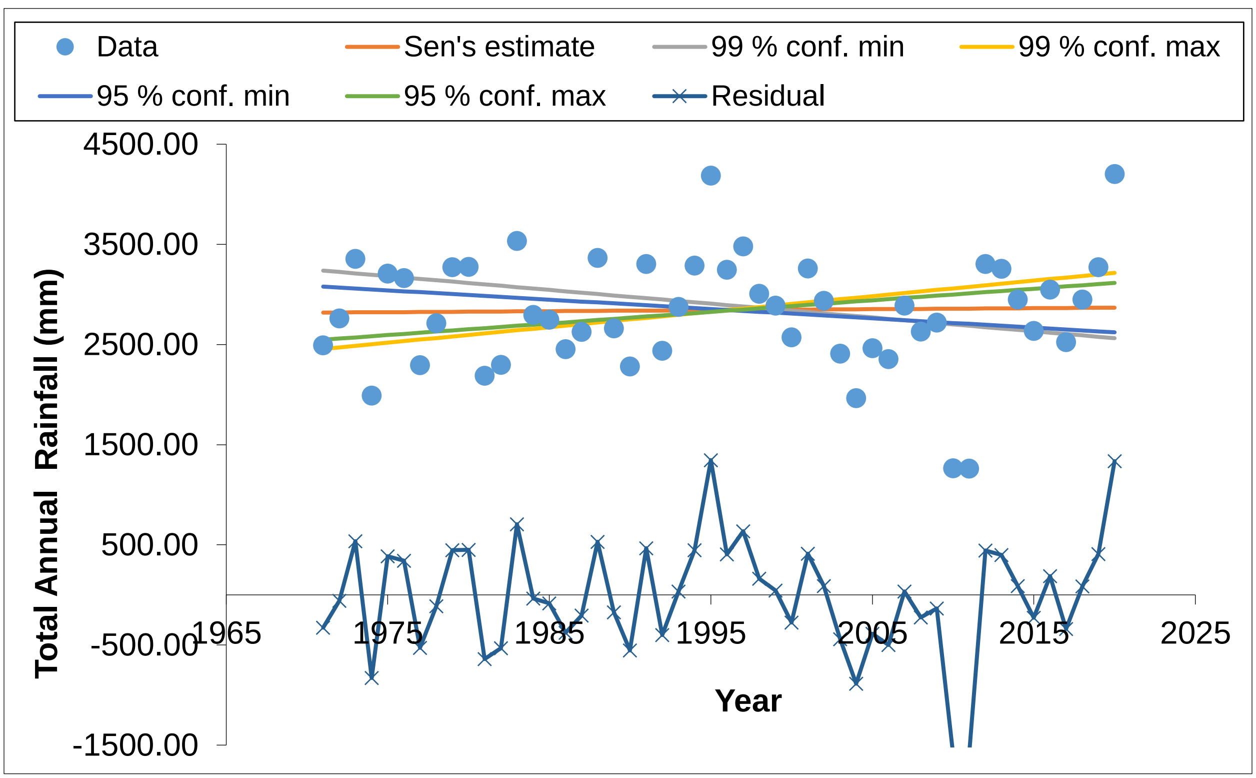


Table 4-4: Mann-Kendall and Sen's slope estimator results (1971 – 2020)

	Mann-Kendall Test statistic				Sen's slope estimate	
Time series	**First year**	**Last Year**	**n**	**Test Z**	**Q**	**B**
January	1971	2020	50	-0.58	-0.314	98.49
February	1971	2020	50	-0.83	-0.530	123.77
March	1971	2020	50	-1.07	-0.876	141.52
April	1971	2020	50	1.93	1.496	45.93
May	1971	2020	50	0.77	1.034	136.04
June	1971	2020	50	0.90	1.588	272.57
July	1971	2020	50	0.33	0.508	290.45
August	1971	2020	50	-0.72	-1.080	444.56
September	1971	2020	50	1.35	1.548	316.02
October	1971	2020	50	-0.32	-0.625	296.15
November	1971	2020	50	-1.34	-1.211	189.02
December	1971	2020	50	-1.16	-0.910	141.09
Annual	1971	2020	50	0.32	0.998	2798.7

The Mann Kendall technique was employed to see if the notice variable has a monotonic increasing or falling trend over time. The findings of the statistical tests that were used are described in (Table 4-4). Significant monthly precipitation trends are identified statistically, and this finding is statistically significant at the 95% confidence level from 1971 to 2020. Monthly and periodic rainfall data were also subjected to trend analyses (Table 4-4). At the 95% confidence level, precipitation patterns indicate a positive trend over periods. However, during the five decades (1971-2020), a large reduction in winter precipitation is statistically significant at the 90% confidence level. During the summer months, precipitation was higher than in the winter, according to the trend analysis.

Quarter Century Trend

The data then was separated into two sections, with the first covering 1971 to 1995 and the second period covering 1996 to 2020. The Bahamas had an average annual rainfall (a.a.r) of 3579.39 mm in the first. In 1974, the minimum average annual rainfall was 1991.6 mm, while the maximum average annual rainfall of 4188.21 mm occurred in 1995. Excess precipitation (>3579.39 mm) and deficient rainfall both occurred once out of the 25 years.

According to the second-period study, The Bahamas' average annual rainfall was 2780.14 mm, which is somewhat higher than the first period's mean rainfall. In 2011, the minimum average annual rainfall was 1261.36 mm, while the maximum average annual rainfall was 4203.70 mm in 2020. Excess precipitation (>3475.17 mm) happened in 2 of the 25 years studied, while deficient rainfall occurred in 3 of the 25 years studied. In the Bahamas, regular rainfall (range 2085.10 mm to 3475.17 mm) happened 23 times out of 25 years, showing that the average annual rainfall is normal.

Based on the trend statistics 'Z' values of the Mann-Kendall test for the first period, except for May, October, and December, all of the months and seasons of the year showed an increasing trend. For the second period, the 'Z' statistics demonstrate that most of the months and seasons exhibit a negative trend except for April, May, July, August, and October.

Figure 4-13: Trend of annual rainfall in The Bahamas (1971 – 1995)

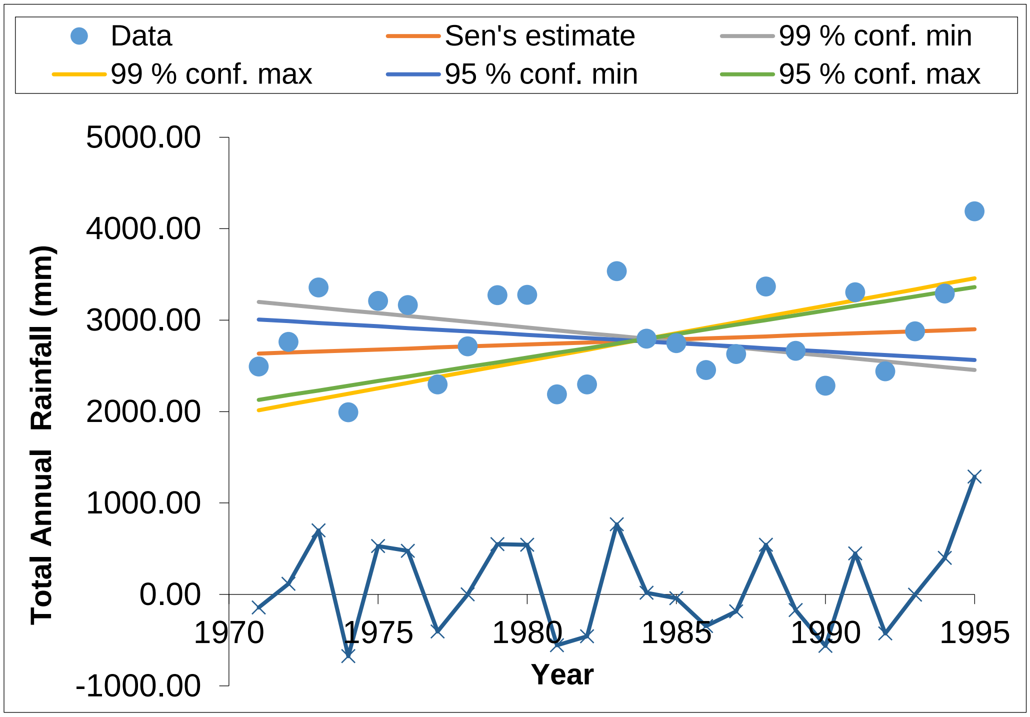


Figure 4-14: Trend of annual rainfall in The Bahamas (1996 – 2020)

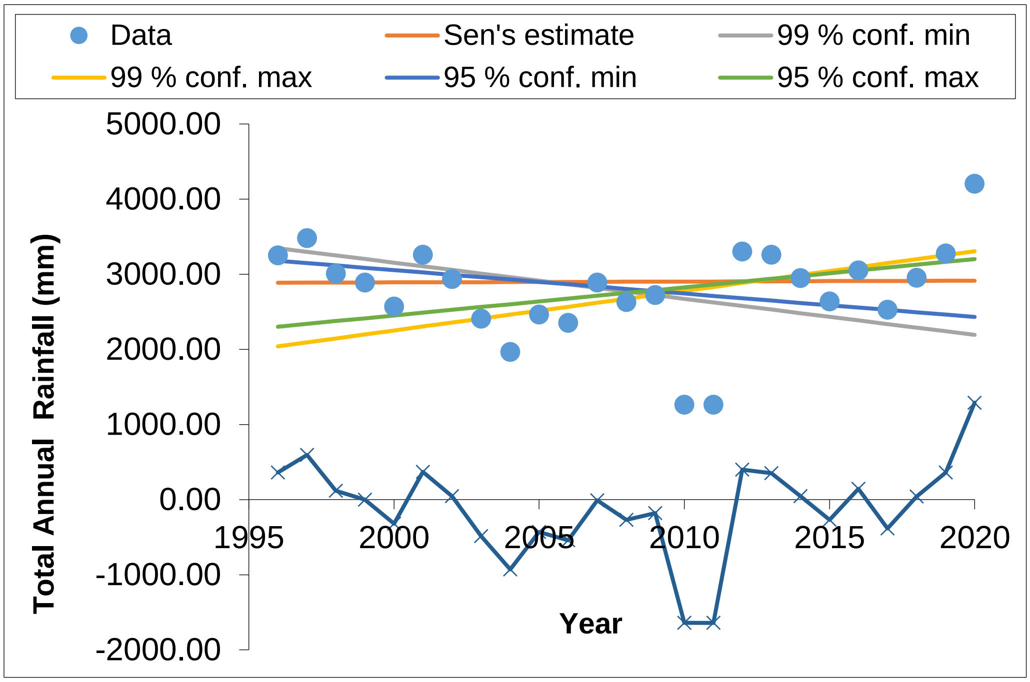


Table 4-5: Trend analysis of quarter-century rainfall

	1971 – 1995			1996 - 2020		
Time series	**Test Z**	**Q**	**B**	**Test Z**	**Q**	**B**
January	1.56	3.231	-7.33	-1.14	-1.933	186.72
February	0.58	0.993	79.31	-0.21	-0.438	118.03
March	1.56	3.382	3.11	-2.22	-4.955	382.52
April	2.73	7.502	-116.57	1.75	3.660	-91.99
May	-0.40	-2.698	281.26	1.24	6.847	-176.78
June	0.68	1.959	251.71	-0.44	-1.376	450.15
July	0.49	2.909	219.36	1.24	5.076	53.80
August	0.54	3.502	304.55	0.35	1.807	270.14
September	0.49	1.295	317.71	-0.68	-2.413	530.35
October	-0.44	-2.215	370.8	0.63	4.630	-0.2487
November	1.00	3.812	53.037	-0.30	-0.479	129.38
December	-1.14	-3.094	207.19	-0.16	-0.296	102.95
Annual	0.96	11.082	2412.7	0.30	1.135	2835.3

Decadal Trend

This analysis divides the data into five groups, one for each decade. A comparison of the Mann-Kendall test 'Z' value and Sen's Estimator values of 'Q' and 'B' is shown in Tables 5 to 7 and Figures 18 to 22. June, November, and December have shown a downward tendency in the first decade, from 1971 to 1980. February, March and December have shown decreasing trend in the second decade from 1981 to 1990 and the next two decades showed the most decreasing trends. Half of the months (January, February, April, June, August and November) in the third decade showed a decreasing trend from 1991 to 2000. Most months from 2001 to 2010 showed a decreasing trend except for February, April, September, and December. Only one month (September) showed a decreasing trend in the decade 2011 to 2020.

Figure 4-15: Decadal variations of a.a.r (71-80)

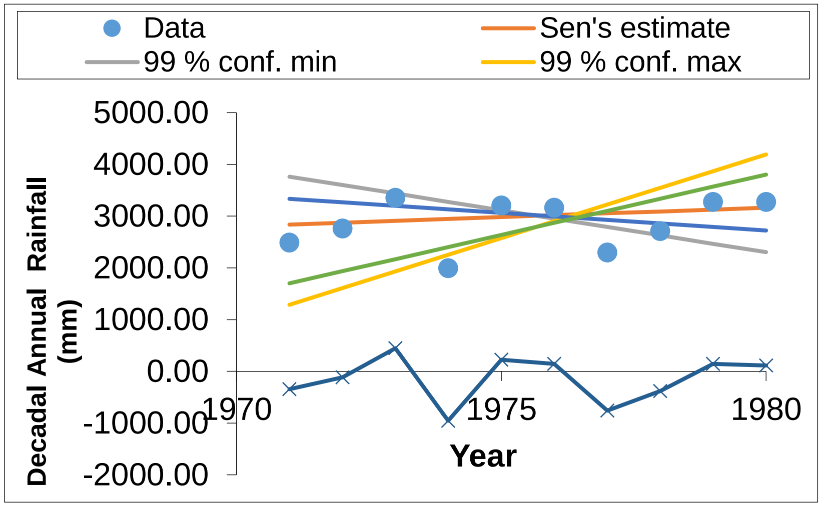


Figure 4-16: Decadal variations of a.a.r (81-90).

