ABSTRACT

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Effective planning and management of forests in a changing climate requires valid and robust predictions of future climate change that are context-specific since climate changes vary by region. Climate models are often used to predict future trends in temperature and precipitation at the global level, but are most useful if downscaled to predict change at regional levels. Monthly temperature and precipitation were predicted using three downscaled regional climate models for the 1990s and the 2050s. Comparison of the 1990's predictions to weather station data from across Maryland indicated inherent model biases affecting accurate predictions, which were used to adjust the model-projected climate variables for the 2050s. The projected daily temperatures were also used to calculate projected growing degree days and frost days. The degree of climate change in Maryland projected by these regional models for the next half-century would have profound impacts on forests across Maryland.

DOWNSCALED CLIMATE CHANGE FORECASTING AND MARYLAND'S FORESTS

By

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Dedication

For my parents, Sandra and Jeffrey Juchs, who supported me through this difficult yet rewarding journey.

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Chapter 1: Introduction and Background

Rationale

With a scientific consensus that anthropogenic climate change is a reality, current research is focusing on predicting what climate changes can be expected and when these changes will occur. While the effects of climate change are global in scale, the type and intensity of impacts is expected to vary between regions (Miles et al., 2006). Thus, climate predictions at the regional level are necessary to provide the information and knowledge needed for adaptation and decision-making, which allows societies to prepare for the impacts of a changing climate.

Predictive climate models are important tools used to determine future trends in temperature and precipitation possible at the global level, but the changes expected at the regional level are more difficult to decipher. To simulate regional changes scientists often downscale models by zooming in on global models to a finer resolution. This improvement in resolution often exacerbates any inherent weaknesses in the model and can lead to compounded errors at the regional level (Schiermeier, 2010). Determining which regional models can correctly simulate local climate is the first step towards providing relevant information to inform real-world decisions (Stainforth et al., 2007b).

Accurate prediction is becoming increasingly important for anticipating the impact of climate change on certain species and the subsequent management and perpetuation of these species. Since climate is a primary force directing the biogeography of plant species, changes in the climate are expected to cause changes in the geographic distributions of plant species (Dullinger et al., 2004; McKenney et al., 2007). Being able to predict the changes in plants at the species and community level due to climate change would be extremely useful for managing vegetative areas for the future. In order to choose the best management strategies for dealing with climate change, it is necessary to have accurate models that take into account regional as well as global differences.

Climate Change Forecasting Models

The ongoing increases of anthropogenic greenhouse gas (GHG) emissions that are leading to substantial changes to the climate over the next decades and centuries have prompted many attempts to estimate or forecast the future climate. Climate modeling has been in development since the 1960s and continues to become more sophisticated, addressing many questions about Earth's complex climate system and attempting to understand how it may change in the future. The origins of climate modeling and forecasting are rooted in the desire to predict weather. Typically, weather forecasting has focused on forecasting conditions within the time scale of a few days. However, predicting the climate requires forecasting for much longer periods of time to assess the frequency and variability of weather events and evaluate how these events may change over time (Climate Change Science, 2008). Climate models are also constrained by certain factors that are not imposed on weather forecast models. Dealing with patterns over long periods of time, climate models must reproduce a climate system that maintains the Earth's overall energy budget. The difference between absorbed solar energy and emitted infrared radiation is influenced by a number of factors, including anthropogenic sources of greenhouse gas emissions, and can change over time with any imbalance resulting in a temperature change. To predict the future climate effectively, models must be capable of simulating the changes that will result from the natural and human-induced changes to the Earth's energy budget.

Current models rely on quantitative methods to investigate changes in the global energy balance and simulate the interactions and dynamics of the climate. Global climate models (GCMs) use computer-based numerical techniques to solve mathematical equations that represent components of the climate system. Using the best current understanding of climate processes, climate models typically include representations of four main climate components: the atmosphere, ocean, cryosphere, and land surface. Simulations of these components are based on physical laws that include the conservation of mass, energy, and momentum as well as observation data (Climate Change Science, 2008).

GCMs use a three dimensional grid over the Earth to depict the climate. The spatial resolution of this grid varies between models but the horizontal dimensions are rectangular with length and width typically ranging between 250 and 600km (For context, Maryland is 163 by 400 km). The grids usually contain 10 to 20 vertical layers of the atmosphere, and up to 30 layers in the oceans simulated. The models compute the processes occurring at each grid cell for a determined time interval. This is repeated and sped-up to simulate the climate in the future (Climate Change Science, 2008).

While the coarse resolution of a GCM is useful for looking at large-scale patterns and making global predictions, it isn't sufficient for predicting changes at the regional or local level. Certain physical processes that occur at a small scale are not able to be accurately modeled with GCMs, with their influence diminished by being averaged over the larger scale (RÄIsÄNen, 2007; Schiermeier, 2010). To project at a smaller scale, regional climate models (RCMs) are often nested within the global climate models. Spatial downscaling lets a modeler derive finer resolution data from the coarse scale of a GCM. Typically, the same equations used for the GCM are used for the RCM; they are just solved for a larger number of grid cells (Schiermeier, 2010). However, processes of local climate such as vegetation or topography are often not included in GCMs. The development of nested RCMs, which creates a statistical relationship between its local scale and the GCMs' large-scale, is able to include some of these processes implicitly through the increased resolution (Climate Change Science, 2008; Laprise et al., 2003).

To cut down on computational intensity and allow for models to be run at high resolutions, many global and regional climate models are run as time-slice experiments where only two slices of time are simulated instead of a continuous period. Typically, one slice represents the recent past or current period and one slice is for some future period of time. In time-slice experiments the coupled ocean model is typically omitted from the GCM which significantly decreases the computational requirements. Instead, observational data provides the historical boundary conditions for sea surface and ice while scenario data is derived by lower-resolution runs of the full GCM, projecting changes based on expected future conditions (NARCCAP, 2007).

To be able to make predictions about the future climate, some assumptions must be made about how socio-economic and biophysical conditions will develop in the future. Since GHG emissions are the primary driver of anthropogenic climate change, predicting future GHG emissions is essential for climate modeling. With the uncertainty surrounding the future, scientists develop scenarios that provide alternative images of the future depending on potential demographic development, socio-economic development, and technological change. Since it is unlikely that one particular emissions path will occur as described, it is necessary to explore the different ways these drivers of GHG emissions may change in the future. The Intergovernmental Panel on Climate Change (IPCC) produced a Special Report on Emissions Scenarios (SRES) that outlined four scenario families (A1, A2, B1, and B2) that create storylines that are possible in the future. The A1 scenario family is characterized by rapid economic development and population growth that peaks in 2050 with 9 billion people and gradually declines. This scenario also predicts a spread of new and efficient technologies but projects the most aggressive temperature changes with an average increase between 1.4° and 6.4°C expected by the end of the century. In contrast, the A2 family depicts a more divided world with increasing population growth but economic development and technological changes that will vary by region leading to a slightly lower average temperature increase than the A1 scenarios. The B1 scenario family predicts a world that is more integrated and also more ecologically conscious. It depicts rapid economic growth with global solutions to social and environmental issues and projects between a 1.1° and 2.9°C increase by 2100. Combining elements from both the A2 and B1 scenario families the B2 scenario family expects a world that is divided but environmentally friendly with local solutions to issues and fragmented technological change. This scenario corresponds to a temperature increase ranging from 1.4°-3.8° C (IPCC, 2007).

Many climate models for the future use one or more of these established scenarios as drivers of forecasted climate change (IPCC, 2007). If only one scenario is used for a particular climate model, typically a scenario at the higher end of the emissions spectrum is chosen due to several factors. From a management perspective, planning to adapt to a larger climate change ensures that adaptation measures will be applicable even if the change that occurs is smaller than expected. Additionally, the current trajectory of emissions is in line with higher emissions scenarios(NARCCAP, 2007).

Creating models that predict an uncertain future while also simulating interactions and processes that may not be entirely understood make climate change modeling inherently problematic (RÄIsÄNen, 2007). While at some point in the future there might be convergence on a single climate model, until that time, the focus will remain on advancing knowledge of the climate system through multiple modeling approaches. Different expertise and interests have led to a multitude of choices for development teams producing climate models (Climate Change Science, 2008).

Weather Research Forecasting Model

Many climate models have been developed as extensions of common weather forecasting models. One such model is the Weather Research Forecasting (WRF) model, which was created through a partnership among the National Center for

Atmospheric Research (NCAR), a consortium of government agencies, and the research community (CIRUN, 2011; WRF, 2011). The WRF model is a community weather prediction system where data is provided freely to the public for both operational forecasting research and atmospheric research (WRF, 2011). WRF has been used for a variety of applications including air-quality research, storm modeling, and regional climate modeling. The model can be run at a large range of resolutions and with a number of different input parameters depending on user needs (Darren J. Kerbyson, 2007).