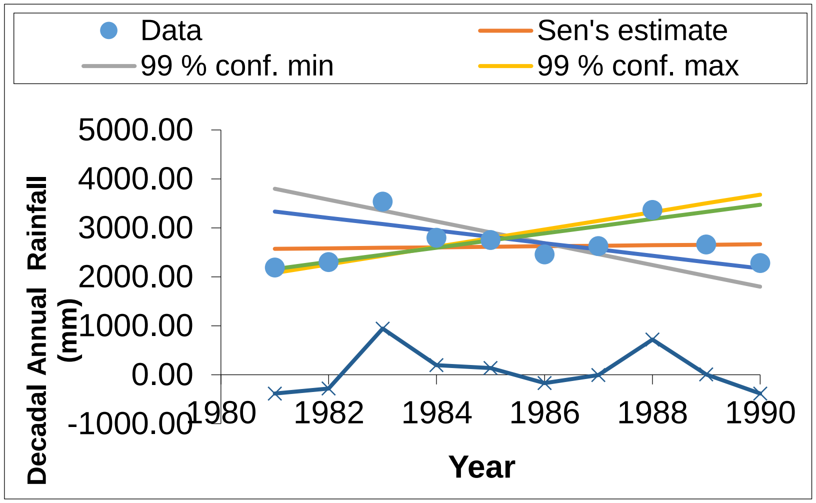


Figure 4-17: Decadal variations of a.a.r (91-2000)

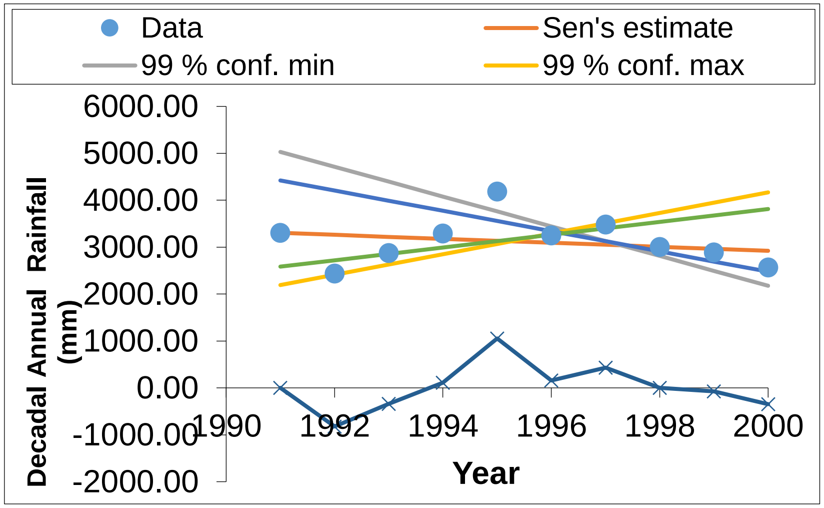


Figure 4-18: Decadal variations of a.a.r (2001-10).

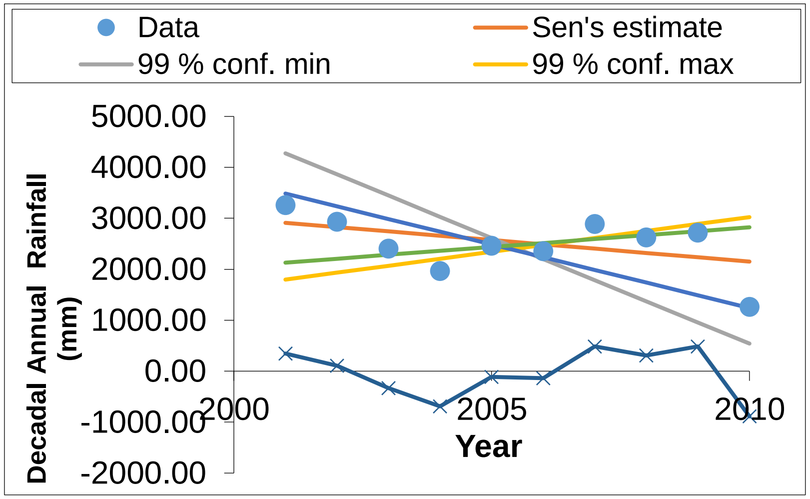


Figure 4-19: Decadal variations of a.a.r (2011-20).

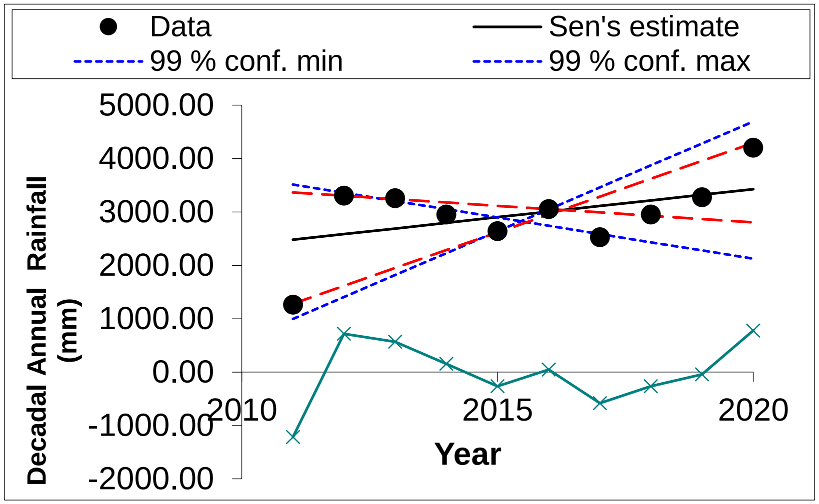


Figure 4-20: Decadal statistical data from 1971-80 & 1981-90.

	Decadal I; 1971 - 1980			Decadal II; 1981 - 1990		
Time series	**Test Z**	**Q**	**B**	**Test Z**	**Q**	**B**
January	0.89	4.064	-16.64	0.18	1.619	22.34
February	0.00	-2.540	166.37	-0.72	-3.556	216.03
March	0.00	-0.445	69.60	-0.36	-9.059	486.16
April	1.97	11.430	-221.11	0.18	4.699	-51.12
May	0.00	-6.604	389.64	1.07	4.318	9.40
June	-0.54	-16.034	743.82	0.89	9.059	-25.61
July	0.36	5.461	199.96	0.72	9.017	35.56
August	0.00	-0.222	417.43	0.72	17.272	-193.42
September	0.18	1.981	332.99	0.00	0.818	283.28
October	1.07	26.815	-288.54	0.18	2.395	83.53
November	-0.18	-1.524	204.6	0.00	0.508	115.19
December	-0.36	-2.096	185.39	-0.54	-16.341	701.25
Annual	0.89	36.407	2108.2	0.00	10.470	2257.7

Figure 4-21: Decadal statistical data from 1991-2000 & 2001-2010

	Decadal I; 1991 - 2000			Decadal II; 2001 - 2010		
Time series	**Test Z**	**Q**	**B**	**Test Z**	**Q**	**B**
January	-0.54	-10.008	612.47	-1.79	-6.350	412.75
February	-0.72	-5.525	357.60	0.00	-0.127	101.22
March	0.00	0.435	98.61	-1.25	-16.408	1003.40
April	-1.61	-14.351	776.03	0.36	3.112	-98.23
May	0.00	-2.258	266.83	-0.72	-14.079	951.67
June	-0.18	-4.499	700.39	-0.54	-12.002	987.08
July	0.36	3.588	156.00	-0.89	-12.446	940.82
August	-0.18	-6.985	726.82	-0.54	-12.700	992.38
September	0.00	0.339	379.14	0.18	4.953	143.95
October	0.36	11.176	-209.42	-0.18	-10.287	782.83
November	-1.79	-19.262	1031.8	-1.61	-18.987	1149.4
December	0.89	5.221	-160.98	0.00	-0.593	126.62
Annual	-0.54	-42.599	5009	-1.07	-84.455	7133.9

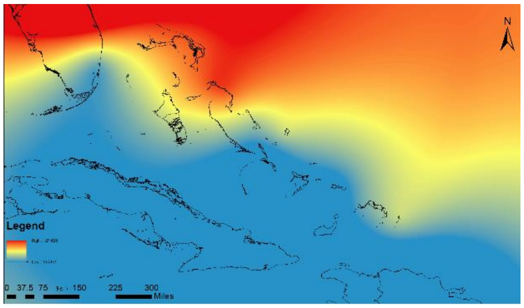
Figure 4-22: Decadal statistical data from 2011-2020

	Decadal I; 2011 - 2020		
Time series	**Test Z**	**Q**	**B**
January	1.43	16.002	-940.05
February	0.00	0.254	75.82
March	0.89	2.794	-118.36
April	0.18	2.286	27.81
May	0.72	26.353	-1384.90
June	1.79	27.009	-1337.52
July	0.89	17.780	-762.00
August	1.97	22.860	-1058.67
September	-0.18	-16.459	1417.549
October	1.07	30.124	-1645.08
November	0.89	8.255	-414.084
December	1.43	6.576	-354.598
Annual	0.89	105.071	-3824.69

4.2.2 PROJECTED PRECIPITATION CHANGES

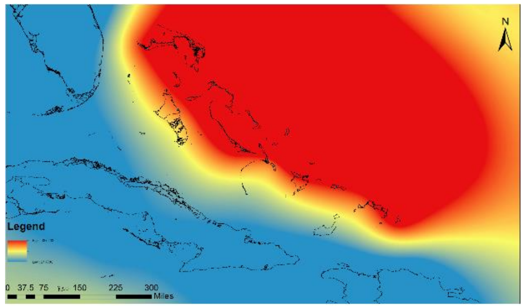
Anthropogenic climate change is not likely to result in uniform changes in hydroclimate across the islands by the end of the twenty-first century (e.g., between 2050 and 2100). The spatial distribution of BCC-CSM-2MR projected changes in mean precipitation for the four forcing scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5) over The Bahamas is shown below (Figure 4-23 to Figure 4-30). As far as the future precipitation patterns are concerned, wetter conditions are predicted for the Northern Bahamas under SSP1-2.6 and SSP2-4.5 but shift to the Central Bahamas under SSP5-8.5 over both near and long-term periods. For near and long-term scenarios of BCC-CSM-2MR (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), we show in Figure 4-23 to Figure 4-30 the spatial distribution of changes in precipitation over the country using kriging interpolation. A northerly shift in precipitation patterns can be observed across all parts of the country during the near-term periods under SSP1-2.6 and SSP3-7.0 scenarios. The opposite happens during the long-term under SSP2-4.5 and SSP5-8.5 scenarios, where the pattern shifts southward. The projected changes in the northern portion of the country will have lower precipitation than the central and southern parts of the country under the near-term SSP5-8.5 forcing scenario.

Figure 4-23: CMIP6-BCC-CSM2-MR SSP126 Near-Term Mean Precipitation(mm/month)



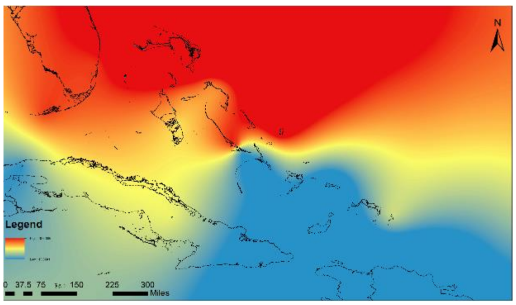
a) Rainfall (10.41 - 127.70 mm)

Figure 4-24: CMIP6-BCC-CSM2-MR SSP2-4.5 Near-Term Mean Precipitation(mm/month)



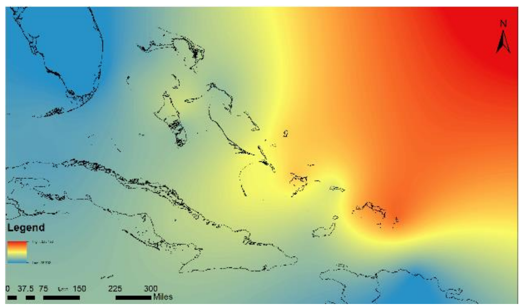
b) Rainfall (27.78 - 137.13 mm)

Figure 4-25: CMIP6-BCC-CSM2-MR SSP3-7.0 Near-Term Mean Precipitation(mm/month)



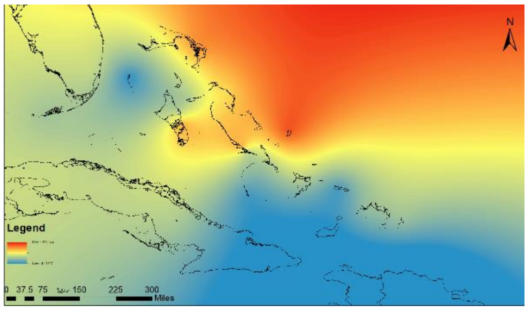
c) Rainfall (15.66 - 128.67 mm)

Figure 4-26: CMIP6-BCC-CSM2-MR SSP5-8.5 Near-Term Mean Precipitation(mm/month)



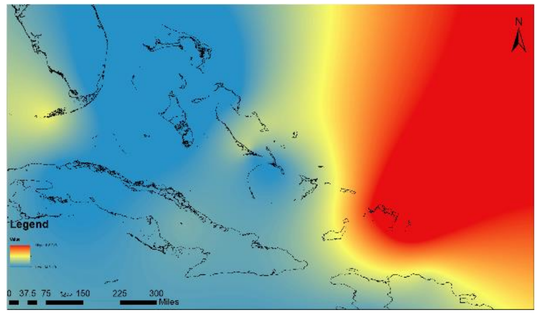
d) Rainfall (26.70 - 233.46 mm)

Figure 4-27: CMIP6-BCC-CSM2-MR SSP1-2.6 Long-Term Mean Precipitation(mm/month)



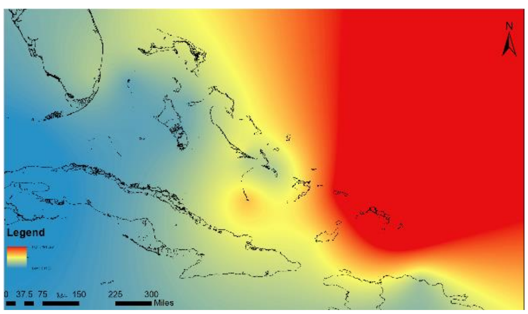
a) Rainfall (11.39 – 131.14 mm)

Figure 4-28: CMIP6-BCC-CSM2-MR SSP2-4.5 Long-Term Mean Precipitation(mm/month)



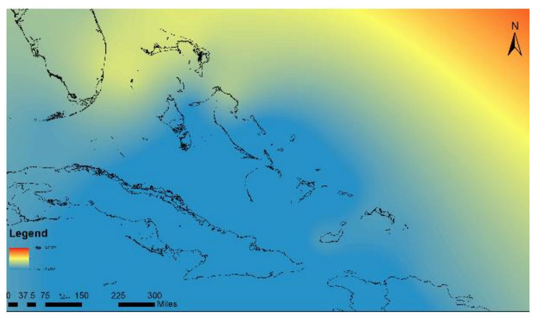
b) Rainfall (14.61 – 116.02 mm)

Figure 4-29: CMIP6-BCC-CSM2-MR SSP3-7.0 Long-Term Mean Precipitation(mm/month)



c) Rainfall (3.18 – 161.33 mm)

Figure 4-30: CMIP6-BCC-CSM2-MR SSP5-8.5 Long-Term Mean Precipitation(mm/month)



d) Rainfall (17.45 – 247.38 mm)

5 DISCUSSION

5.1 HISTORICAL METEOROLOGICAL DATA FROM BDM

Concerning the first question regarding analysis of observed data during the last 50 years from meteorological stations in the northern region of The Bahamas, the coefficients of variation of the temperatures and precipitation ranged from 1.6 – 3.7% for maximum temperatures, 3.7 – 15.1% for minimum temperatures, and 31.3 – 90.6% for precipitation. The coefficient of variation depicts the high degree of variability in precipitation. However, an examination of historical temperature data reveals rising trends. Mann-Kendall monotonic trend analysis found a warming trend at maximum temperatures, while a slight cooling trend was observed at the minimum temperatures.