One of WRF's many applications is as the atmospheric component of the Chesapeake Bay Forecast System (CBFS) developed by the University of Maryland and the Earth System Science Interdisciplinary Center (ESSIC). The CBFS is a prediction tool that will, "provide customizable, user-specified forecasts showing multiple aspects of the region's climate, air and water quality, local chemistry and ecosystems months into the future"(CIRUN, 2011). The CBFS uses the predictive capabilities of three models: WRF; the Soil and Water Assessment Tool (SWAT); and the Regional Ocean Modeling System (ROMS) to forecast the Chesapeake Bay watershed's current condition as well as changes that may occur under specific land-use, climate, development, and demographic scenarios (CIRUN, 2011).

As part of this initiative to use high-resolution weather forecasts for future forest management I obtained unpublished results of a WRF model and analogous data generated from the Canadian Regional Climate Model (CRCM) and Hadley Regional Model 3 (HRM3) models from John Strack (ESSIC). The WRF model version 3.0 was used to downscale coarse resolution (2.5 degree) climate projections from the Geophysical Fluid Dynamic Laboratory (GFDL) CM2.1 Global Climate Model. Two 10-year time-slices were downscaled for the 1990s and 2050s.A "Climate of the 20th Century" run was completed for 1990-1999 which simulated an emission scenario for the past and a future time-slice for 2050-2059 using the SRES A2 emission scenario. The A2 scenario depicts a heterogeneous world with high population growth, slow economic development and slow technological change which corresponds to an estimated increase of 3.4°C (with a likely range of 2.0°-5.4°C) by 2090-2099 from the temperatures of 1980-1999 (IPCC, 2007).

Along with sea surface temperatures, the outer grid's (96km) lateral boundaries were updated every six hours with the GFDL CM2.1 predicted temperatures, winds, pressure, and relative humidity. This allowed for large-scale storms systems generated by the GFLD CM2.1 to move through the downscaled grids making WRF's large-scale weather patterns similar to the GCM predictions. However, the finer scale of the WRF model allows for more accurate and complete simulations of the local terrain, land cover, and land-sea boundary effects than the global model.

Canadian Regional Climate Model

In addition to development from weather forecasting models, some regional models are developed as part of collaborative efforts to predict the future climate at a regional level. The North American Regional Climate Change Assessment Program (NARCCAP) is an international program that produces high-resolution climate change simulations over North America for use in impact studies while attempting to investigate the uncertainties at such a fine scale (Mearns, 2007).

One of these models that NARCCAP ran simulations on is the Canadian Regional Climate Model . The CRCM was originally developed as a limited-area model at the Université du Québec à Montréal for independent model runs. However, for the NARCCAP simulations, the CRCM is nested within the third version of the Coupled Global Climate Model (CGCM3) developed by the Canadian Centre for Climate Modeling and Analysis (NARCCAP, 2007; Plummer et al., 2006).

The CGCM3 global climate model was run to downscale the CRCM to a 50-km resolution. The lateral boundaries of the CRCM were updated every six hours with the CGCM3-predicted pressure, temperature, water vapor and horizontal wind as well as the interpolated surface fields like vegetation and topography (Laprise et al., 2003; NARCCAP, 2007).

For the NARCCAP, the CRCM was run for two different time-slices. The current period was defined as 1971-2000 and the future period was 2041-2070. For my research, I utilized the CRCM downscaled data on temperature and precipitation for the current period of 1990-1999 and the future period of 2050-2059. These two subsets of the original model time-slices and the SRES A2 emissions scenario were chosen to match those for the WRF model.

Hadley Regional Model 3

Another model simulation produced by NARCCAP was the downscaling of the Hadley Regional Model 3 from a custom run of the global climate model Hadley Centre Coupled Model, version 3 (HADCM3) (Mearns, 2007).

The HRM3 was developed at the Hadley Centre at the UK Met office as was its parent model the HADCM3. For the NARCCAP simulations the HRM3 is nested within the HADCM3 to downscale to a 50-km resolution. Like the CRCM, the lateral boundaries of the HRM3 were updated every six hours with the HADCM3-predicted changes to the atmosphere, ocean, ice sheet and land surface components (NARCCAP, 2007; Pope et al., 2007).The time-slices and the emissions scenario for the subset of CRCM data were identical to those chosen for the WRF model and CRCM data subsets.

Model Comparisons

Although almost all GCMs use the same dynamical equations to simulate the various climate components, different models use different numerical algorithms to solve these equations. Even models that use the same algorithms can differ in spatial resolution and the placement and shape of the model's grid cells, which can lead to different projections (Climate Change Science, 2008). Thus, the output values from the WRF, CRCM, and HRM3 could vary due to differences in their underlying algorithms and grid configuration. Also, the difference in grid size between WRF (8km) versus CRCM and HRM3 (50km) could contribute to additional differences between model predictions.

Due to the inability of one model to fully describe the climate system, many applications use a suite of multiple models, which provide a range of projected change to reduce the uncertainties associated with individual models and, are considered to be more useful in the long run than individual predictions for changes in temperature and precipitation (Climate Change Science, 2008).

Climate Variability in Maryland

The state of Maryland is comprised of a diverse landscape that is often classified in three physiographic regions: the Coastal Plain, the Piedmont plateau and the Appalachian Plateau (which includes the Valley and Ridge region). The climates of these regions differ in seasonal temperature and precipitation ranges and each region is subject to variable site-specific environmental events. For example, hurricanes and tropical storms occur in the Coastal Plain region, but rarely affect the Appalachian Plateau (Boesch, 2008). The unique geology, dominant vegetation types and substantially different extent of urban development also distinguish these three regions and will undoubtedly influence how each region will be affected by climate change.

While Maryland's regions differ in their mean seasonal temperature ranges, they experienced similar increases in the mean annual temperature from 1977 to 1999. During this time period, the number of days of extreme high temperatures (in excess of 32.2°C) has also risen and is expected to double by the end of the century. While temperatures are known to be increasing, no trend has emerged suggesting the impact of climate change on Maryland's precipitation, most likely due to Maryland's normally variable precipitation (Boesch, 2008).

Due to the computational intensity of running global models, regions the size of the state of Maryland are often represented with only a few grid cells. This results in models that overlook significant regional variation (Boesch, 2008). With a geographic area as climatically diverse as Maryland, downscaled, fine-resolution models are needed for local, state and regional environmental managers and government officials to address the realities of global warming at the local or regional levels.

Climate Change and its Impact on Vegetation

Human activities leading to a doubling of pre-industrial atmospheric carbon dioxide concentrations have contributed to a climate that is rapidly changing on the global scale (Woodall et al., 2009). Forest ecosystems are likely to be significantly affected by these persistent changes in temperature and precipitation in addition to alterations in disturbance regimes and other natural conditions. Being able to effectively predict the environmental changes that plants will be exposed to is needed to manage vegetative areas for the future and increasing forest resistance, resilience and adaptation to the changing climate (Evans and Perschel, 2009).

The scientific literature suggests that plant species may experience marked redistributions in response to climate change (McKenney et al., 2007). The habitat ranges of certain trees may shift to cope with a warming climate and some species may be driven to higher elevations. While the increasing temperature is expected to cause rapid changes in habitat suitability, the migration rates of long-lived tree species is predicted to be much slower (Evans and Perschel, 2009). Many plant species have migrated successfully in the past when subjected to climate change; however, it is unclear whether the projected future climate change will occur at a rate that will exceed a species' ability to migrate (Woodall et al., 2009). Climate change simulations run for the next 50 to 100 years suggest that the preferred range of many tree species could shift ranges an order of magnitude faster than the changes that occurred since the last glaciation period (Neilson et al., 2005). The quality and quantity of forest ecosystems has declined in the last decade (MEA, 2005). Forests are often fragmented, potentially reducing the ability of a species to migrate successfully and magnifying the negative impacts of climate change (Evans and Perschel, 2009; Woodall et al., 2009). It is predicted that most of the 7% to 11% of plant diversity projected to be lost if North America experiences a 3°C change will occur with rare species and those species with small geographic ranges (McKenney et al., 2007). Future development and land-use changes will likely exacerbate these range restrictions and become increasingly problematic for threatened or endangered species (Evans and Perschel, 2009).

In addition to the direct effects of temperature and precipitation changes on forest ecosystems, trees will be subject to a number of indirect impacts of climate change. These effects, which include changes to disturbance regimes and alterations of insect and disease dynamics, are thought to possibly be even more influential on species' future ranges than direct effects (Evans and Perschel, 2009). Changes in the climate at multiple scales are expected to affect the occurrence, timing, frequency, duration, extent and intensity of disturbances including hurricanes, ice storms, drought and fires. Disturbances can cause significant changes to forests by altering community structure or causing large-scale tree mortality (Dale et al., 2001).