Throughout the year, precipitation is not uniformly distributed. In the winter, frontal systems dominate, while convective storms dominate in the summer. The planetary wind pattern affects average annual precipitation and evaporation peaks in the summer and drops in the winter. The highest monthly precipitation occurs from May to October, while the lowest occurs in February.

June to October has the most elevated monthly temperatures, with January and February the lowest.

The statistical characteristics of historical yearly, seasonal, and monthly rainfall (Table 4-3), as well as maximum and minimum temperature (Table 4-1 and Table 4-2 respectively), were investigated. The results show that the data are normally distributed, despite the slight positive skewness. In terms of rainfall variability, the summer months have a lower coefficient of variation, which implies that June to September is the most consistent. In contrast, January and April had the highest CVs, with 90.6% and 77.1%, respectively. The rest of the months had a similar rainfall trend, indicating little fluctuation during the research period.

5.2 CLIMATE CHANGE PROJECTIONS

Choosing a specific model for a given study topic is subjective and complex. The majority of CMIP6 models can simulate The Bahamas' primary climate variables. CMIP6 models used in the study showed excellent agreement between precipitation and temperature based on the BCC-CSM-2MR and MIROC-ES2L models, respectively.

There have not been many studies specifically for The Bahamas, but most studies for the Caribbean basin projected an apparent increase in temperatures by the end of the twenty-first century (Centella-Artola, et al. 2015) (Campbell, Taylor and Bezanilla-Morlot, et al. 2021) (Vichot-Llano, et al. 2021). On the other hand, precipitation major determinants fluctuate across the basin at subregions of the country, making forecasting challenging. These studies used a diverse set of time periods, quantities, climate models, emission scenarios, and downscaling methods. As a result, drawing broad conclusions is difficult.

According to projections from SSP2-4.5, SSP3-7.0, and SSP5-8.5 forcing scenarios, the annual precipitation over the Northwest and Central Bahamas depicts a drier response compared to the present climate. The magnitude and frequency of this change increase over time in proportion to the radiation forcing strength. While precipitation shifts during winter and spring have been consistent with the annual pattern, summer and autumn precipitation response has been inconsistent (Figure 7-1 to Figure 7-32). The change in precipitation over the entire country will be negative by the end of the twenty-first century, according to the SSP5-8.5.

According to Centella-Artola, et al. (2015), the annual precipitation cycle is very similar to the regional cycles. As Campbell, Taylor, and Stephenson, et al. (2011) predicted, SRES climate simulations A2 and B2 expect a decrease in future precipitation over Caribbean countries, including the Bahamas. Nevertheless, the country's complexity warrants further investigation since past research has found significant differences between precipitation patterns in the northwestern and southeastern regions of the country (Taylor, Clarke, et al. 2018).

In general, the magnitude of radiative forcing correlates with the effect of warming, with the fastest increase occurring under SSP5-8.5 and a slower increase under SSP1-2.6. Nearly all regions in the country under SSP1-2.6 saw their temperatures decline after 2070 since radiative forcing decreased gradually after peaking before 2070. A high-emission scenario is associated with greater uncertainty in temperature change trajectory than the other scenarios. As the century draws to a close, uncertainties increase, irrespective of the scenario. Under both SSP3-7.0 and SSP5-8.5 scenarios, the spread is expected to rise most slowly, but nevertheless significantly, during the twenty-first century. Research utilizing CMIP5 models has previously yielded similar findings (Vichot-Llano, et al. 2021).

5.3 CONSEQUENCES FOR WATER RESOURCES

The third question is the likely and the expected consequences for water resources. The Bahamas already has a vulnerability and scarcity of freshwater resources. Surface water runoff is moderately low, and there are no freshwater rivers due to very small altitudes in the Bahamian islands (ICF Consulting 2008). Thin ‘lenses’ of freshwater are deposited and preserved through precipitation on top of shallow salt water, less than two metres below the ground surface.

Sea-level rise is already causing a problem for The Bahamas, where aquifers are experiencing high levels of salt intrusion (Gulley, et al. 2016). The freshwater lens in the reservoir will diminish as saline levels rise, and the water quality will degrade. The Bahamas has been affected by previous flooding from extreme weather events, resulting in pollutants such as seawater and sewage in groundwater. The most recent example was Hurricane Dorian’s passage in 2019 in the Northern Bahamas (Deopersad, et al. 2020). Rising sea levels may make it increasingly difficult to address these challenges. Water supply interruptions caused by climate change would have economic effects and significantly impact human health and well-being (Corvalan, et al. 2005). Stakeholders in the water industry must be better trained to detect and respond to climate change concerns.

Finally, this study evaluated whether climate-resilient adaptation strategies exist in The Bahamas or should be developed to lessen climate change's adverse effects. The Bahamas identified the water sector for adaptation to climate change as a national priority, as part of its first Nationally Determined Contribution (NDC) (GoB 2016), and previously as part of the National Climate Change Adaptation Policy (GoB 2005). Unfortunately, The Bahamas do not have a very coordinated national water plan or strategy that recognizes and guides the needs of other sectors and stakeholders despite the significance of the water sector to the country or its climate change and development policies. A revised legal framework for the water sector is needed to address changing (physical and institutional) conditions and challenges.

6 CONCLUSION

According to many studies, the increase of anthropogenic greenhouse gases in the atmosphere is projected to cause hydroclimatic changes in The Bahamas through the twenty-first century. Climate predictions are increasingly crucial for effective decision-making and appropriate adaptation methods using high-resolution climate models. A deeper understanding of climate and hydrological processes at a smaller scale is necessary to meet the diverse water resource requirements of the Bahamas. The study was conducted to accomplish the primary objective of examining the impacts of climate change on precipitation and potable water resources in the Bahamas. All of the posed research questions were addressed during the study.

The study examines past and future climate forecasts using data gathered from The Bahamas Department of Meteorology and the sixth phase of Coupled Model Intercomparison Project (CMIP6) socioeconomic scenarios. Community scenarios, or SSPs, lie at the core of the CMIP6. They differ from the CMIP3, and CMIP5 in that future scenarios begin in a different year, including a new set of emission and land-use criteria. In this study, CMIP6 models were used to assess the baseline period derived from historical simulation (1985–2014) and future climate change means for three time periods (near term (2015–2040), the midterm (2041–2070) and the long term (2071–2100)) based on climate projections under four SSP-RCP scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5). This study aims to review some fundamental vulnerability problems related to current and prospective future hydrological responses resulting from climate change and identify areas where more research is needed.

Despite widespread recognition of climate change, relatively little research has been done on its impact on groundwater. Only if historical data is available can the characteristics of climate change be studied. Only two stations in The Bahamas have continuous data dating back over five decades, making historical data challenging to come by. Furthermore, the driving forces responsible for such changes are still uncertain. To understand how climate change, precipitation patterns, and the loss of fresh groundwater resources affect the different regions of the Bahamas, we need to understand their relationships.

The findings in this study revealed from an analysis of fifty years of Department of Meteorology ground station data showed a coefficient of variation ranging for temperature (precipitation) from 3.7% to 15.1% (31.3 to 90.6%). A high coefficient of variance underscores the variability of precipitation. Temperature records indicate that rising trends have been detected based on temperature data analysis. According to the Mann-Kendall trend analysis test, the maximum temperature examination resulted in an overall warming trend, but the minimum mean temperature resulted in a cooling trend.

The study also found that the CMIP6 projects a continuous increase in temperature over The Bahamas under all scenarios. According to the high emissions scenario SSP5-8.5, the country temperature is expected to increase by approximately 5°C. An essential aspect of the study is an increase in aridity resulting mainly from a substantial reduction in annual mean precipitation, especially under the high emission scenario SSP5-8.5.

The Bahamas, in particular, a developing country and a member of the SIDS nations, is more susceptible to severe climate changes than developed countries. Since country’s socioeconomic systems cannot adequately adapt to climate variability, they are particularly vulnerable. Therefore, the country’s variability in temperature and precipitation should be considered in the design of climate change adaptation strategies.

There is a direct relationship between climate variability and surface waters, including changes in air temperatures, precipitation, and evapotranspiration. However, climate variability interacting with groundwater is more complex and poorly understood. Groundwater levels may fluctuate more frequently and for a more extended period due to rising sea levels and a reduction in infrastructure and resources in coastal areas, leading to saline intrusion into coastal aquifers.

Consequently, convincing potable water stakeholders, planners and development organizations to consider the impact of climate change in their projects and water resource systems can be very difficult on occasions. Considering that climate change may negatively affect water supplies, it would be prudent to perform further investigations and assessments to determine the extent of difficulties that the country may face. When communicating the results, it is important to explain the uncertainties related to climate change on water resources. This will be useful when developing adaptation strategies for various ecological zones and climate scenarios. Water availability and hydrology are projected to affect policy significantly, with well-established trends that should be factored into future planning.

This study found that outdated data on freshwater water resources were frequently encountered (Alternative sources need to be explored to compensate for the decline in groundwater resources, especially in New Providence. According to FAO (2015), desalination is becoming more popular, and it will most certainly continue to do so. The availability of fresh groundwater is decreasing, while water demands are increasing. FAO (2015) further explained that rainwater catchment is infrequently employed, providing only 3% or less of the total water supply. The depletion of resources and quality deterioration are two separate but interrelated problems. A decline in groundwater quality can be caused by pollution and excessive extraction.

Table 2-2) and unreliable, so this should be addressed immediately by stakeholders in the water industry to coordinate and respond to climate change more effectively. The climate change sensitivity of the Bahamas' many aquifers needs to be assessed more thoroughly. As water availability varies by island, the supply-demand balance is heavily influenced by population concentration. For example, New Providence, the largest population centre, has significantly fewer freshwater lenses than is required, necessitating heavy reliance on reverse osmosis plants and the importation of water from other islands. Because the Bahamas' rainfall is highly variable every year, a volume assessment of precipitation may be insufficient unless climate change is considered in the context of time and space.

Due to the limitations of this study, which only examined trends in hydroclimatic variables and the effects of climate change on rainfall and potable water, future studies should include modelling The Bahamas' hydrology to incorporate as many factors as possible. Large-scale planning for adaptation strategies to climate change impacts is essential to avert catastrophic human despair. This study can assess the possible future change in the Bahamas hydroclimate. Still, the data from higher resolution climate models may be more beneficial for policymakers and stakeholders to analyze hydroclimate changes at a local scale. A viable alternative is to dynamically downscale regional climate models. Furthermore, the CMIP6 models fail to account for factors such as island size or local topography (Sobel, Burleyson and Yuter 2011). However, both factors have been demonstrated to affect hydroclimatic variability (Herrera and Ault 2017).

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8 APPENDIX I - GLOSSARY

Anthropocene The Anthropocene is a hypothesised new geological epoch that would emerge from significant human-driven changes to the Earth System's structure and functioning, particularly the climate system. Diverse fields and the general public have already used the notion to represent humanity's significant impact on earth's processes.

Anthropocenic Resulting from or produced by human activities.

Anthropogenic emissions Human-caused emissions of greenhouse gases (GHGs), precursors of GHGs, and aerosols. Fossil fuel combustion, deforestation, land use and land use changes (LULUC) and animal production, fertilisation, waste management, and industrial processes are all examples of these activities.

Carbon dioxide (CO_2) CO_2 is the most significant human greenhouse gas (GHG) influencing the earth's radiative balance. It has a Global Warming Potential (GWP) of 1 because it is the standard against which other GHGs are assessed. Land use and land-use change are both terms that can be used interchangeably (LUC).

Climate Change Any change in climate over time, whether caused by natural variability or human activity, is referred to as climate change.

Extreme event Extreme weather events, such as a severe storm or a heatwave, are unusual meteorological circumstances for a specific location and/or period. An extraordinary average over time of a series of weather occurrences, such as significant rainfall across a season, is an extreme climate event.

Resilience When faced with adversity, resilience is the ability to maintain one's integrity.

Sensitivity Is the degree to which climate-related stimuli affect a system, either negatively or positively. The effect might be direct (for example, a change in crop output in response to a change in temperature mean, range, or variability) or indirect (for example, damages caused by increased coastal flooding owing to sea-level rise).

Vulnerability It is the degree to which climate change can adversely affect a system, including factors such as climate variability and extreme conditions. A system's vulnerability depends on its sensitivity, its rate of climate variation, and its ability to adapt.