Predicting the impact of climate change on forest structure and function is exceedingly complex and difficult. Invasive species pose one of the most serious threats to forest ecosystems and climate change is likely to exacerbate problems related to invasive species. Invasive plants tend to be site generalists with effective dispersal strategies and the ability to mature quickly. Thus, invasive plants would generally benefit from changes that cause range shifts of other species (Evans and Perschel, 2009) and alter forest diversity, succession and nutrient cycling as well as biotic interactions (Dale et al., 2001). However, the long-term consequences of climate change on the spread of invasive species are speculative, due in part to habitat requirements that are highly species-specific and difficult to generalize. For example, the effects of climate change and subsequent shifts in habitat will increase plant stress of certain species and alter their susceptibility to insects and pathogens. Concurrently, climate change will directly affect the survival of certain insects and pathogens, but whether the effect is favorable or not will again be species-dependent. However, disruptions to stable forest dynamics including existing food webs and predator-prey relationships will likely intensify the effects of insect and pathogen outbreaks (Dale et al., 2001; Evans and Perschel, 2009).

Other species-specific factors such as dispersal ability and genetic variability, as well as biotic interactions, will also be very influential in the future distributions of species under climate change (Iverson et al., 2008; McKenney et al., 2007). Current species associations are expected to change with an altered climate, as impacts will vary by region and location and species will be subject to differential effects (Iverson et al., 2008). The individualized responses to warming trends suggest that species will redistribute independently, which is expected to lead to the formation of new community types and novel habitats for new species migrating into an area (McKenney et al., 2007; Petit et al., 2008). To examine the potential changes in communities and associations, investigations at local and regional levels are necessary.

Research Objectives

The overall goals of my research were to assess the potential effectiveness of using downscaled regional climate models to accurately predict climate change and its impact on Maryland forests for the 2050's. The objectives set to achieve this goal included:1) Compare downscaled WRF, CRCM, and HRM3 climate model's predicted monthly temperature and precipitation for 1990-1999 for the three physiographic regions of Maryland to corresponding weather station observation data collected from 14 Maryland locations; 2) Evaluate the accuracy and biases of the downscaled models; 3) Use the results to generate projected monthly maximum and minimum temperatures and precipitation for winters and summers for the 2050's. 4) Use downscaled WRF model, CRCM, and HRM3 simulations to obtain projections for Maryland regions for growing degree days, frost days, and number of days over 32.2°C and over 37.8°C for the 2050s; and 5) Based on these research findings, assess the potential impacts of climate change on forests in Maryland, both within and across physiographic regions.

Chapter 2: Model Assessments

Introduction

Calibration and validation of climate change forecast models are among the greatest challenges confronting climate scientists. Given that we are facing a climate system that is without precedent, the reliability of long-term climate projections cannot be directly assessed. Unlike daily weather predictions based on short-term weather forecasting models that can be quickly verified against developing weather conditions, the evolution of climate change occurs over time scales that are too long for validation purposes (Stainforth et al., 2007a). Since there are no observed periods that are analogous with the climate change expected over the 21st century, a different approach to model verification is necessary (Climate Change Science, 2008; RÄIsÄNen, 2007). As a way of assessing model validity, climate models are evaluated for their ability to resemble the processes and behavior of the real climate system (RÄIsÄNen, 2007)

This validation approach uses historical weather observations to determine how closely future climate models mimic natural systems and serves as a baseline for comparisons with climate predictions for the future. Observation data from the past can be difficult to obtain but the National Climatic Data Center (NCDC) serves to provide climate data necessary for conducting studies on environmental issues. The NCDC archives weather data from satellites, radar, remote sensing, original records and a variety of other sources obtained by the National Weather Service, Military Services, Federal Aviation Administration, the Coast Guard, and voluntary cooperative observers for educational and research purposes (NCDC, 2011).

Running climate models to predict for the past allows for comparison of the model's predictions with the historic records over that time period to assess the model's accuracy. This step is especially important for regional models, as it is uncertain whether downscaled climate models can accurately predict the subtle differences in climate expected at the regional level. Failure of the model to reproduce the conditions present in the observation data is a way of identifying the model's inadequacies and limitations. The errors and biases inherent to the model can then be taken into account when using model predictions for the future (Stainforth et al., 2007a).

To provide reliable forecasts for the future, it must be demonstrated that regional models can accurately mimic the natural variability of a given areas (RÄIsÄNen, 2007). In the current study, temperatures and precipitation were generated by three downscaled regional climate change models for 1990-1999 to compare to corresponding historic weather records from locations across Maryland's physiographic regions. The physiographic regions of Maryland range seasonally in their temperatures and amount of precipitation and serve as an excellent model for evaluating the prediction accuracy of these regional climate models at a fine-scale. Weather records collected from 14 weather stations throughout Maryland provide the basis for comparisons between the observed and predicted values needed to assess model accuracy and potential validity for projecting future climate conditions.

Data Description and Analysis

Model Data

Monthly temperatures and precipitation were predicted using the WRF, CRCM, and HRM3 models for 1990-1999. For each regional climate model, three dependent variables (monthly average minimum temperature, monthly average maximum temperature, and monthly cumulative precipitation) were predicted for downscaled grids corresponding to 14 weather station locations across Maryland's physiographic regions. The grid with its center point nearest to each weather station location was selected as the model counterpoint. The grid resolution was 8km for the WRF model and 50 km for the CRCM and the HRM3. Each model generated 1680 predicted values (10 years x 12 months x 14 locations) for each three dependent variable (total N=15120). The high resolution, down-scaled weather predictions from a WRF model and analogous data generated from CRCM and HRM3 were provided by John Strack (ESSIC).

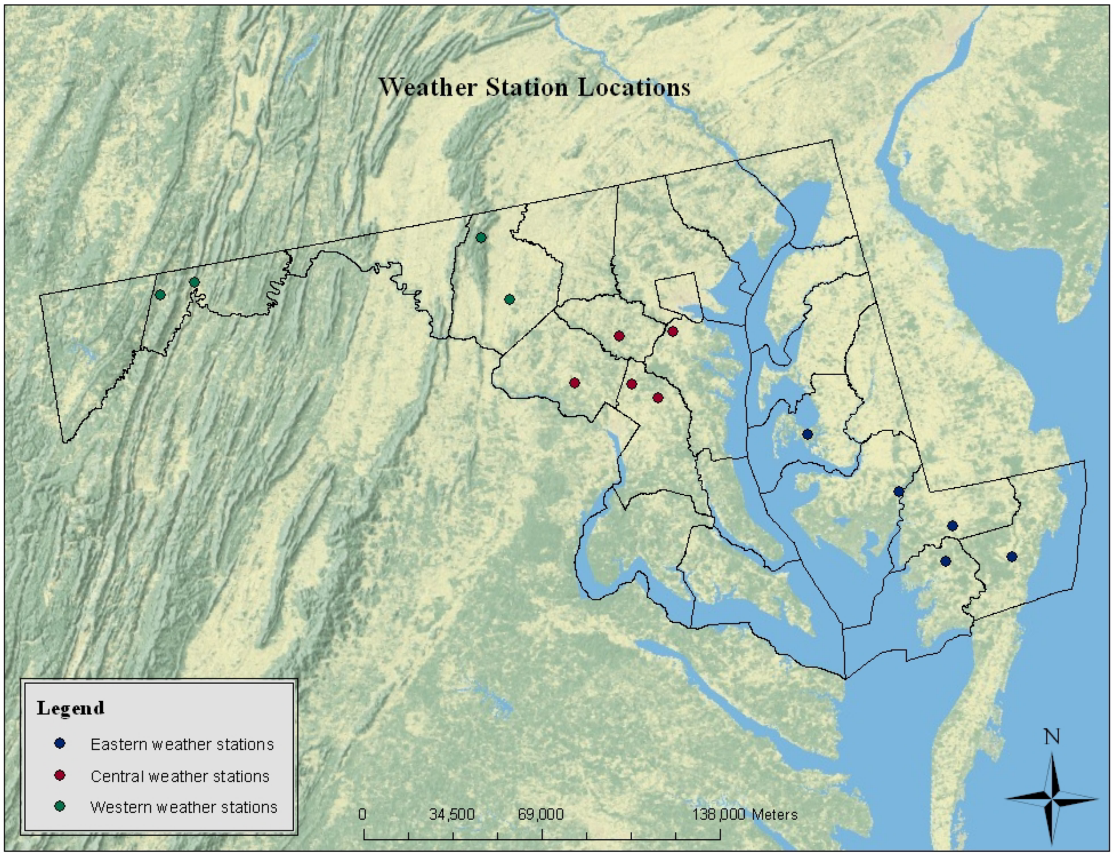
Observation Data

NCDC monthly summarized station and divisional data were obtained for 14 weather stations located across Maryland. Weather stations that had nearly complete records available for 1990-1999 were chosen from each of Maryland's physiographic regions (Table 2-1; Figure 2-1). There were five Eastern, five Central, and four Western locations chosen for analyses. The dependent variables (average monthly maximum temperature, average monthly minimum temperature, and total accumulated monthly precipitation) obtained for each weather station were the same as the dependent variables predicted using the regional climate models.