9 APPENDIX II – LOCATIONS OF INTERESTS

Table 7-1: The names and points of interest in The Bahamas

ICAO	IATA	WMO	City	Island/State	Country	Latitude	Longitude
MYGW	WTD	78061	West End	Grand Bahama	Bahamas	26.6868	-78.9790
MYGF	FPO	78062	Freeport	Grand Bahama	Bahamas	26.5565	-78.6956

MYAM	MHH	78066	Marsh Harbour	Central Abaco	Bahamas	26.5114	-77.0845
MYAT	TCB	78067	Treasure Cay	Abaco	Bahamas	26.7453	-77.3911
MYBS	BIM	78070	Alice Town	South Bimini	Bahamas	25.7333	-79.2652
MYNN	NAS	78073	Nassau	New Providence	Bahamas	25.0393	-77.4701
MYEM	GHB	78076	Governor's Harbour	Eleuthera	Bahamas	25.2847	-76.3310
MYEH	ELH	78077	North Eleuthera	Eleuthera	Bahamas	25.4756	-76.6813
MYER	RSD	78080	Rock Sound	Eleuthera	Bahamas	24.8950	-76.1763
MYAB		78083	Mangrove Cay	Andros	Bahamas	24.2877	-77.6844
MYAF	ASD	78086	Fresh Creek	North Andros	Bahamas	24.6984	-77.7925
MYCB	TBI	78087	New Bight	Cat Island	Bahamas	24.3148	-75.4576
MYSM	ZSA	78088	Cockburn Town	San Salvador	Bahamas	24.0641	-74.5311
MYRP	RCY	78089	Port Nelson	Rum Cay	Bahamas	23.6834	-74.8363
MYEF	GGT	78091	Moss Town	Exuma	Bahamas	23.5625	-75.8776
MYEG		78092	George Town	Exuma	Bahamas	23.4666	-75.7817
MYLD	LGI	78094	Deadman's Cay	Long Island	Bahamas	23.1785	-75.0883
MYRD	DCT	78101	Duncan Town	Ragged Island	Bahamas	22.1819	-75.7293
MYMM	MYG	78109	Mayaguana	Mayaguana	Bahamas	22.3806	-73.0111
MYCI	CRI	78103	Colonel Hill	Crooked Island	Bahamas	22.7454	-74.1825
MYAP	AXP	78104	Spring Point	Acklins	Bahamas	22.4419	-73.9708
MYIG	IGA	78121	Matthew Town	Inagua	Bahamas	20.9745	-73.6610
KEYW	EYW	72201	Key West	Florida	United States	24.5537	81.7550
KMIA	MIA	72202	Miami	Florida	United States	25.7932	-80.2906
KMLB	MLB	72204		Florida	United States	28.1013	80.6451
KFLL	FLL	72205	Fort Lauderdale	Florida	United States	26.0726	-80.1527
MUVR	VRA	78229	Varadero	Matanzas	Cuba	23.0344	-81.4353
MUCM	CMW	78255	Camagüey		Cuba	21.4247	77.8452
MUHA	HAV	78224	Havana	Ciudad de la Habana	Cuba	22.9892	-82.4091
MTPP	PAP	78439	Port-au-Prince		Haiti	18.5758	72.2959
MDPP	POP	78457	Puerto Plata		Dominican Republic	19.7552	70.5637
TXKF	BDA	78016	Hamilton		Bermuda	32.3634	64.7053
MBGT		78118		Turks Island	Turks and Caicos Islands	21.4422	71.1460
MBPV		78114	Providenciales		Turks and Caicos Islands	21.7763	72.2713

```
#!/usr/bin/env python3
# -*-coding:utf-8 -*-
```

```
# ---------------------------------------------------------------
############################################################################
###########################################################
############################################################################
###########################################################
############################################################################
###########################################################
#===================================================================
# HEADER
#===================================================================
# ---------------------------------------------------------------
# title           :ncBase.py
# author          :Orson M. Nixon
# date            :2021/11/25
# version         :0.1
# usage           :
# notes           :commands must be declared using the do_* method format to
be accepted
#
#
# Copyright (C) 2021 Orson M. Nixon (omnixon@gmail.com) and contributors
#
#===================================================================
# END_OF_HEADER
#===================================================================
############################################################################
#####################
############################################################################
#####################

__author__ = 'Orson M. Nixon'
__credits__ = ['Orson M. Nixon', '']
__license__ = 'GPL'  # GNU Public License
__version__ = '1.0.1'
__maintainer__ = 'Orson M. Nixon'
__email__ = 'omnixon@gmail.com'
__status__ = 'Prototype'
__date__ = '2021/11/12'
__username__ = 'omnixon'
__description__ = 'CIMP6 Monthly Temperature and Precipitation Data
Extraction.'
############################################################################
#####################
#---------------------------------------------------------------------------
--------------------#
import fnmatch
import os, re, sys, platform, subprocess, time

############################################################################
###########################################################
############################################################################
###########################################################
############################################################################
###########################################################
#
```

```
# Base Class
#
##############################################################################
###########################################################
class Base(object):
    debug = False
    # file_report = "report.txt"
    # report = os.path.join(os.path.curdir , file_report)
    attributes = {}  # used in prepare()
    listed_keys = ['debug', 'file_report', 'report', 'filename',
                   'latitude', 'longitude', 'latlonlist', 'index',
                   'dates', 'dataarray', 'df']


##############################################################################
###############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #

##############################################################################
###############################
    def __init__(self, *args, **settings):
        ##############

        _dict = {}
        # Set default values for listed keys
        for item in self.listed_keys:
            _dict[item] = 'None'

        # Update the dictionary with all settings
        _dict.update(settings)

        # Have the keys of settings as instance attributes
        self.__dict__.update(_dict)

        # If the kwargs contain the key 'debug', the following get method
will
        # return its value, or else it would remain whatever value was in
        # self.debug's variable before
        # self.debug = settings.get("debug",self.debug)

        if self.debug:
            print("From Base.__init__()")
        ##############
        self.attributes = settings.copy()  # Copy from class variable
        # self.attributes.update(settings) # Apply

        #########################################################
        for key, value in settings.items():
```

```
            # print("{} is {}".format(key,value))
            self.attributes[key] = value
            setattr(self, key, value)
        ########################################################
        self.initialize(**settings)

#############################################################################
####################


#############################################################################
##############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #

#############################################################################
##############################
    def initialize(self, **kwargs):
        ##############
        if self.debug:
            print("From Base.initialize")
        ##############

        allowed_keys = list(self.__dict__.keys())
        self.__dict__.update((key, value) for key, value in kwargs.items() if
key in allowed_keys)

        for key, value in kwargs.items():
            self.attributes[key] = value
            setattr(self, key, value)
            if key in allowed_keys:
                # print( '{0} = {1}'.format(key, value))
                setattr(self, key, value)

        ########################################################


#############################################################################
####################


#############################################################################
##############################
    # This function will generate the file names in a directory
    # tree by walking the tree either top-down or bottom-up. For each
    # directory in the tree rooted at directory top (including top itself),
    # it yields a 3-tuple (dirpath, dirnames, filenames).
    #
    # Parameters:
```

```
    #
    #
    # Returns:
    #
    #
#############################################################################
###############################
    def getListOfFiles(self, directory, pattern="*.nc"):
        ##############
        if self.debug:
            print("From Base.getListOfFiles")
        ##############

        allFiles = list()
        files = list()
        # List which will store all of the full filepaths.
        filelist = []
        ##########################################

        if os.path.exists(directory):
            os.chdir(directory)
            # create a list of file and sub directories names in the given
directory
            listOfFile = os.listdir(directory)
            # Iterate over all the entries
            for root, dirs, files in os.walk(directory):
                for file in files:
                    filename = os.path.join(root, file)
                    if fnmatch.fnmatch(file, pattern):
                        # append the file name to the list
                        filelist.append(filename)
            #############################################################
        ########################################################
        return filelist

#############################################################################
#####################


#############################################################################
###############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #
#############################################################################
###############################
    def __str__(self):
        ##############
```

```
        if self.debug:
            print("From Base.__str__")
        ##############
        printable_string = '\n{0!s:_^80}\n'.format('Base')

        for k, v in self.__dict__.items():
            printable_string += '  {0!s:<29}{1!s:<50}\n'.format(k, v)

        if self.attributes:
            printable_string += '\n{0!s:40}\n'.format('Settings')
            for k, v in self.attributes.items():
                printable_string += '  {0!s:<29}{1!s:<50}\n'.format(k, v)

        ########################################################
        return printable_string
        ########################################################


#############################################################################
#####################


#############################################################################
###############################

#############################################################################
###############################
    # End of class

#############################################################################
###############################

#############################################################################
###############################
#############################################################################
##########################################################
#############################################################################
##########################################################
#############################################################################
##########################################################
#
# NetCDF Converter Class
#
#############################################################################
##########################################################
from ncLocation import Location


class NetCDFConverter(Base):


#############################################################################
###############################
    # Initialize NetCDF Converter.
    #
```

```
    # Parameters:
    #
    #
    # Returns:
    #
    #
############################################################################
##############################
    def __init__(self, file_name = "", *args, **settings):
        ##############
        #######################################################
        super(NetCDFConverter, self).__init__(*args, **settings)
        #######################################################
        # if "debug" in settings:
        #    self.debug = settings.get('debug', False)

        if self.debug:
            print("From NetCDFConverter.__init__()")
        ##############
        self.filename = file_name
        self.latitude = []
        self.longitude = []
        self.latlonlist = []
        self.index = None
        self.dates = None
        self.data = None
        self.dataarray = None
        # self.initialize(**settings)
        #######################################################


############################################################################
####################


############################################################################
##############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #
############################################################################
##############################
    def findLatIndex(self, lat):
        ##############
        if self.debug:
            print("From NetCDFConverter.findLatIndex")
        ##############
        sqDiff = (self.latitude - lat) ** 2
```

```
        minIndex = sqDiff.argmin()
        # for latindex in range(len(self.latitude)):
        #    if self.latitude[latindex] == lat:
        #        return latindex
        ##############
        #########################################################
        return minIndex

##############################################################################
#####################


##############################################################################
###############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #

##############################################################################
###############################
    def findLonIndex(self, lon):
        ##############
        if self.debug:
            print("From NetCDFConverter.findLonIndex")
        ##############
        # for lonindex in range(len(self.longitude)):
        #    if self.longitude[lonindex] == lon:
        #        return lonindex
        sqDiff = (self.longitude - lon) ** 2
        minIndex = sqDiff.argmin()
        #
        #########################################################
        return minIndex

##############################################################################
#####################


##############################################################################
###############################
    # Get nearest indices to (latitude, longitude).
    #
    # Parameters:
    #       latitude : float
    #           Latitude in degrees
    #       longitude : float
    #           Longitude in degrees
    #
    # Returns:
    #
```

```
    #
    #
    #

##############################################################################
###############################
    def getNearestIndices(self, latitude, longitude):
        ##############
        if self.debug:
            print("From NetCDFConverter.getNearestIndices")
        ########################################################
        # index of nearest latitude
        idx_lat = int(round((latitude - 90.0) / self.delta_lat))
        # avoid out of bounds latitudes
        if idx_lat < 0:
            idx_lat = 0  # if latitude == 90, north pole
        elif idx_lat > self.lat_size:
            idx_lat = self.lat_size  # if latitude == -90, south pole
        # adjust longitude from -180/180 to 0/360
        longitude = longitude % 360.0
        # index of nearest longitude
        idx_lon = int(round(longitude / self.delta_lon)) % self.lon_size
        ########################################################
        #
        ########################################################
        if self.debug:
            print("From a methodTemplate")
            print('Nearest latitude index is : {0}'.format(idx_lat))
            print('Nearest longitude index is : {0}'.format(idx_lon))

        ########################################################
        return idx_lat, idx_lon

##############################################################################
#####################


##############################################################################
###############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #

##############################################################################
###############################
    def openNetcdf(self, filename, mode='r'):
        ##############
        if self.debug:
            print("From NetCDFConverter.openNetcdf")
        ########################################################
```

```
        from netCDF4 import Dataset
        import os

        # checking that the file exists
        exists = os.path.exists(filename)
        if exists:
            data = netcdf.Dataset(filename, mode=mode)
        #########################################################
        # data variables and dimensions
        variables = set(data.variables.keys())
        dimensions = set(data.dimensions.keys())
        self.keys = tuple(variables - dimensions)
        # size of lat/lon dimensions
        self.lat_size = data.dimensions['lat'].size
        self.lon_size = data.dimensions['lon'].size
        # spatial resolution in degrees
        self.delta_lat = -180.0 / (self.lat_size - 1)  # from north to south
        self.delta_lon = 360.0 / self.lon_size  # from west to east
        # time resolution in hours
        self.time_size = data.dimensions['time'].size
        self.start_time = data['time'][0]
        self.stop_time = data['time'][-1]
        self.time_range = self.stop_time - self.start_time
        self.delta_time = self.time_range / (self.time_size - 1)
        if self.debug:
            print('Keys: {0}'.format(self.keys))
        #    print('Latitude size is : {0}, \nLongitude size is: 
{1}'.format(self.lat_size, self.lon_size))
        #    print('time_size is : {0}'.format(self.time_size))
        #    print('delta_time is : {0}'.format(self.delta_time))
        #########################################################
        return data

##############################################################################
#####################


##############################################################################
###############################
    # Sets the location for the query.
    #
    # Parameters:
    #       time: datetime or DatetimeIndex
    #           Time range of the query.
    #
    # Returns:
    #
    #

##############################################################################
###############################
    def setLocation(self, time, latitude, longitude):
        ##############
        if self.debug:
            print("From NetCDFConverter.setLocation")
```

```
        ##############

        ########################################################
        if isinstance(time, datetime.datetime):
            tzinfo = time.tzinfo
        else:
            tzinfo = time.tz

        if tzinfo is None:
            self.location = Location(latitude, longitude)
        else:
            self.location = Location(latitude, longitude, tz=tzinfo)

################################################################################
#####################


################################################################################
###############################
    # Submits a query to convert the netcdf data to a pandas DataFrame.
    #
    # Parameters:
    #       latitude: float
    #           The latitude value.
    #       longitude: float
    #           The longitude value.
    #       start: datetime or timestamp
    #           The start time.
    #       end: datetime or timestamp
    #           The end time.
    #       vert_level: None, float or integer
    #           Vertical altitude of interest.
    #       variables: None or list
    #           If None, uses self.variables.
    #       close_netcdf_data: bool
    #           Controls if the temporary netcdf data file should be closed.
    #           Set to False to access the raw data.
    #
    # Returns:
    #       data : DataFrame
    #           column names are the weather model's variable names.
    #

################################################################################
###############################
    def getData(self, latitude, longitude, start, end,
                 vert_level=None, query_variables=None,
                 close_netcdf_data=True):
        ##############
        if self.debug:
            print("From NetCDFConverter.getData")
        ##############
        self.data = None
        ########################################################
        #if vert_level is not None:
```

```
        #    self.vert_level = vert_level

        #if query_variables is None:
        #    self.query_variables = list(self.variables.values())
        #else:
        #    self.query_variables = query_variables

        self.latitude = latitude
        self.longitude = longitude
        #self.set_query_latlon()  # modifies self.query
        self.setLocation(start, latitude, longitude)

        self.start = start
        self.end = end
        #self.query.time_range(self.start, self.end)

        #self.netcdf_data =  self.openNetcdf()
        # might be better to go to xarray here so that we can handle
        # higher dimensional data for more advanced applications
        #self.data = self._netcdf2pandas(self.netcdf_data,
self.query_variables)

        if close_netcdf_data:
            print("closing netcdf file")
            #self.netcdf_data.close()

        return self.data

##############################################################################
#####################


##############################################################################
###############################
    # Converts time data into a pandas date object.
    #
    # Parameters:
    #       time: netcdf
    #           Contains time information.
    #
    # Returns:
    #       pandas.DatetimeIndex
    #