Table 2-1. Weather station locations used for observation data.

Stations by Region	**Abbreviation**	**Coordinates (Lat/ Long)**
EASTERN		
Princess Anne	PA	38°13'N / 75°41'W
Royal Oak 2 SSW	RO	38°43'N / 76°11' W
Salisbury	SA	38°22'N / 75°35'W
Snow Hill 4N	SH	38°14'N / 75°23'W
Vienna	VI	38°29'N / 75°49'W
CENTRAL		
Baltimore Washington International Airport	BA	39°10'N / 76°41'W
Beltsville	BE	39°02'N / 76°56'W
Clarksville 3 NNE	CL	39°15'N / 76°56'W
Glenn Dale Bell	GD	38°58'N / 76°48'W
Rockville 1 NE	RV	39°06'N / 77°09'W
WESTERN		
Catoctin Mountain Park	CT	39°39'N / 77°29'W
Cumberland 2	CU	39°39'N / 78°45'W
Frederick Police Barracks	FD	39°25'N / 77°26'W
Frostburg 2	FR	39°40'N / 78°56'W

Figure 2-1. Weather station locations by region.



Statistical Analysis

Analysis of variance (ANOVA) and planned mean comparisons (FLSD procedure) were used to assess each model's ability to accurately predict the climate from 1990-1999 in Maryland's different physiographic regions. The monthly dependent variables at each weather station were compared to the monthly model data associated with that weather station location. ANOVA's were conducted separately for each climate model and sources of variation were partitioned depending on hypotheses to be tested. For each climate model, ANOVA's were conducted separately by location, season, and region in order to fully understand the effects at different levels. Factors analyzed included years, months, seasons, regions, locations, treatments and their interactions. In all cases, years served as replications and treated as a random block effect in the analyses.

The tests of significance related to differences between treatments (observed vs. predicted) and the interaction of treatments with season and region were of primary interest, because they are directly related to model accuracy. Tests of significance and F-values are presented in tables to show the significance and magnitude of treatment-related effects. Statistical analyses were conducted using SAS version 9.2 (SAS Institute, Cary, NC, USA). ANOVA's were performed using PROC GLM and Type III sums of squares to adjust for unequal sample sizes. Using the results from the ANOVA's, means were compared with LSD values at the .05 level.

Initially, ANOVA's were conducted for each location to investigate whether the predicted values differed from the observed values at the local level. Since seasonal effects are very important to the impact of temperature and precipitation on forests, ANOVA's were then conducted by season. Winter months were December, January, and February; spring months were March, April, and May; summer months were June, July, and August; and fall months were September, October, and November.

Although the initial ANOVA's were useful in determining the significant differences due to location, an ANOVA was also conducted by region to test hypotheses of treatment differences within each of Maryland's physiographic regions.

Results

WRF Model

Analysis of Variance by Location

Analysis of variance was conducted to compare the WRF predictions to the observed data at each of 14 locations. F-values and significance differences ($p<0.05$) are presented as relative measures of differences due to selected sources of variation of most interest. The average monthly maximum temperatures were significantly different between treatments (suggested revision not applicable- just talking about WRF here not all three models) (observed vs. predicted) for all 14 locations (Table 2-2). As indicated by the F-values, there were large differences for average maximum temperatures between treatments, the largest occurred for Baltimore, Glenn Dale, and Royal Oak. In all the locations, except Princess Anne, there was a relatively small but significant month X treatment interaction. Most locations also showed small but statistically significant year X treatment interactions.

The significant differences between treatments for the average minimum temperatures (Table 2-3) were similar but smaller than the differences for the average maximum temperatures. Cumberland, Frederick, Glenn Dale, and Snow Hill showed the biggest differences between treatments. For all locations, except Catoctin, there was a significant month X treatment interaction that was small relative to treatment differences.

As would be expected, the monthly precipitation data were more variable than the temperature data. The coefficients of variation for precipitation ranged from 47% to 58%, compared to 3%-5% for maximum temperature and 4%-7% for minimum temperature. Treatment differences were significant for nine of the 14 locations, and Princess Anne, Salisbury, and Vienna showed the biggest differences (Table 2-4). Whereas temperature differences among months were obviously large, only Baltimore, Cumberland, Frostburg, and Glenn Dale showed significant differences due to month.

Table 2-2. F-Values from ANOVA comparing observed to WRF-predicted average monthly maximum temperatures.[1]

WRF Location F-Values for Maximum Temperatures

	Eastern					Central					Western			
	PA	**RO**	**SA**	**SH**	**VI**	**BA**	**BE**	**CL**	**GD**	**RV**	**CT**	**CU**	**FD**	**FR**
Year	2	5	4	4	3	4	6	5	3	4	4	3	3	4
Month	374	836	555	663	633	786	607	544	684	616	536	545	480	524
Trt	162	612	206	306	235	674	102	70	717	118	93	362	229	13
Month*Trt	2	17	3	18	3	22	5	6	16	10	6	2	4	3

Table 2-3. F-Values from ANOVA comparing observed to WRF-predicted average monthly minimum temperatures.[2]

WRF Location F-Values for Minimum Temperatures

	Eastern					Central					Western			
	PA	**RO**	**SA**	**SH**	**VI**	**BA**	**BE**	**CL**	**GD**	**RV**	**CT**	**CU**	**FD**	**FR**
Year	5	4	3	3	3	5	5	3	3	5	6	5	6	5
Month	288	772	474	583	455	782	449	432	562	526	383	477	443	410
Trt	8	13	30	346	5	20	12	10	176	30	80	119	202	5
Month*Trt	3	16	4	12	4	23	5	8	13	8	1	5	2	3

[1] Significant values (P<0.05) highlighted in yellow
[2] Significant values (P<0.05) highlighted in yellow

Table 2-4. F-Values from ANOVA comparing observed to WRF-predicted monthly total accumulated precipitation.[3]

WRF Location F-Values for Accumulated Precipitation

	Eastern					Central					Western			
	PA	**RO**	**SA**	**SH**	**VI**	**BA**	**BE**	**CL**	**GD**	**RV**	**CT**	**CU**	**FD**	**FR**
Year	<1	1	<1	<1	<1	<1	1	<1	1	<1	<1	<1	<1	<1
Month	<1	2	<1	2	1	2	1	1	2	2	<1	2	1	2
Trt	36	3	26	10	50	5	5	2	7	18	2	20	14	8
Month*Trt	<1	1	1	1	<1	2	<1	<1	<1	1	<1	<1	<1	<1

Analysis of Variance by Season

Since the impacts of temperature and precipitation on forests are very different between seasons, Analysis of variance was conducted separately for each season to compare the WRF predictions to the observed data. In general, the differences for spring and fall followed the same patterns but less marked than those shown for summer and winter and F-values are only shown for summer and winter seasons. The differences between the observed and WRF- predicted average monthly maximum temperatures were large and significant for both summer and winter. (Table 2-5). As expected, the maximum temperatures differed between regions. The effects of Trt X Region and Trt X Location (Region) were also significant, indicating that the accuracy of the WRF predictions varied by region. However, the differences related to region were much smaller than those due to treatment.

The differences for the average minimum temperatures were much smaller than the differences for the average maximum temperatures, with treatment not being significant for summer (Table 2-5). Regional effects were highly significant for summer and winter with a much smaller but still significant effect of locations within

[3] Significant values (P<0.05) highlighted in yellow

regions. Summer and winter exhibited similar significant differences for the interaction of treatment X region and treatment X location (region).

The precipitation data had a fairly consistent pattern across all four seasons with significant differences for year and treatment effects (Table 2-6; spring and fall not shown). Winter exhibited the biggest differences between the observed and predicted accumulated precipitation and for both summer and winter the effects of year and region were small but significant. The largest differences for year and the interaction of year X treatment were occurred for spring. Only summer showed slightly significant differences for the interaction of treatment X location (region).