##############################################################################
###############################
    def setTime(self, variables, name='time', units=None, tzinfo=None,
**kwargs):
        ##############
        if self.debug:
            print("From NetCDFConverter.setTime")
        ##############
        timevar_units = 'days since 0001-01-01 00:00:00'
        ########################################################
        times = variables[name]
```

```
        t_cal = variables[name].calendar
        if variables[name].ndim > 1:
            _str_data = variables[name][:, :]

            if units == None:
                units = timevar_units
            times = [parse(_str_data[i, :].tostring()) for i in 
range(len(_str_data[:, 0]))]
            data = netcdf.date2num(times, units)
        else:
            #data = variables[name][:]
            data = netcdf.num2date(variables[name][:].squeeze(), units = 
variables[name].units, calendar = t_cal)


        if units == None:
            try:
                self._units = variables[name].units
            except:
                self._units = units
        else:
            self._units = units

        if tzinfo == None:
            self._tzinfo = pytz.utc
        else:
            self._tzinfo = tzinfo

        units_split = self._units.split(' ', 2)
        assert len(units_split) == 3 and units_split[1] == 'since', \
            'units string improperly formatted\n' + self._units
        self.origin = parse(units_split[2])

        self._units = units_split[0].lower()

        # compatibility to CF convention v1.0/udunits names:
        if self._units in ['second', 'sec', 'secs', 's']:
            self._units = 'seconds'
        if self._units in ['min', 'minute', 'mins']:
            self._units = 'minutes'
        if self._units in ['h', 'hs', 'hr', 'hrs', 'hour']:
            self._units = 'hours'
        if self._units in ['day', 'd', 'ds']:
            self._units = 'days'

        file_times = netcdf.num2date(variables[name][:].squeeze(), 
variables[name].units,
                                     only_use_cftime_datetimes=False, 
only_use_python_datetimes=True)
        #dtime = netcdf.num2date(times[:], times.units)
        self.start_time = netcdf.num2date(times[0], units = times.units, 
calendar = t_cal)
        self.end_time = netcdf.num2date(times[-1], units = times.units, 
calendar = t_cal)
        self.time = pd.DatetimeIndex(pd.Series(file_times),
```

```
tz=self._tzinfo).strftime('%m/%Y')

        # Now we convert dates to pandas format
        #dates_pd = pd.to_datetime(data)
        # Convert timestamps to periods, since we dealing with monthly values
        #periods = dates_pd.to_period(freq='M')

        if self.debug:
            print("From NetCDFConverter.setTime")
            #print("Time dimension: {0}".format(times))
            #print("Data: {0}".format(data))
            #print("Units: {0}".format(self._units))
            #print("Pandas format dates: {0}".format(dates_pd))
            #print("Periods: {0}".format(periods))
            #print("Dates: {0}".format(dates))
            #print("Units: {0}".format(self._units))
            #print("First: {0}".format(self.start_time.strftime('%Y-%b-%d
%H:%M')))
            #print("Last: {0}".format(self.end_time.strftime('%Y-%b-%d
%H:%M')))
            #print("Times: {0}".format(self.time))

        return self.time

##############################################################################
#####################


##############################################################################
###############################
    # Transforms data from netcdf to pandas DataFrame.
    #
    # Parameters:
    #       data: netcdf
    #           Data returned from query.
    #       query_variables: list
    #           The variables requested.
    #
    # Returns:
    #
    #

##############################################################################
###############################
    def _netcdf2pandas(self, netcdf_data, query_variables):
        ##############
        if self.debug:
            print("From NetCDFConverter._netcdf2pandas")
        ##############

        #########################################################
        try:
            time_var = 'time'
            self.set_time(netcdf_data.variables[time_var])
        except KeyError:
```

```
            time_var = 'time1'
            self.set_time(netcdf_data.variables[time_var])

        data_dict = {key: data[:].squeeze() for key, data in
                     netcdf_data.variables.items() if key in query_variables}

        return pd.DataFrame(data_dict, index=self.time)

############################################################################
####################


############################################################################
##############################
    #
    #
    # Parameters:
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    #
    # Returns:
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    #

############################################################################
##############################
    def processFile(self, file, model="MRI-ESM2-0 ", mode='r', lat = 25, lon
= 77, *args, **kwargs):
        plotlist = np.array([])
        df = None
        # Reading in the netCDF4 file
        self.data = self.openNetcdf(file, mode)

        # Find the type of element
        filename = file.split(os.sep)[-1]
        ##
        #######################################################
        # Accessing the data from the variables
        time_range = self.setTime(self.data.variables)

        # Storing the lat data into the variable
        self.latitude = self.data.variables['lat'][:]
        # Storing the lon data into the variable
        self.longitude = self.data.variables['lon'][:]
        #self.latlonlist = self.getLatLonList()

        # Squared difference between the specified lat,lon and the lat,lon of
the netCDF
        sq_diff_lat = (self.latitude - kwargs['latitude']) ** 2
        sq_diff_lon = (self.longitude - kwargs['longitude']) ** 2
        # Find the nearest latitude and longitude for the station
        lat_idx = np.abs(self.latitude - kwargs['latitude']).argmin()
        lon_idx = np.abs(self.longitude - kwargs['longitude']).argmin()

        # Identify the index of the min value for lat and lon
        min_index_lat = lat_idx
```

```
        min_index_lon = lon_idx
        #min_index_lat = sq_diff_lat.argmin()
        #min_index_lon = sq_diff_lon.argmin()
        #min_index_lat = self.findLatIndex(kwargs['latitude'])
        #min_index_lon = self.findLonIndex(kwargs['longitude'])

        # Accessing the data from the variables
        var_data = 0.0
        if 'tasmax' in self.keys:
            #print("Element values:
{0}".format(self.data.variables['tasmax']))
            var_data = self.data.variables['tasmax']
            element = 'tasmax'
        elif 'tasmin' in self.keys:
            var_data = self.data.variables['tasmin']
            element = 'tasmin'
        elif 'pr' in self.keys:
            var_data = self.data.variables['pr']
            element = 'pr'
        #var_data = self.data.variables[element]
        column_names = ["Latitude", "Longitude", "ICAO", "BlckNo", element]
        df = pd.DataFrame(0.0, index=self.setTime(self.data.variables),
columns=column_names)

        for t_index in np.arange(0, len(time_range)):
            df.loc[time_range[t_index]]['ICAO'] = kwargs['station']
            df.loc[time_range[t_index]]['Latitude'] = kwargs['latitude']
            df.loc[time_range[t_index]]['Longitude'] = kwargs['longitude']
            df.loc[time_range[t_index]]['BlckNo'] = int(kwargs['blckNo'])
            if 'tas' in element:
                df.loc[time_range[t_index]][element] = (var_data[t_index,
min_index_lat, min_index_lon]) - 273.15
            else:
                df.loc[time_range[t_index]][element] = var_data[t_index,
min_index_lat, min_index_lon]

        ########################################################
        if self.debug:
            print("From NetCDFConverter.processFile")
            #print(filename)
            #print("Variable Keys: \n{0}".format(self.data.variables.keys()))
            print("df: {0}".format(df))
            print("Element and model: {0}".format(element, model))
            print("Latitude: {0} \nLongitude: {1}".format(min_index_lat,
min_index_lon))
            print("Station: {0}".format(kwargs['station']))
            print("Element values: {0}".format(var_data))
            # print(data.variables['time'].size)
        ########################################################
        self.data.close()
        return df, column_names

#############################################################################
####################
```

```
##############################################################################
###############################
    #
    #
    # Parameters:
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    #
    # Returns:
    #
    #

##############################################################################
###############################
    def getLatLonList(self):
        ##############
        if self.debug:
            print("From NetCDFConverter.getLatLonList")
        ##############
        list = []
        for i in range(len(self.latitude)):
            for j in range(len(self.longitude)):
                list.append((self.latitude[i], self.longitude[j]))

        #########################################################
        return list

##############################################################################
#####################


##############################################################################
###############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #

##############################################################################
###############################
    def ncdump(self, nc_fid, verb=True):
        ##############
        if self.debug:
            print("From NetCDFConverter.ncdump")
        ##############
        nc_attrs = None
        nc_dims = None
        nc_vars = None

        def print_ncattr(key):
            try:
```

```
                print("\t\ttype:", repr(nc_fid.variables[key].dtype))
                for ncattr in nc_fid.variables[key].ncattrs():
                    print('\t\t%s:' % ncattr,
repr(nc_fid.variables[key].getncattr(ncattr)))
            except KeyError:
                print("\t\tWARNING: %s does not contain variable attributes"
% key)

        # NetCDF global attributes
        nc_attrs = nc_fid.ncattrs()
        if verb:
            print("NetCDF Global Attributes:")
            for nc_attr in nc_attrs:
                print('\t%s:' % nc_attr, repr(nc_fid.getncattr(nc_attr)))

        # Dimension shape information.
        nc_dims = [dim for dim in nc_fid.dimensions]  # list of nc dimensions
        if verb:
            print("NetCDF dimension information:")
            for dim in nc_dims:
                print("\tName:", dim)
                print("\t\tsize:", len(nc_fid.dimensions[dim]))
                print_ncattr(dim)

        # Variable information.
        nc_vars = [var for var in nc_fid.variables]  # list of nc variables
        if verb:
            print("NetCDF variable information:")
            for var in nc_vars:
                if var not in nc_dims:
                    print('\tName:', var)
                    print("\t\tdimensions:",
nc_fid.variables[var].dimensions)
                    print("\t\tsize:", nc_fid.variables[var].size)
                    print_ncattr(var)

        ########################################################
        return nc_attrs, nc_dims, nc_vars

############################################################################
####################


############################################################################
##############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #

############################################################################
```

```
###############################
    def processFiles(self, files, mode='r'):
        ##############
        if self.debug:
            print("From NetCDFConverter.processFile")
        ##############

        ##############
        for i in range(len(files)):
            plotlist = np.array([])
            # Open netCDF4 file
            file = netcdf.Dataset(files[i], mode)
            # nc_attrs, nc_dims, nc_vars = self.ncdump(file)

            # Find the type of element
            filename = files[i].split(os.sep)[-1]
            element = filename.partition('_')
            value = None

            # Extract variable
            # vars = file.variables['element[0]']

            for j in range(len(self.latlonlist)):
                if element[0] == 'pr':
                    # print ('pr')
                    value = file.variables['pr'][:,
self.findLatIndex(self.latlonlist[j][0]),
                                    self.findLonIndex(self.latlonlist[j][1])]
                elif element[0] == 'tasmax':
                    # print ('tasmax')
                    value = file.variables['tasmax'][:,
self.findLatIndex(self.latlonlist[j][0]),
                                    self.findLonIndex(self.latlonlist[j][1])]
                elif element[0] == 'tasmin':
                    # print ('tasmin')
                    value = file.variables['tasmin'][:,
self.findLatIndex(self.latlonlist[j][0]),
                                    self.findLonIndex(self.latlonlist[j][1])]
                ##########################
                plotlist = np.append(plotlist, value)
                # print("Plot list is {} and size {}".format(plotlist,
len(plotlist)))
            ##########################
            ma.resize(plotlist, (len(files), 1))
            # dataarray[:, i] = plotlist
            # np.append(self.dataarray, plotlist, axis = 0)
            # self.dataarray = np.append(self.dataarray, plotlist, axis = 0)
            # print("Data array is {}".format(self.dataarray))
            # print (vars.get_dims())

            ########################################################
            # Close NetCDF file.
            file.close()
        ########################################################
```

```
##############################################################################
#####################


##############################################################################
###############################
    #
    #
    # Parameters:
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    #
    # Returns:
    #
    #
##############################################################################
###############################
    def process(self, startDate='1/1/1971', endDate='12/31/2020', freq="M"):
        ##############
        if self.debug:
            print("From NetCDFConverter.process")
        ##############
        files = self.getListOfFiles(self.netcdf_dir, self.nc_pattern)

        file = netcdf.Dataset(files[0])
        self.latitude = file.variables['lat'][:]
        self.longitude = file.variables['lon'][:]
        self.latlonlist = self.getLatLonList()

        self.index = pd.MultiIndex.from_tuples(self.latlonlist, names=['Lat',
'Lon'])
        self.dates = pd.date_range(start=startDate, end=endDate, freq="M")
        self.dataarray = np.zeros((len(self.latlonlist), len(self.dates)))

        nc_attrs, nc_dims, nc_vars = self.ncdump(file)

        precip = file.variables['prec']  # precipitation variable
        # precip = file.variables['prec'][:]
        time_var = file.variables['time']

        dtime = netcdf.num2date(time_var[:], time_var.units)

        ########################################################
        # Close original NetCDF file.
        file.close()

        # self.processFiles(files)
        ##############
        # df = pd.DataFrame(data = self.dataarray, index = self.index,
columns = self.dates)

        # df.replace(-9999, np.nan, inplace = True)
        # df.to_csv('master_dataset.csv', encoding='utf-8')
        ##############
```

```
        if self.debug:
            # print (self.latlonlist)
            # print (self.index)
            # print (self.dates)
            # print (self.dataarray)
            # print (precip )
            print("The variable is {}".format(precip))
            print(dtime)
            # print (df)
        ##############
        ########################################################


#############################################################################
#####################


#############################################################################
###############################
    #
    #
    # Parameters:
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    #
    # Returns:
    #
    #

#############################################################################
###############################
    def getLocationLatLong(self, location="Nassau"):
        ##############
        if self.debug:
            print("From NetCDFConverter.getLocationLatLong")
        ########################################################
        geolocator = Nominatim(user_agent='netCDF_Extraction')
        # loc = geolocator.geocode(location + ',' + country)
        try:
            loc = geolocator.geocode(location)
            if loc:
                lat = loc.latitude
                lon = loc.longitude
                loc = geolocator.reverse(str(lat) + ',' + str(lon),
language='en')
                city = loc.raw["address"].get("city")
                country = loc.raw["address"].get("country")
                return (city, country, lat, lon)
            else:
                return None
        except:
            raise Exception("There was a problem with the geolocator
function")
        # print("latitude is :", lat, "\nlongtitude is:", lon)
        ########################################################
        return None
```

```
################################################################################
#####################


################################################################################
###############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #
################################################################################
###############################
    def getLocations(self, locations):
        ##############
        if self.debug:
            print("From NetCDFConverter.getLocations")
        ########################################################
        geolocator = Nominatim(user_agent='ncExtraction')
        df = None
        # loc = geolocator.geocode(location + ',' + country)
        cities = []
        countries = []
        latitudes = []
        longitudes = []
        try:
            for location in locations:
                print(location)
                city, country, lat, lon = self.getLocationLatLong(location)
                cities.append(city)
                countries.append(country)
                latitudes.append(lat)
                longitudes.append(lon)
        except:
            raise Exception("There was a problem with the geolocator
function")

        print(cities)
        print(countries)
        print(latitudes)
        data = {
            'City':cities,
            'Country':countries,
            'Latitude':latitudes,
            'Longitude': longitudes}
        df = pd.DataFrame(data, columns = ['City', 'Country', 'Latitude',
'Longitude'])
        ########################################################
        return df
```

```
##############################################################################
#####################


##############################################################################
###############################
    #
    #
    # Parameters:
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    #
    # Returns:
    #
    #

##############################################################################
###############################
    def readNetcdfs(self, files, dim="time"):
        ##############
        if self.debug:
            print("From NetCDFConverter.readNetcdfs")
        ########################################################
        combined = None
        ########################################################
        paths = sorted(self.getListOfFiles(files))
        datasets = [xr.open_dataset(p) for p in paths]
        print(datasets)
        #combined = xr.concat(datasets, dim)
        return combined

##############################################################################
#####################


##############################################################################
###############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #

##############################################################################
###############################
    def convertGeoTIFFtoNetCDF(self, file):
        ##############
        if self.debug:
            print("From NetCDFConverter.convertGeoTIFFtoNetCDF")
        ##############

        ########################################################
        geotiff_da = xr.open_rasterio(file)
```

```
##############################################################################
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##############################################################################
###############################
    #
    #
    # Parameters:
    #
    #
    # Returns:
    #
    #

##############################################################################
###############################
    def dfToCSV(self, df, csvFilePath, sep=",", columns=None):
        ##############
        if self.debug:
            print("From NetCDFConverter.dfToCSV")
        ##############
        mode = 'a' if os.path.exists(csvFilePath) else 'w'
        print("Mode: {0}".format(mode))
        ########################################################
        if not os.path.isfile(csvFilePath):
            #filename = Path(csvFilePath)
            #filename.touch(exist_ok=True)
            open(csvFilePath, mode='w').close()
            if columns is not None:
                df.to_csv(csvFilePath, mode=mode, index=True, sep=sep,
columns=columns)
            else:
                df.to_csv(csvFilePath, mode=mode, index=True, sep=sep)
        elif len(df.columns) != len(pd.read_csv(csvFilePath, nrows=1,
sep=sep).columns):
            raise Exception(
                "Columns do not match!! Dataframe has " +
str(len(df.columns)) + " columns. CSV file has " + str(
                    len(pd.read_csv(csvFilePath, nrows=1, sep=sep).columns))
+ " columns.")
        elif not (df.columns == pd.read_csv(csvFilePath, nrows=1,
sep=sep).columns).all():
            raise Exception("Columns and column order of dataframe and csv
file do not match!!")
        else:
            if columns is not None:
                df.to_csv(csvFilePath, mode=mode, index=True, sep=sep,
header=False, columns=columns)
            else:
                df.to_csv(csvFilePath, mode=mode, index=True, sep=sep,
header=False)
```

```
################################################################################
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################################################################################
##############################
    #
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    # Parameters:
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    # Returns:
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    #

################################################################################
##############################
    def __str__(self):
        ##############
        if self.debug:
            print("From NetCDFConverter.__str__")
        ##############
        printable_string = '\n{0!s:_^80}\n'.format('NetCDFConverter')

        for k, v in self.__dict__.items():
            printable_string += '  {0!s:<29}{1!s:<50}\n'.format(k, v)

        if self.attributes:
            printable_string += '\n{0!s:40}\n'.format('Settings')
            for k, v in self.attributes.items():
                printable_string += '  {0!s:<29}{1!s:<50}\n'.format(k, v)

        ########################################################
        return printable_string

################################################################################
####################


################################################################################
##############################

################################################################################
##############################
    # End of class

################################################################################
##############################

################################################################################
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####################
#-------------------------------------------------------------------------------
--------------------#
```

```
import os
import shutil

import sys
import zipfile
from pathlib import Path
import pandas as pd

from ncXarray import Reader
import netCDF4 as netcdf

from ncBase import Base
from ncConverter import NetCDFConverter

config = {}

def unzipModelData(pattern = "*.zip", **config):
    base = Base(**config)
    files = base.getListOfFiles(config['zip_dir'], pattern)
    print(f'Hi, {len(files)}')
    count = 0
    if files:
        for file in files:
            print('Zipped file {0}:'.format(file))
            count = count + 1
            if zipfile.is_zipfile(file):  # if it is a zipfile, extract file
                with zipfile.ZipFile(file) as zipObject: # treat the file as
a zip
                    listOfFileNames = zipObject.namelist()
                    for fileName in listOfFileNames:
                        if fileName.endswith('.nc'):
                            zipObject.extract(fileName,
config['unzipped_dir'])
                            print('NetCDF file: {0}'.format(file))
                            print('File count: {0}'.format(count))
                            print('All the netcdf files are extracted')
                    zipObject.close()

def moveModelData(pattern = "*.nc", **config):
    base = Base(**config)
    files = base.getListOfFiles(config['unzipped_dir'], pattern)
    for file in files:
        print('Moving file: {0}'.format(file))
        shutil.move(file, config['netcdf_dir'])

#########################################################################
def extractNetCDF_Data(element, pattern = "*.nc", **config):
    # Use a breakpoint in the code line below to debug your script.
    base = Base(**config)
    files = base.getListOfFiles(config['netcdf_dir'], pattern)
    sorted(files)
    count = 0

    for file in files:
        head, tail = os.path.split(file)
```

```
        data = netcdf.Dataset(file, 'r')
        times = data.variables['time']
        year = times.units[11:15]


    cities = pd.read_csv(config['city_csv'])
    for index, row in cities.iterrows():
        location = (row["City"])
        location_latitude = (row["Latitude"])
        location_longitude = (row["Longitude"])
        for file in files:
            # Reading-in the data
            data = netcdf.Dataset(file, 'r')
            time = data.variables['time']
            # Storing the lat and lon data of the netCDF file into variables
            lat = data.variables['lat'][:]
            lon = data.variables['lon'][:]

            # Squared difference between the specified lat,lon and the
lat,lon of the netCDF
            sq_diff_lat = (lat - location_latitude) ** 2
            sq_diff_lon = (lon - location_longitude) ** 2

            # Identify the index of the min value for lat and lon
            min_index_lat = sq_diff_lat.argmin()
            min_index_lon = sq_diff_lon.argmin()
            # Accessing the average temparature data
            times = data.variables['time']
            head, tail = os.path.split(file)
            exists = os.path.exists(file)

            # Creating the date range for each year during each iteration
            jd = netcdf.num2date(times[:], times.units)
            if exists and "historical" in file:
                dates = pd.date_range(start=config['startDate'],
end=config['endDate'], freq="D")
                count = count + 1
            else:
                dates = pd.date_range(start=config['startDate'],
end=config['endDate'], freq="D")
                variables = set(data.variables.keys())
                dimensions = set(data.dimensions.keys())
                keys = tuple(variables - dimensions)

                time_size = data.dimensions['time'].size
                start_time = data['time'][0]
                stop_time = data['time'][-1]
                time_range = stop_time - start_time
                delta_time = time_range / (time_size - 1)


########################################################################
def dfToExcel(df, filepath, sep=","):
    if not os.path.isfile(filepath):
        # Create a Pandas Excel writer using XlsxWriter as the engine.
```

```
        writer = pd.ExcelWriter(filepath, engine='xlsxwriter')
        # Convert the dataframe to an XlsxWriter Excel object.
        df.to_excel(writer, sheet_name='Sheet1')
    elif len(df.columns) != len(pd.read_excel(filepath, nrows=1,
sep=sep).columns):
        raise Exception(
            "Columns do not match!! Dataframe has " + str(len(df.columns)) +
" columns. Excel file has " + str(
                len(pd.read_excel(filepath, nrows=1, sep=sep).columns)) + "
columns.")
    elif not (df.columns == pd.read_excel(filepath, nrows=1,
sep=sep).columns).all():
        raise Exception("Columns and column order of dataframe and csv file
do not match!!")
    else:
        df.to_excel(filepath, mode='a', index=False, sep=sep, header=False)
    ###

#########################################################################
def dfToCSV(df, csvFilePath, sep=",", columns=None):
    if not os.path.isfile(csvFilePath):
        df.to_csv(csvFilePath, mode='w', index=False, sep=sep)
    elif len(df.columns) != len(pd.read_csv(csvFilePath, nrows=1,
sep=sep).columns):
        raise Exception(
            "Columns do not match!! Dataframe has " + str(len(df.columns)) +
" columns. CSV file has " + str(
                len(pd.read_csv(csvFilePath, nrows=1, sep=sep).columns)) + "
columns.")
    elif not (df.columns == pd.read_csv(csvFilePath, nrows=1,
sep=sep).columns).all():
        raise Exception("Columns and column order of dataframe and csv file
do not match!!")
    else:
        df.to_csv(csvFilePath, mode='a', index=False, sep=sep, header=False)

#########################################################################
def extractNetCDF_XR(element, model, pattern = "*.nc", **config):
    # Defining the names, lat, lon for the locations of your interest into a
csv file
    # this will read the file locations
    locations = pd.read_csv(config['city_csv'])
    print(locations)
    # Loop through locations acquiring all the information one by one from
the rows
    for index, row in locations.iterrows():
        # one by one we will extract the information from the csv and put it
into temp. variables
        station = (row["ICAO"])
        block = (row["WMO"])
        location = (row["City"])
        location_latitude = (row["Latitude"])
        location_longitude = (row["Longitude"])
        city ={
            'station': station,
```

```
            'blckNo': block,
            'location': location,
            'latitude': location_latitude,
            'longitude': location_longitude
        }

        nc = NetCDFConverter(**config)
        files = nc.getListOfFiles(config['netcdf_dir'], pattern)
        sorted(files)

        if files:
            for file in files:
                df = None
                column_names = None
                mode = 'r'
                filename = Path(file)
                csv_file = filename.with_suffix('.csv')
                head, tail = os.path.split(csv_file)
                sep = ','

                ###############################
                csv_file = os.path.join(config['csv_dir'], station + '_' +
tail)
                df, column_names = nc.processFile(file, model, mode, **city)
                if config['debug']:
                    print('-----------------------------------------------------
----')

                    print('CSV tail: {0}'.format(tail))
                    print('CSV file: {0}'.format(csv_file))
                    print()
                ###############################
                nc.dfToCSV(df, csv_file, sep, column_names)
    ###################################################

def netcdfReader_XR(element, model, pattern = "*.nc", **config):
    ########################################
    base = Base(**config)
    pattern = "tasmax*historical*.nc"
    files = base.getListOfFiles(config['netcdf_dir'], pattern)
    sorted(files)
    ########################################
    # Defining the names, lat, lon for the locations of your interest into a
csv file
    # this will read the file locations
    locations = pd.read_csv(config['city_csv'])
    ########################################
    # Loop through locations acquiring all the information one by one from
the rows
    for index, row in locations.iterrows():
        location = (row["City"])
        location_latitude = (row["Latitude"])
        location_longitude = (row["Longitude"])
        date = "01/01/1970"
        for file in files:
            reader = Reader(file, **config)
```

```
            reader.selectLocation(location_latitude, location_longitude)
            reader.selectTime(date)
            reader.test()

    ########################################
    if config['debug']:
        #print(time)
        print("Files: {0}".format(len(files)))
        print("Config: {0}".format(reader))

########################################################################
def writeToExcelByPandas(excel_file_path, data_frame, index=False,
sheet_name='Sheet 1'):
    excel_writer = pd.ExcelWriter(excel_file_path, engine='xlsxwriter')
    data_frame.to_excel(excel_writer, index=index, sheet_name=sheet_name)
    excel_writer.save()
    print(excel_file_path + ' has been created.')

########################################################################
def readCsvByPandas(csv_file, sep=','):
    data_frame = None
    if (os.path.exists(csv_file)):
        data_frame = pd.read_csv(csv_file, sep=',')
        print("------------------data frame all----------------------")
        print(data_frame)
    else:
        print(csv_file + " do not exist.")

    return data_frame

########################################################################
def readExcelByPandas(file, sheet=None, startrow=0 , startcol=0):
    df = pd.DataFrame()
    if (os.path.exists(file)):
        if file.endswith('.xlsx'):
            #df.append(pd.read_excel(file), sheet_name=sheet,
startrow=startrow , startcol=startcol, ignore_index=True)
            all_dfs = pd.read_excel(file, sheet_name = sheet)
            print("------------------data frame all----------------------")
            print(all_dfs)

    else:
        print(file + " do not exist.")

    return df

########################################################################
def mergeCSV(**config ):

    locations = pd.read_csv(config['city_csv'])

    for element in config['elements']:
        print('Element: {0}'.format(element))
        merge_csv_file = None
        for model in config['models']:
```

```
            print('Model: {0}'.format(model))
            for experiment in config['experiments']:
                all_df = []
                print('Experiment: {0}'.format(experiment))
                merged_df = None
                merge_csv_file = None
                csv_pat = "*{0}*{1}*{2}*.csv".format(element, model,
experiment)

                base = Base(**config)
                files = base.getListOfFiles(config['csv_dir'], csv_pat)
                if files:
                    for file in files:
                        df = pd.read_csv(file, sep=',')
                        head, tail = os.path.split(file)
                        # df['file'] = file.split('/')[-1]
                        df['ICAO'] = tail.split('_')[0]
                        df['Model'] = model
                        df['Experiment'] = experiment
                        # df['File'] = tail
                        all_df.append(df)

                    filename = element + '_' + model + '_' + experiment + '_'
+ "merged.csv"
                    merge_csv_file = os.path.join(config['csv_dir'],
'merged', filename)
                    merged_df = pd.concat(all_df, ignore_index=True,
sort=True)
                    merged_df.to_csv(merge_csv_file)

                    if config['debug']:
                        print('---------------------------------------------
--------')
                        print('Merged csv filename:
{0}'.format(merge_csv_file))
                        print('Merged df: {0}'.format(merged_df))
                all_df = []
                merge_csv_file = None
                merged_df = None

    ###############

##########################################################################
def mergeCsvToExcel(**config ):

    locations = pd.read_csv(config['city_csv'])

    for element in config['elements']:
        print('Element: {0}'.format(element))
        merge_excel_file = None
        for model in config['models']:
            print('Model: {0}'.format(model))
            for experiment in config['experiments']:
                all_df = []
                print('Experiment: {0}'.format(experiment))
```

```
                merged_df = None
                merge_excel_file = None
                csv_pat = "*{0}*{1}*{2}*.csv".format(element, model,
experiment)

                base = Base(**config)
                files = base.getListOfFiles(config['csv_dir'], csv_pat)
                if files:
                    for file in files:
                        df = readCsvByPandas(file, sep=',')
                        head, tail = os.path.split(file)
                        # df['file'] = file.split('/')[-1]
                        df['ICAO'] = tail.split('_')[0]
                        df['Model'] = model
                        df['Experiment'] = experiment
                        #df['File'] = tail
                        all_df.append(df)
                    filename = "element + '_' + model + '_' + experiment +
'_' + merged.xlsx".format(element, model, experiment, config['xls_pattern'])
                    filename = "{0}_{1}_{2}_merged{3}".format(element, model,
experiment, config['xls_pattern'])
                    merge_excel_file = os.path.join(config['excel_dir'],
'merged', filename)
                    merged_df = pd.concat(all_df, ignore_index=True,
sort=True)
                    writeToExcelByPandas(merge_excel_file, merged_df)

                if config['debug']:
                    print('---------------------------------------------------
----')
                    print('Merged csv filename:
{0}'.format(merge_excel_file))
                    print('Merged df: {0}'.format(merged_df))
                all_df = []
                merge_excel_file = None
                merged_df = None

    ###############

def mergeExcelCombine(**config):
    for element in config['elements']:
        print('Element: {0}'.format(element))
        merge_excel_file = None
        for model in config['models']:
            print('Model: {0}'.format(model))
            for experiment in config['experiments']:
                dflist = []
                sheets = []
                xls_pat = "*{0}*{1}*merged{2}".format(model, experiment,
config['xls_pattern']) #
                filename = "{0}_{1}{2}".format(model, experiment,
config['xls_pattern'])
                excel_file = os.path.join(config['excel_dir'], 'combine',
filename)
                writer = pd.ExcelWriter(excel_file, engine='xlsxwriter')
```

```
                base = Base(**config)
                files = base.getListOfFiles(config['excel_dir'], xls_pat)
                all_df = pd.DataFrame()
                if files:
                    for file in files:
                        head, tail = os.path.split(file)
                        sheet = (tail.split('_')[0])

                        df = pd.read_excel(file, 'Sheet 1')
                        df.to_excel(writer, sheet_name=sheet, startrow=0 ,
startcol=0)

                    #####
                    writer.save()
                print('DF List: {0}'.format(dflist))
                dflist = []
                sheets = []


    #writer.save()

##########################################################################
def process(**config ):
    print('processing')
    for element in config['elements']:
        for model in config['models']:
            zip_pat = "*{0}*{1}*.zip".format(element,model)
            zip_pat = "*.zip".format(element,model)
            unzipModelData(zip_pat, **config)
            nc_pat = "*.nc".format(element, model)
            moveModelData(nc_pat, **config)

            nc_pat = "*{0}*{1}*.nc".format(element, model)
            extractNetCDF_XR(element, model, nc_pat, **config)

    mergeCSV(**config)
    mergeCsvToExcel(**config)
    mergeExcelCombine(**config)

##########################################################################
def main():
    import platform
    if platform.system() == "Windows":
        root = "C:\\"
    elif platform.system() == "Linux":
        root = os.path.expanduser("~")
    else:
        root = ""
        print("Sorry, we don't currently have support for the " +
sys.platform + "OS")
    print("Main")

    bhs_location = ["MYGF", "MYNN", "MYAM", "MYAF", "MYLD", "MYRD", "MYEG",
"MYIG", "MYSM", "MYCB"]
    elements = ["tasmax", "tasmin", "pr"]
```

```
    models = ["BCC-CSM2-MR", "CNRM-CM6-1", "CNRM-ESM2-1", "CanESM5", "GFDL-
ESM4", "IPSL-CM6A-LR",
              "MIROC-ES2L", "MIROC6", "MRI-ESM2-0"]
    experiments = ['historical', 'ssp126', 'SSP2-4.5', 'SSP3-7.0', 'SSP5-
8.5']
    config = {
        'report': os.path.join(os.path.curdir, "report.txt"),
        'folderclimatedata': os.path.join(root, "ClimatData"),
        'netcdf_dir': os.path.join(root, "ClimatData", "Future", "netcdf"),
        'tiff_dir': os.path.join(root, "ClimatData", "Future", "GeoTiff"),
        'excel_dir': os.path.join(root, "ClimatData", "Future", "excel"),
        'csv_dir': os.path.join(root, "ClimatData", "Future", "csv"),
        'city_csv': os.path.join(root, "ClimatData", "Future", "csv",
"cities.csv"),
        'zip_dir': os.path.join(root, "ClimatData", "Future", "zipped"),
        'unzip_dir': os.path.join(root, "ClimatData", "Future", "unzipped"),
        'temp_dir': os.path.join(root, "ClimatData", "Future", "temp"),
        'test_csv_file': os.path.join(root, "ClimatData", "Future", "csv",
                                      "tasmax_Amon_GISS-E2-1-
G_ssp460_r1i1p1f2_gn_20150116-21001216_v20200115.csv"),
        'test_nc_file': os.path.join(root, "ClimatData", "Future", "netcdf",
                                     "tasmax_Amon_GISS-E2-1-
G_ssp460_r1i1p1f2_gn_20150116-21001216_v20200115.nc"),
        'xls_pattern': ".xlsx",
        'nc_pattern': "tasmax*.nc*",
        'file_report': "report.txt",
        'startDate': "1/1/1971",
        'endDate': "12/31/2020",
        'freq': "M",
        'location': bhs_location,
        'elements': elements,
        'models': models,
        'experiments': experiments,
        'debug': True
    }
    process(**config)


    if config['debug']:
        print(config)

    ##############################################################
#########################################################################

#########################################################################
# Press the green button in the gutter to run the script.
if __name__ == '__main__':
    #print_hi('PyCharm')

    try:
        print("Processsing main")
        main()
    except Exception:
        print(" ")
    finally:
```

```
    print('\nPress any key to exit')
##########################################################################
```