Table 2-5. F-values from ANOVA comparing observed to WRF-predicted seasonal average maximum and monthly minimum temperatures.[4]

WRF Season F Values for Maximum and Minimum Temperatures

	Maximum Temperatures		**Minimum Temperatures**	
	Summer	**Winter**	**Summer**	**Winter**
Year	6	18	5	20
Region	32	328	233	290
Loc (Region)	32	10	18	16
Trt	1059	1321	<1	105
Trt*Region	39	11	46	44
Trt*Loc (Region)	36	5	11	12

[4] Significant values (P<0.05) highlighted in yellow

Table 2-6. F-values from ANOVA comparing observed to WRF-predicted seasonal total accumulated precipitation.[5]

WRF Season F Values for Accumulated Precipitation		
	Summer	**Winter**
Year	6	8
Region	4	7
Loc (Region)	3	<1
Trt	70	127
Trt*Region	2	3
Trt*Loc (Region)	3	<1

Analysis of Variation by Region

To investigate potential regional differences in model accuracy, WRF predictions were compared to the observed data for each physiographic region of Maryland. The average monthly maximum temperatures for summer were highly significantly different between treatments for all three regions. The magnitude of the difference between treatments for each region were Eastern> Central> Western (Table 2-7). The effects of locations and location X treatment interactions were highly significant for all three regions, indicating local differences even within a region.

Differences between the observed and WRF-predicted average summer minimum temperatures were much smaller than for summer maximum temperatures for the Eastern and Central regions. For the Western region, the treatment differences for summer minimum and maximum temperature were similar and much less than the differences found in the other regions (Table 2-8). Like the maximum temperatures, the average minimum temperatures were significant for the interaction of location X treatment.

[5] Significant values (P<0.05) highlighted in yellow

Winter maximum and minimum temperatures followed a slightly different pattern of significance than the summer temperatures (Table 2-9). For the winter maximum temperatures treatment was highly significant with the largest differences in the central region. Location X treatment interactions although significant in the eastern and western regions were small in relation to the treatment main effect.

The difference between the observed and predicted values for winter minimum temperatures varied greatly across the regions (Table 2-10). Only the central and western regions showed significant differences between treatments with the western region exhibiting the largest differences. The interactions of location X treatment were significant for all three physiographic regions.

The regional analyses of monthly precipitation showed significant differences between treatment effects for both summer and winter (Table 2-11). For the Eastern and Central regions, the difference between the observed and WRF-predicted precipitation was greater in the winter than the summer. Conversely, in the Western region, the difference between the observed and WRF-predicted precipitation was greater in the summer than the winter. The location X treatment interactions were not significant except for small differences in the summer for the eastern and central regions.

Table 2-7. F-values from ANOVA comparing observed to WRF-predicted average summer maximum temperatures by region.[6]

WRF Region F Values for Summer Maximum Temperatures

	Eastern	Central	Western
Year	9	4	4
Loc	106	74	54
Month	274	191	82
Trt	2174	1146	168
Loc*Trt	61	145	44
Month*Trt	12	13	<1

Table 2-8. F-values from ANOVA comparing observed to WRF-predicted average summer minimum temperatures by region.[7]

WRF Region F Values for Summer Minimum Temperatures

	Eastern	Central	Western
Year	5	7	7
Loc	54	51	92
Month	350	377	201
Trt	20	95	205
Loc*Trt	53	30	36
Month*Trt	21	19	<1

Table 2-9. F-values from ANOVA comparing observed to WRF-predicted average winter maximum temperatures by region.[8]

WRF Region F Values for Winter Maximum Temperatures

	Eastern	Central	Western
Year	8	10	7
Loc	13	10	18
Month	47	47	35
Trt	503	832	457
Loc*Trt	3	<1	15
Month*Trt	5	7	<1

6 Significant values (P<0.05) highlighted in yellow
7 Significant values (P<0.05) highlighted in yellow
8 Significant values (P<0.05) highlighted in yellow

Table 2-10. F-values from ANOVA comparing observed to WRF-predicted average winter minimum temperatures by region.[9]

WRF Region F Values for Winter Minimum Temperatures

	Eastern	Central	Western
Year	10	10	10
Loc	31	27	14
Month	55	72	47
Trt	1	20	189
Loc*Trt	23	28	5
Month*Trt	8	10	5

Table 2-11. F-values from ANOVA comparing observed to WRF-predicted seasonal total accumulated precipitation by region.[10]

WRF Region F Values Accumulated Precipitation

	Eastern		Central		Western	
	Summer	Winter	Summer	Winter	Summer	Winter
Year	4	4	3	4	2	3
Loc	3	<1	4	<1	<1	3
Month	6	14	5	23	<1	14
Trt	15	48	19	79	42	25
Loc*Trt	3	<1	4	<1	1	3
Month*Trt	2	5	<1	2	5	2

CRCM

Analysis of Variation by Location

The analysis of variance conducted to compare the CRCM predictions to the observed data for 14 locations, showed the average monthly maximum temperatures were significantly different between treatments (observed vs. predicted) for all the locations except Catoctin (Table 2-11). There were small differences for average monthly maximum temperatures between treatments, the largest occurred for

[9] Significant values (P<0.05) highlighted in yellow
[10] Significant values (P<0.05) highlighted in yellow

Clarksville, Cumberland, and Frederick. In all the locations, there was a relatively small but significant month X treatment interaction.

The significant differences for the average minimum temperatures (Table 2-12) were similar but larger than the differences for the average maximum temperatures for all locations except Clarksville and Glenn Dale. The biggest differences between treatments occurred with Frederick, Rockville, and Royal Oak. Only three of the locations showed a significant month X treatment interaction.

For the CRCM model the monthly precipitation data did not follow the patterns seen in the temperature data. The coefficients of variation for precipitation ranged from 42% to 53%, compared to 4%-6% for maximum temperature and 7%-9% for minimum temperature. Catoctin was the only location showing a significant difference in precipitation between treatments (Table 2-13). In contrast to the large differences among months seen with the maximum and minimum temperatures, differences in precipitation due to month were small or not significant. Seven locations had significant month X treatment interactions.

Table 2-12. F-Values from ANOVA comparing observed to CRCM-predicted monthly maximum temperature.[11]

CRCM Location F-Values for Maximum Temperature

	Eastern					**Central**					**Western**			
	PA	**RO**	**SA**	**SH**	**VI**	**BA**	**BE**	**CL**	**GD**	**RV**	**CT**	**CU**	**FD**	**FR**
Year	2	2	2	2	2	2	5	4	2	3	3	2	3	3
Month	350	619	568	582	617	625	447	413	497	567	532	512	457	498
Trt	15	11	14	15	19	26	21	30	22	7	1	51	27	9
Month*Trt	3	5	8	7	4	8	5	10	5	11	13	5	7	5

[11] Significant values (P<0.05) highlighted in yellow

Table 2-13. F-Values from ANOVA comparing observed to CRCM-predicted monthly minimum temperature.[12]

CRCM Location F-Values for Minimum Temperature

	Eastern					Central					Western			
	PA	RO	SA	SH	VI	BA	BE	CL	GD	RV	CT	CU	FD	FR
Year	3	2	2	1	3	2	4	2	1	3	3	2	4	2
Month	268	488	474	477	475	423	369	289	420	428	397	454	364	469
Trt	17	117	70	32	51	60	22	9	12	87	39	71	87	15
Month*Trt	1	1	<1	1	<1	1	1	2	<1	1	1	7	<1	4

Table 2-14. F-Values from ANOVA comparing observed to CRCM-predicted monthly total accumulated precipitation.[13]

CRCM Location F-Values for Accumulated Precipitation

	Eastern					Central					Western			
	PA	RO	SA	SH	VI	BA	BE	CL	GD	RV	CT	CU	FD	FR
Year	<1	<1	<1	<1	<1	1	1	1	<1	2	1	1	2	1
Month	2	2	2	2	2	3	2	2	2	2	1	2	3	3
Trt	<1	3	<1	<1	1	<1	2	<1	<1	<1	9	<1	<1	4
Month*Trt	2	3	2	2	1	4	3	2	3	3	2	1	2	1.2

Analysis of Variation by Season

For the CRCM model analyzed by season, the average monthly maximum and minimum temperatures were highly significantly different and similar differences between treatments (Table 2-15). For both the average maximum and minimum temperatures, the differences between treatments were larger for winter than for summer. Region exhibited a highly significant effect for both summer and winter. Although generally significant, other sources of variation were small relative to the main effects of region and treatment.

Precipitation, unlike maximum and minimum temperatures, was not significant different between the observed and predicted values for either summer or

[12] Significant values (P<0.05) highlighted in yellow
[13] Significant values (P<0.05) highlighted in yellow

winter. (Table 2-16). The only significant effects were year for both seasons and region for winter.

Table 2-15. F-values from ANOVA comparing observed to CRCM-predicted seasonal monthly maximum and monthly minimum temperatures.[14]

CRCM Season F Values for Maximum and Minimum Temperatures

	Maximum Temperatures		**Minimum Temperatures**	
	Summer	**Winter**	**Summer**	**Winter**
Year	8	19	3	19
Region	54	189	72	104
Loc (Region)	9	8	9	6
Trt	68	498	189	381
Trt*Region	4	7	<1	2
Trt*Loc (Region)	6	4	6	2

Table 2-16. F-values from ANOVA comparing observed to CRCM-predicted seasonal monthly total accumulated precipitation.[15]

CRCM Season F Values for Accumulated Precipitation

	Summer	**Winter**
Year	10	9
Region	2	7
Loc (Region)	<1	<1
Trt	<1	2
Trt*Region	2	<1
Trt*Loc (Region)	<1	<1

Analysis of Variation by Region

The CRCM model predictions for the average summer maximum and minimum temperatures differed significantly from the observed temperatures for all three regions and the location X treatment interactions were relatively small (Table 2-17, Table 2-18). In general, the difference between treatments was greater for the summer minimum temperatures than the summer maximum temperatures.