10 APPENDIX III – NEAR AND LONG-TERM SEASONS.

Figure 7-1: BCC SSP1-2.6 Near Term Winter Rainfall (38.31 – 337.81mm)

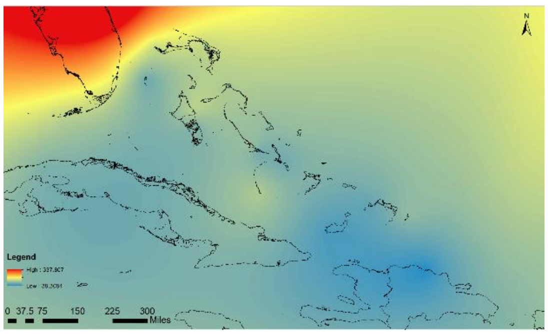

Figure 7-2: BCC SSP2-4.5 Near Term Winter Rainfall (26.15 – 138.29mm)

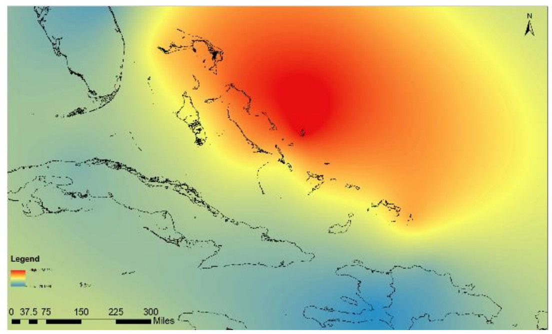

Figure 7-3: BCC SSP3-7.0 Near Term Winter Rainfall (15.39 – 128.81mm)

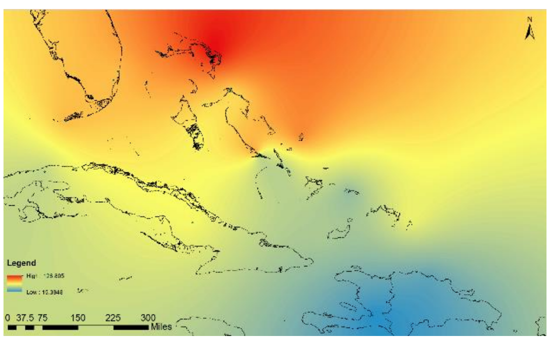

Figure 7-4: BCC SSP5-8.5 Near Term Winter Rainfall (23.78 – 147.14mm)

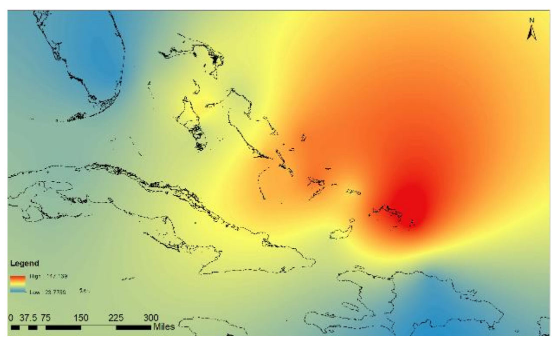

Figure 7-5: BCC SSP1-2.6 Near Term Spring Rainfall (5.15 – 214.08mm)

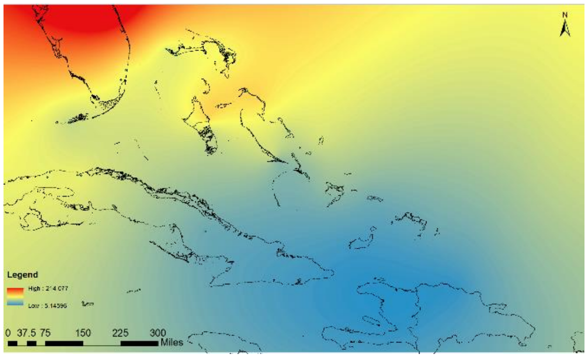

Figure 7-6: BCC SSP2-4.5 Near Term Spring Rainfall (26.16 – 138.29mm)

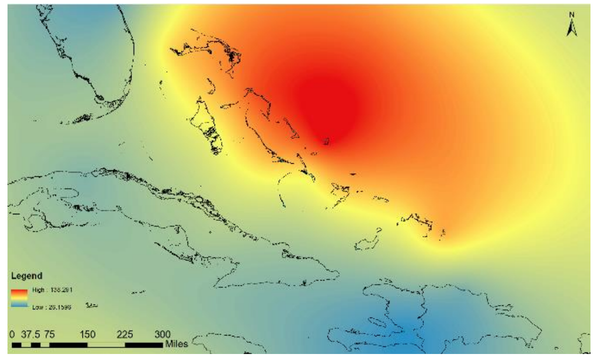

Figure 7-7: BCC SSP3-7.0 Near Term Spring Rainfall (12.82 – 51.11mm)

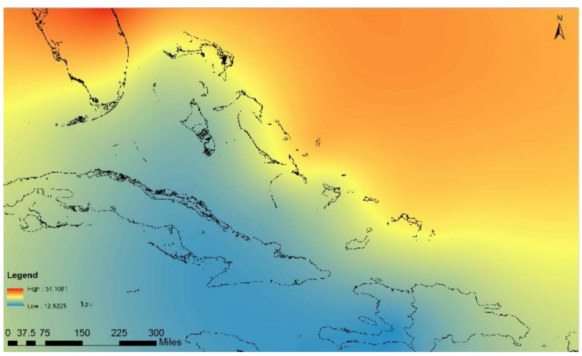

Figure 7-8: BCC SSP5-8.5 Near Term Spring Rainfall (5.11 – 72.61mm)

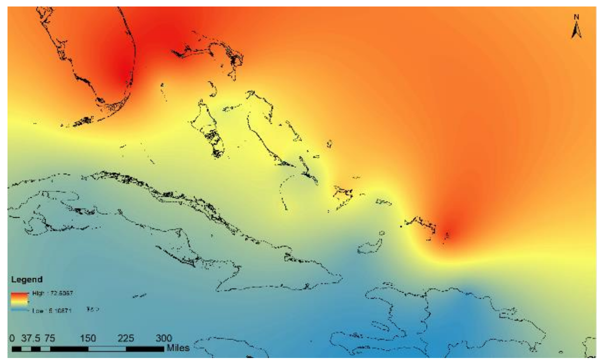

Figure 7-9: BCC SSP1-2.6 Near Term Summer Rainfall (34.04 – 204.30mm)

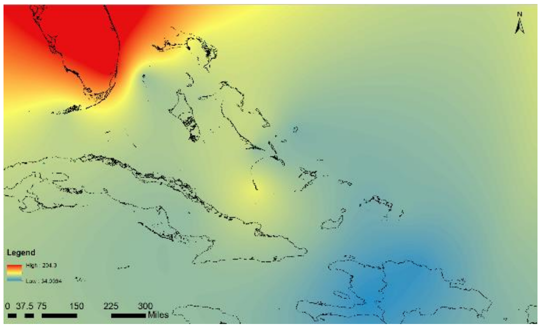

Figure 7-10: BCC SSP2-4.5 Near Term Summer Rainfall (13.26 – 103.24mm)

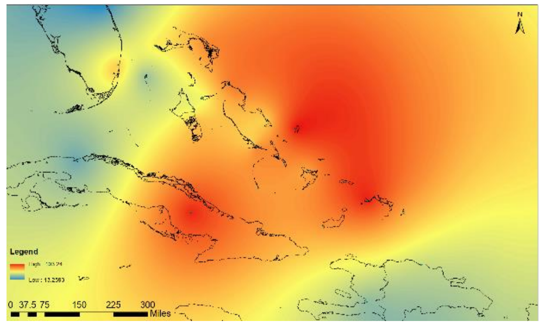

Figure 7-11: BCC SSP3-7.0 Near Term Summer Rainfall (33.61 – 72.51mm)

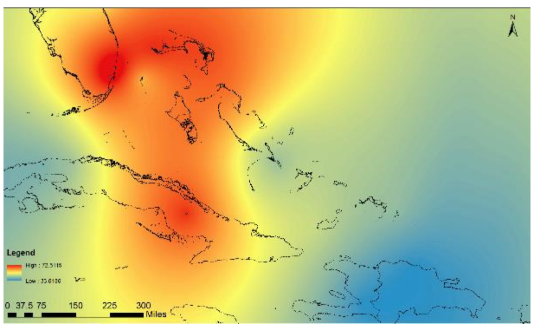

Figure 7-12: BCC SSP5-8.5 Near Term Summer Rainfall (17.30 – 87.18mm)

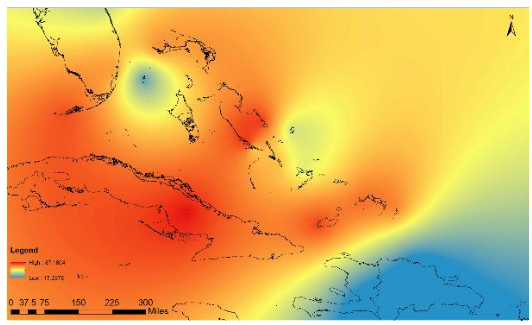

Figure 7-13: BCC SSP1-2.6 Near Term Autumn Rainfall (38.31 – 337.81mm)