[14] Significant values (P<0.05) highlighted in yellow
[15] Significant values (P<0.05) highlighted in yellow

Similar to the summer temperatures, the winter maximum and minimum temperatures showed highly significant and relatively large differences between the observed and predicted values for all three regions (Table 2-19, Table 2-20) and treatment X location interactions were small or not significant.

The CRCM precipitation data did not show significant differences between treatments as found for the temperature data (Table 2-21).

Table 2-17. F-values from ANOVA comparing observed to CRCM-predicted average summer maximum temperatures by region.[16]

CRCM Region F Values for Summer Maximum Temperatures

	Eastern	Central	Western
Year	7	6	5
Loc	2	3	46
Month	157	129	91
Trt	41	23	73
Loc*Trt	<1	4	28
Month*Trt	11	8	7

Table 2-18. F-values from ANOVA comparing observed to CRCM-predicted average summer minimum temperatures by region.[17]

CRCM Region F Values for Summer Minimum Temperatures

	Eastern	Central	Western
Year	2	3	2
Loc	8	12	44
Month	185	175	129
Trt	139	165	131
Loc*Trt	11	14	16
Month*Trt	10	6	7

[16] Significant values (P<0.05) highlighted in yellow
[17] Significant values (P<0.05) highlighted in yellow

Table 2-19. F-values from ANOVA comparing observed to CRCM-predicted average winter maximum temperatures by region.[18]

CRCM Region F Values for Winter Maximum Temperatures

	Eastern	**Central**	**Western**
Year	8	8	7
Loc	4	11	18
Month	25	27	22
Trt	244	291	96
Loc*Trt	<1	2	14
Month*Trt	2	7	6

Table 2-20. F-values from ANOVA comparing observed to CRCM-predicted average winter minimum temperatures by region.[19]

CRCM Region F Values for Winter Minimum Temperatures

	Eastern	**Central**	**Western**
Year	9	11	7
Loc	1	1	21
Month	20	36	44
Trt	155	154	178
Loc*Trt	4	2	1
Month*Trt	2	7	12

Table 2-21. F-values from ANOVA comparing observed to CRCM-predicted seasonal total accumulated precipitation by region.[20]

CRCM Region F Values Accumulated Precipitation

	Eastern		**Central**		**Western**	
	Summer	Winter	Summer	Winter	Summer	Winter
Year	3	5	6	3	5	4
Loc	<1	<1	<1	<1	<1	<1
Month	<1	3	<1	10	3	5
Trt	<1	1	3	3	<1	<1
Loc*Trt	<1	<1	<1	<1	2	1
Month*Trt	12	1	12	2	3	2

18 Significant values (P<0.05) highlighted in yellow
19 Significant values (P<0.05) highlighted in yellow
20 Significant values (P<0.05) highlighted in yellow

HRM3

Analysis of Variation by Location

For the HRM3 model, the average monthly maximum temperatures were significantly different between treatments for all the locations except Catoctin (Table 2-21). Some locations showed large differences for average maximum temperature between treatments, the largest occurred for Salisbury and Snow Hill. In nine of the locations there was a relatively small but significant month X treatment interaction.

The significant differences at each location for the average minimum temperatures (Table 2-21) were similar in magnitude and relative rank to the differences for the average maximum temperatures. Cumberland, Frederick, Glenn Dale, and Snow Hill showed the biggest differences between treatments. For all locations, there was a significant month X treatment interaction. For the monthly precipitation data there were fewer patterns across all the locations than with the temperature data. The coefficient of variation for precipitation ranged from 47% to 64%, compared to 4%-6% for maximum temperature and 5%-7% for minimum temperature. Treatment differences were significant for seven of the 14 locations, and Frederick, Frostburg, and Rockville showed the biggest differences (Table 2-22). Whereas temperature differences among months were obviously large, only five locations, Frederick, Rockville, Royal Oak, Salisbury, and Vienna, showed significant differences due to month. Four locations showed small significant differences for month X treatment interactions.

Table 2-22. F-Values from ANOVA comparing observed to HRM3-predicted monthly maximum temperature.[21]

HRM3 Location F-Values for Maximum Temperature														
	Eastern					**Central**					**Western**			
	PA	**RO**	**SA**	**SH**	**VI**	**BA**	**BE**	**CL**	**GD**	**RV**	**CT**	**CU**	**FD**	**FR**
Year	2	3	5	5	4	4	4	5	4	3	3	3	4	5
Month	390	514	637	701	600	533	478	366	499	514	486	544	446	522
Trt	66	38	202	208	103	17	7	8	41	38	<1	28	73	68
Month*Trt	<1	2	5	5	1	2	3	2	2	2	2	1	1	3

Table 2-23. F-Values from ANOVA comparing observed to HRM3-predicted monthly minimum temperature.[22]

HRM3 Location F-Values for Minimum Temperature														
	Eastern					**Central**					**Western**			
	PA	**RO**	**SA**	**SH**	**VI**	**BA**	**BE**	**CL**	**GD**	**RV**	**CT**	**CU**	**FD**	**FR**
Year	4	4	3	3	3	4	3	3	3	4	5	4	5	4
Month	406	654	734	731	539	666	606	440	486	634	520	652	529	582
Trt	41	7	269	481	11	<1	5	31	25	24	<1	13	16	79
Month*Trt	4	6	3	4	4	4	4	6	3	4	4	5	4	5

Table 2-24. F-Values from ANOVA comparing observed to HRM3-predicted monthly total accumulated precipitation.[23]

HRM3 Location F-Values for Accumulated Precipitation														
	Eastern					**Central**					**Western**			
	PA	**RO**	**SA**	**SH**	**VI**	**BA**	**BE**	**CL**	**GD**	**RV**	**CT**	**CU**	**FD**	**FR**
Year	<1	1	<1	1	<1	1	1	1	1	1	<1	2	1	1
Month	2	2	2	2	3	2	1	<1	2	2	1	2	2	1
Trt	<1	<1	10	12	<1	<1	1	<1	4	42	20	<1	37	27
Month*Trt	2	2	2	2	3	1	2	1	1	2	2	<1	2	<1

Analysis of Variation by Season

The average monthly maximum temperatures were significantly different between the observed and predicted values (Table 2-25). These differences were large for summer and winter with relatively smaller but still significant differences for

[21] Significant values (P<0.05) highlighted in yellow
[22] Significant values (P<0.05) highlighted in yellow
[23] Significant values (P<0.05) highlighted in yellow

spring and fall (data not shown). The effect of region was highly significant for both summer and winter with winter showing large differences. Differences among locations (regions) were also significant yet smaller. Interactions for treatment X region and treatment X location (region) were significant but small except treatment X region in the summer.

The significant differences for the average minimum temperatures were similar but larger than the differences for the average maximum temperatures for most of the effects and interactions (Table 2-25). All seasons (including fall and spring) showed significant differences between the observed and predicted values of minimum temperature, with summer exhibiting the largest difference. There was a large significant regional effect for both summer and winter with much smaller differences for the locations within regions. Both seasons had significant treatment X region interactions as well as treatment X location (region) interactions.

The analysis of accumulated precipitation by season showed a large and significant difference between treatments in the summer and a much smaller significant difference in the winter (Table 2-26).

Table 2-25. F-values from ANOVA comparing observed to HRM3-predicted seasonal monthly maximum and monthly minimum temperatures.[24]

HRM3 Season F Values for Maximum and Minimum Temperatures

	Maximum Temperatures		Minimum Temperatures	
	Summer	**Winter**	**Summer**	**Winter**
Year	3	32	8	26
Region	40	165	164	236
Loc (Region)	19	7	12	14
Trt	78	166	366	17
Trt*Region	61	6	15	20
Trt*Loc (Region)	17	4	13	12

Table 2-26. F-values from ANOVA comparing observed to HRM3-predicted seasonal monthly total accumulated precipitation.[25]

HRM3 Season F Values for Accumulated Precipitation

	Summer	**Winter**
Year	12	9
Region	2	1
Loc (Region)	9	8
Trt	114	5
Trt*Region	<1	2
Trt*Loc (Region)	7	7

Analysis of Variance by Region

The HRM3 model predictions for the summer maximum and minimum temperatures were significantly different from the observed data for all three regions and the treatment differences were generally larger for the summer minimum temperatures, especially for the western region. For both summer minimum and maximum temperatures, the eastern region exhibited much larger treatment differences than the central and western regions (Table 2-27, Table 2-28). In the western region, the location X treatment interaction for summer minimum temperature was greater than the main effect of treatment, indicating the accuracy of

[24] Significant values (P<0.05) highlighted in yellow
[25] Significant values (P<0.05) highlighted in yellow

the HRM3 prediction differed among the locations within the western region. This was not the case for the summer maximum temperature.

For winter maximum and minimum temperatures, there were significant differences between the observed and predicted values for all three regions (Table 2-29, Table 2-30). The differences between treatments were greater for the winter maximum than minimum temperatures. Differences in the maximum temperatures were most pronounced for the eastern and central regions, whereas the differences in the minimum temperatures were largest in the central region.

For all three regions, the monthly total accumulated precipitation was highly variable in the significance of effects and interactions (Table 2-31). The eastern region showed differences between the observed and predicted precipitation and the effect of month for the summer season but not for winter. All of the effects and interactions for the central region were significantly different with the summer precipitation being highly significant for treatment. Like the eastern region, only summer precipitation was significantly different between treatments for the western region. Location effects and the interaction of location X treatment were also significant for both seasons.

Table 2-27. F-values from ANOVA comparing observed to HRM3-predicted average summer maximum temperatures by region.[26]

HRM3 Region F Values for Summer Maximum Temperatures

	Eastern	Central	Western
Year	4	2	1
Loc	65	18	35
Month	183	114	68
Trt	590	23	4
Loc*Trt	53	<1	49
Month*Trt	3	<1	<1

Table 2-28. F-values from ANOVA comparing observed to HRM3-predicted average summer minimum temperatures by region.[27]

HRM3 Region F Values for Summer Minimum Temperatures

	Eastern	Central	Western
Year	10	13	8
Loc	60	16	68
Month	385	354	254
Trt	992	285	241
Loc*Trt	55	39	46
Month*Trt	22	9	10

Table 2-29. F-values from ANOVA comparing observed to HRM3-predicted average winter maximum temperatures by region.[28]

HRM3 Region F Values for Winter Maximum Temperatures

	Eastern	Central	Western
Year	14	16	12
Loc	5	8	15
Month	39	44	35
Trt	134	99	20
Loc*Trt	2	<1	15
Month*Trt	4	3	2

[26] Significant values (P<0.05) highlighted in yellow
[27] Significant values (P<0.05) highlighted in yellow
[28] Significant values (P<0.05) highlighted in yellow

Table 2-30. F-values from ANOVA comparing observed to HRM3-predicted average winter minimum temperatures by region.[29]

HRM3 Region F Values for Winter Minimum Temperatures

	Eastern	Central	Western
Year	10	12	10
Loc	37	2	12
Month	37	38	32
Trt	10	37	25
Loc*Trt	28	6	7
Month*Trt	6	3	1

Table 2-31. F-values from ANOVA comparing observed to HRM3-predicted seasonal total accumulated precipitation by region.[30]

HRM3 Region F Values Accumulated Precipitation

	Eastern		Central		Western	
	Summer	Winter	Summer	Winter	Summer	Winter
Year	5	5	7	4	4	3
Loc	<1	6	8	4	24	16
Month	13	<1	8	6	6	3
Trt	36	<1	57	7	36	2
Loc*Trt	<1	4	8	5	19	15
Month*Trt	5	13	3	8	2	5

Comparisons of Means for Model Prediction Accuracy

To examine the predictive power of the WRF model, CRCM, and HRM3, the predicted average monthly maximum and minimum temperatures for summer and winter for 1990-1999 were compared to the observation means from that time period. All differences noted were significantly different according to an LSD value ($\alpha=0.05$). Means are presented and compared for each location within a region because location and location X treatment effects were usually significant in the

[29] Significant values ($P<0.05$) highlighted in yellow
[30] Significant values ($P<0.05$) highlighted in yellow

ANOVA's for each region. The location means are organized by region to facilitate comparisons between regionals.

For the 1990s WRF predictions, the average maximum summer temperature was underestimated for all of the Eastern locations, all Central region locations except for Rockville, and Cumberland and Frederick but not Catoctin or Frostburg within the Western region (Table 2-32). Although the difference between the predicted and observed means varied by location (Table 2-7), the average underestimation was 4.9°C, 4.5°C , and 2.4°C for the Eastern, Central, and Western regions, respectively (Figure 2-2) . The WRF model showed little variation in the predictions for each region with the model-simulated average summer maximum temperatures being fairly consistent across the state.

In contrast to the WRF averages, the CRCM average summer maximum temperature consistently slightly overestimated the observed values (Table 2-15, Table 2-32, Figure 2-2). For the CRCM overall average difference between the observed and predicted summer maximum temperatures was 1.3°C.

HRM3 underestimated the actual 1990s average summer maximum temperatures for the Eastern and Central locations (Table 2-25, Table 2-32, Figure 2-2). For the Western region, the direction of the deviations between observed and predicted varied by location. Catoctin and Frederick were in the same grid cell but the observed average summer maximum temperature was 4 degrees lower at Catoctin than Frederick. HRM3 underestimated the maximum summer temperature for Cumberland (1.0°C) but overestimated the maximum summer temperature for Frostburg (4°C).

As noted, it is common practice to use predictions from multiple models for climate analysis. Thus, the mean tables in this thesis include model means that are calculated as the average of the WRF, CRCM, and HRM3 predicted means. The model average calculated for each location underestimated the average summer maximum temperatures for all locations except Catoctin, Frostburg, and Rockville (Table 2-32). The average of the summer maximum temperatures predicted by the model average differed from the observation data by 0.1°-3.4°C.

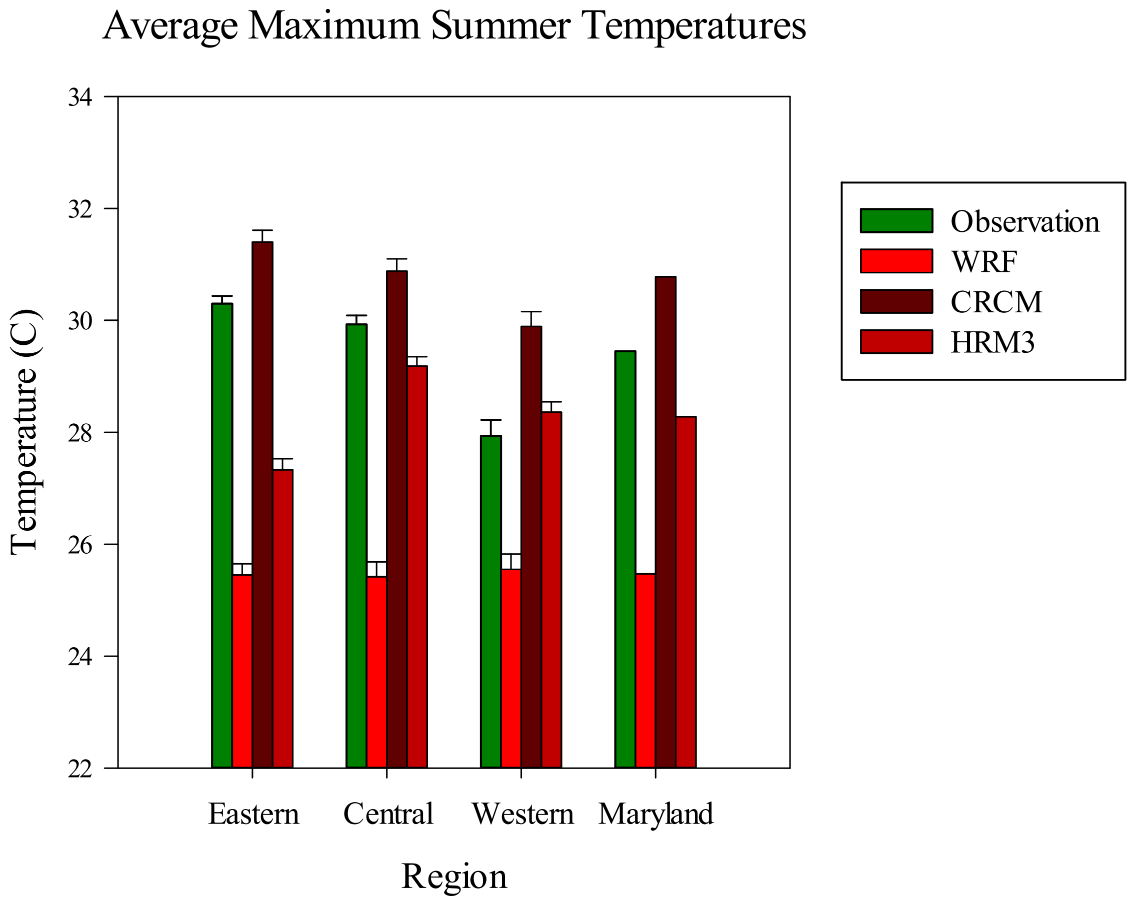
Looking at the statewide model means can determine whether the biases for each region average out to provide accurate predictions at the state level. For the statewide averages the individual model biases were still evident with the WRF model and HRM3 underestimating the statewide summer maximum temperatures and the CRCM overestimating the average observed values (Figure 2-2).