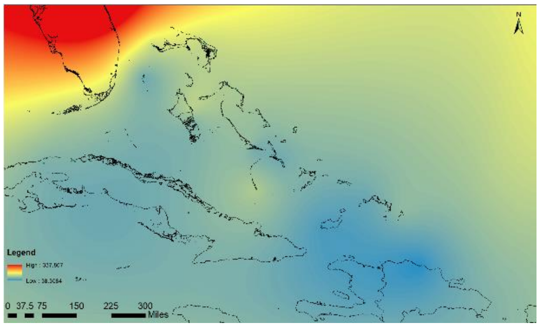

Figure 7-14: BCC SSP2-4.5 Near Term Autumn Rainfall (63.85 – 228.71mm)

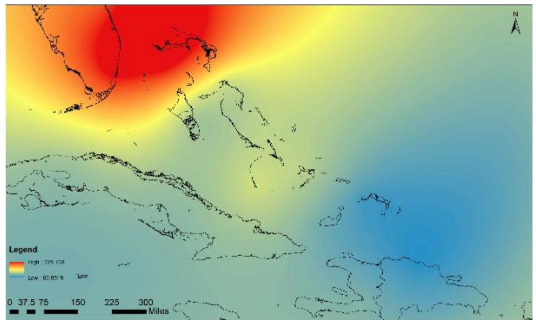

Figure 7-15: BCC SSP3-7.0 Near Term Autumn Rainfall (50.05 – 135.79mm)

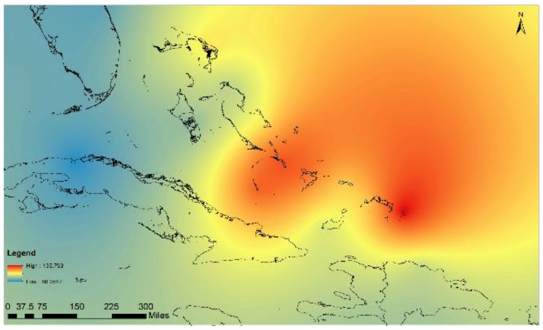

Figure 7-16: BCC SSP5-8.5 Near Term Autumn Rainfall (51.65 – 286.63mm)

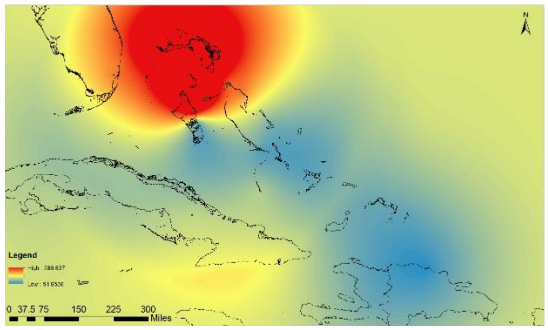

Figure 7-17: BCC SSP1-2.6 Long Term Winter Rainfall (16.15 – 93.97mm)

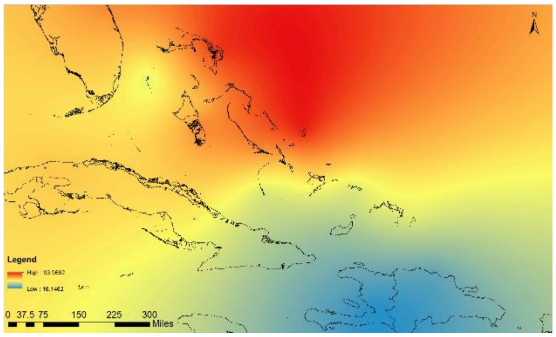

Figure 7-18: BCC SSP2-4.5 Long Term Winter Rainfall (14.37 – 116.72mm)

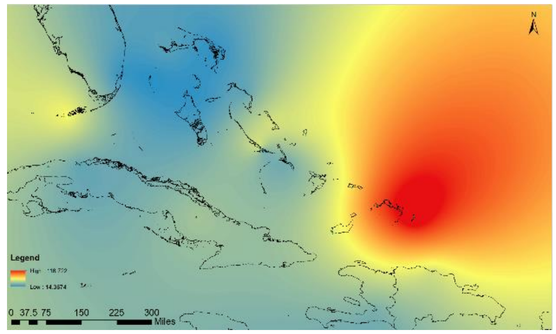

Figure 7-19: BCC SSP3-7.0 Long Term Winter Rainfall (3.21 – 162.74mm)

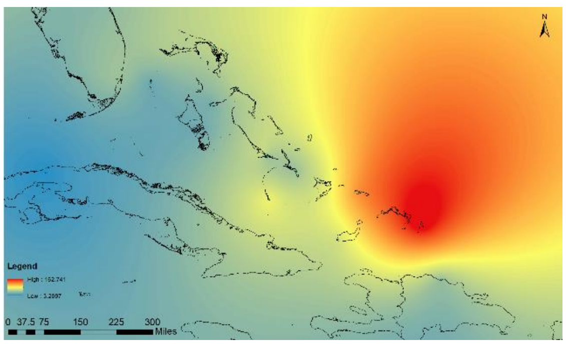

Figure 7-20: BCC SSP5-8.5 Long Term Winter Rainfall (10.27 – 231.24mm)

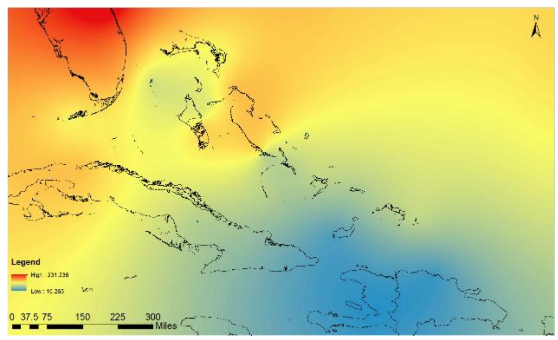

Figure 7-21: BCC SSP1-2.6 Long Term Spring Rainfall (12.89 – 94.31mm)

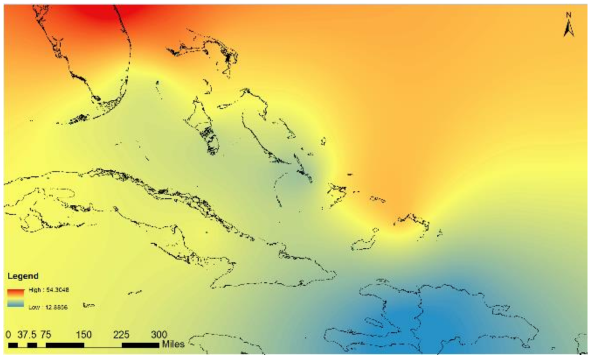

Figure 7-22: BCC SSP2-4.5 Long Term Spring Rainfall (9.63 – 55.45mm)

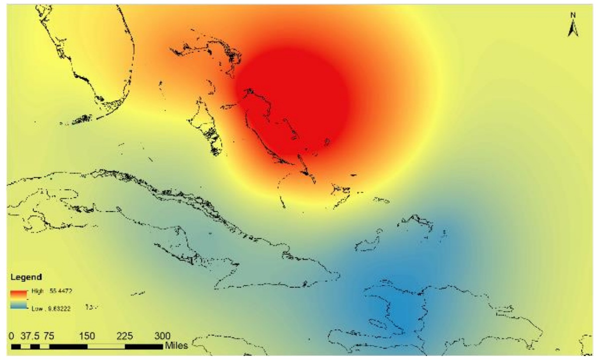

Figure 7-23: BCC SSP3-7.0 Long Term Spring Rainfall (34.11 – 67.30mm)

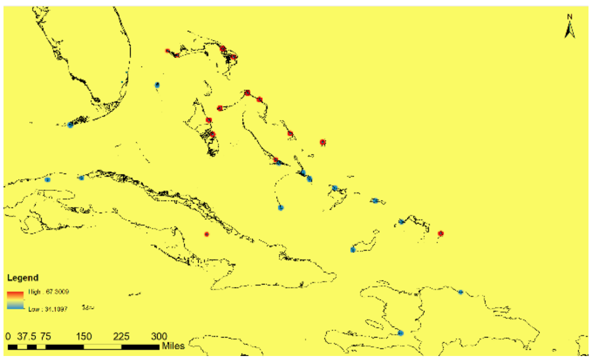

Figure 7-24: BCC SSP5-8.5 Long Term Spring Rainfall (14.40 – 82.71mm)

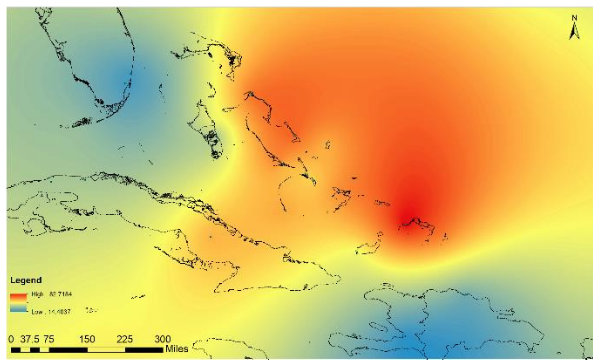

Figure 7-25: BCC SSP1-2.6 Long Term Summer Rainfall (54.27 – 62.73mm)

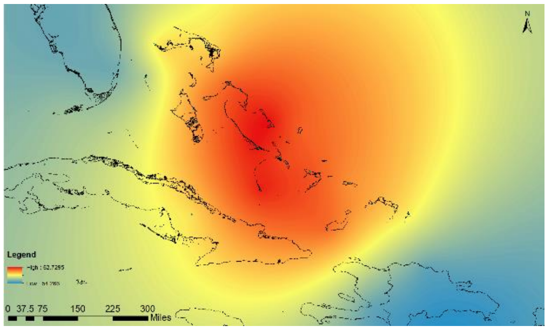

Figure 7-26: BCC SSP2-4.5 Long Term Summer Rainfall (16.60 – 74.61mm)

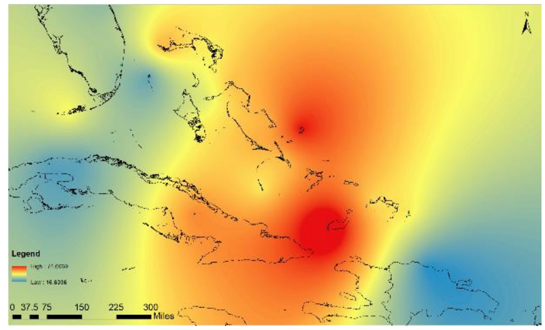

Figure 7-27: BCC SSP3-7.0 Long Term Summer Rainfall (20.48 – 78.50mm)

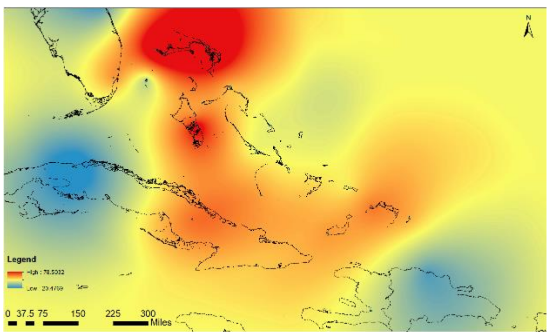

Figure 7-28: BCC SSP5-8.5 Long Term Summer Rainfall (21.81 – 103.50mm)

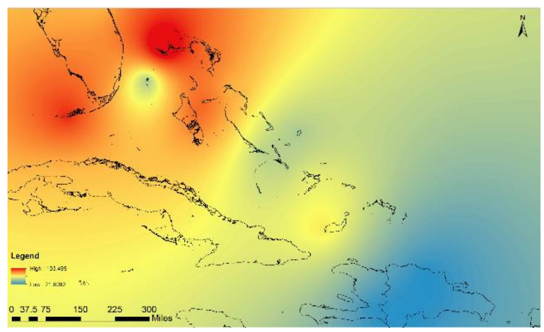

Figure 7-29: BCC SSP1-2.6 Long Term Autumn Rainfall (87.96 – 90.86mm)

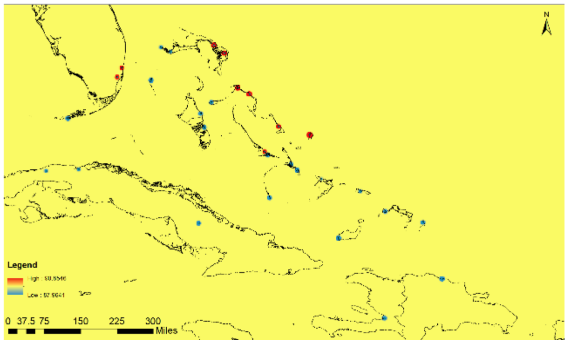

Figure 7-30: BCC SSP2-4.5 Long Term Autumn Rainfall (50.87 – 347.68mm)

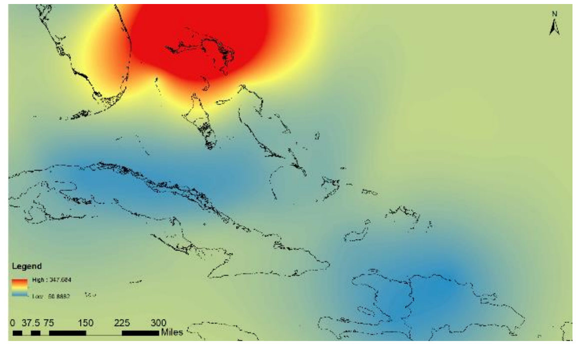

Figure 7-31: BCC SSP3-7.0 Long Term Autumn Rainfall (28.89 – 91.76mm)

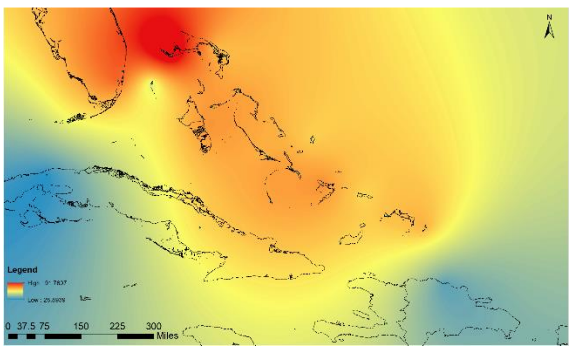

Figure 7-32: BCC SSP5-8.5 Long Term Autumn Rainfall (29.62 – 74.79mm)