Table 2-32.Average summer maximum temperatures observed and predicted by WRF, CRCM, and HRM3, and model average for 1990-1999 for locations across Maryland.[31]

Average Summer Maximum Temperature (°C)					
EASTERN	**Observation**	**WRF**	**CRCM**	**HRM3**	**Model Average**
Princess Anne	30.4	26.9	31.5	28.4	28.9
Royal Oak	29.9	23.0	31.1	29.6	27.9
Salisbury	30.1	26.7	31.5	25.2	27.8
Snow Hill	30.1	23.4	31.5	25.2	26.7
Vienna	31.0	27.2	31.5	28.4	29.0
CENTRAL					
Baltimore	30.1	22.0	30.8	29.5	27.4
Beltsville	29.9	27.2	30.6	29.5	29.1
Clarksville	30.1	27.3	30.7	29.5	29.1
Glenn Dale	30.7	22.4	31.1	29.7	27.7
Rockville	28.9	28.2	31.1	27.6	29.0
WESTERN					
Catoctin	26.6	25.8	30.4	27.6	28.0
Cumberland	30.0	25.3	29.0	28.9	27.8
Frederick	30.2	25.9	31.1	27.6	28.2
Frostburg	25.0	25.2	29.0	29.2	27.8
LSD (Loc*Trt)		**0.86**	**1.18**	**0.92**	

[31] Significant model overestimations of the observed temperatures are highlighted pink, significant model underestimations are highlighted in blue, and model predictions that are not significantly different from the observed are highlighted green

Figure 2-2. Average summer maximum temperatures observed and predicted by WRF, CRCM, and HRM3, for 1990-1999 for Maryland and its regions.



Differences between the observed and WRF-predicted summer minimum temperatures were much smaller and did not show a consistent bias found for the summer maximum temperatures differences between treatments (Table 2-8, Table 2-33). The WRF model predicted minimum summer temperatures that were larger than the observed 1990's minimum temperatures for the Eastern and Central regions (Figure 2-4). However, in the Western region, the WRF model predicted minimum temperatures were less than the observed minimum temperatures.

For the CRCM, the predicted summer minimum temperatures tended to underestimate those observed (Table 2-8; Table 2-33, Figure 2-4). The CRCM predictions were significantly less than the observed means for ten out of 14 locations.

Conversely, the HRM3 predictions tended to overestimate the actual average summer minimum temperature (Table 2-25; Table 2-33, Figure 2-4). The HRM3 predicted summer minimum temperatures higher than those observed at 12 out of 14 locations. Some of the locations within a region were in the same grid (Salisbury, Snow Hill; Baltimore, Beltsville, Clarksville; Catoctin, Frederick). This was also true for CRCM but for different locations. This did not occur with the WRF predictions, which were downscaled to 8 km grids.

In general, the model predictions for summer minimum temperatures were more accurate than the predicted summer maximum temperatures and the deviation from the observed averages was the smallest (ranging from 0.3°-2.3°C) when using the model averages.

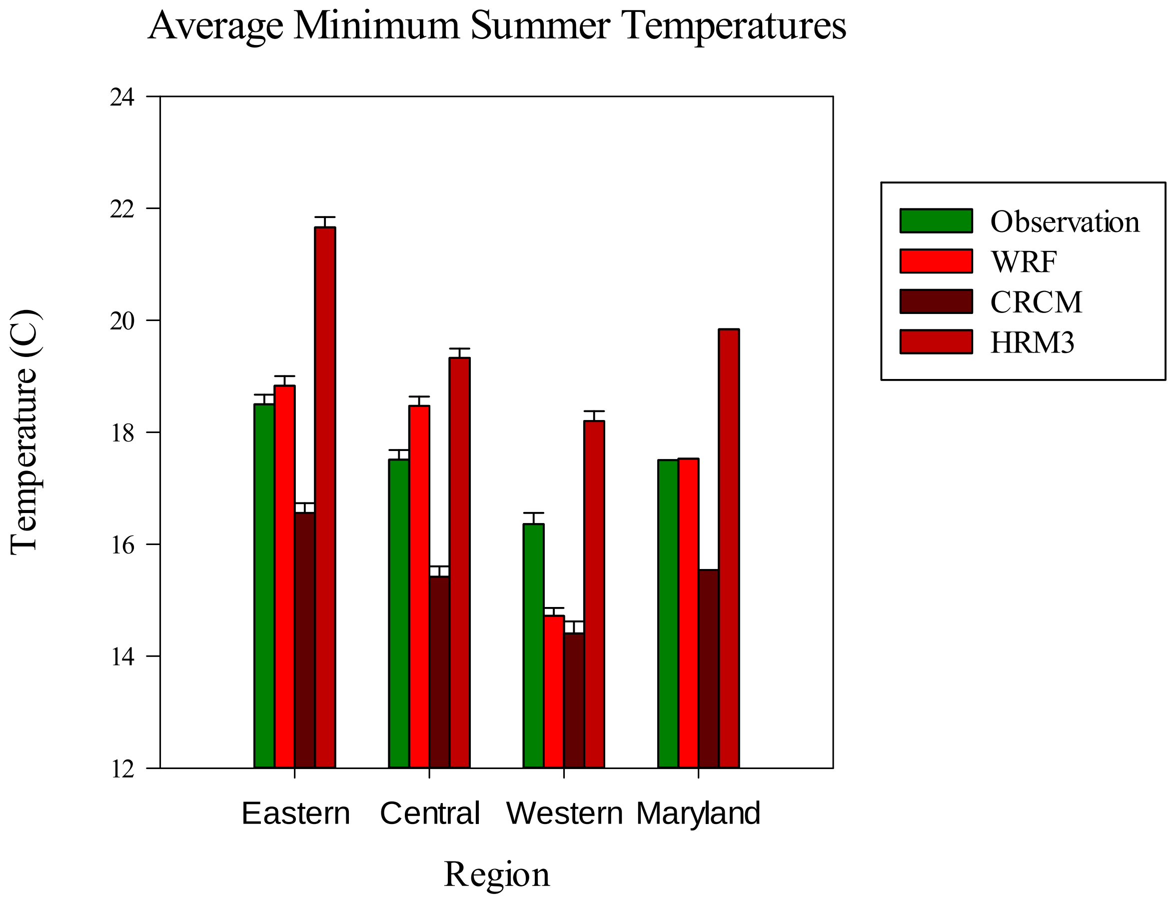
For the statewide averages, the variation in the WRF bias across region averaged out across the state making the WRF statewide prediction of average minimum summer temperatures very close to the actual statewide average for this measure (Figure 2-4). The consistent underestimating of the CRCM and the overestimating of the HRM3 led to statewide averages that varied considerably from the observed average for minimum summer temperature.

Table 2-33. Average summer minimum temperatures observed and predicted by WRF, CRCM, and HRM3, and model average for 1990-1999 for locations across Maryland.[32]

Average Summer Minimum Temperature (°C)					
EASTERN	**Observation**	**WRF**	**CRCM**	**HRM3**	**Model Average**
Princess Anne	16.6	18.0	16.6	20.8	18.5
Royal Oak	19.4	19.7	16.3	20.4	18.8
Salisbury	19.2	17.9	16.6	23.2	19.3
Snow Hill	17.9	20.8	16.6	23.2	20.2
Vienna	18.6	17.6	16.6	20.8	18.3
CENTRAL					
Baltimore	18.3	19.1	15.0	19.5	17.9
Beltsville	17.7	17.1	15.6	19.5	17.4
Clarksville	15.5	17.9	15.0	19.5	17.5
Glenn Dale	17.0	19.4	16.3	20.0	18.6
Rockville	18.5	18.8	15.2	18.3	17.5
WESTERN					
Catoctin	16.8	14.8	14.3	18.3	15.8
Cumberland	16.1	14.6	14.1	18.2	15.6
Frederick	18.4	15.2	15.2	18.3	16.3
Frostburg	14.2	14.2	14.1	17.9	15.4
LSD (Loc*Trt)		**0.89**	**1.06**	**0.94**	

32 Significant model overestimations of the observed temperatures are highlighted pink, significant model underestimations are highlighted in blue, and model predictions that are not significantly different from the observed are highlighted green

Figure 2-4. Average summer minimum temperatures observed and predicted by WRF, CRCM, and HRM3, for 1990-1999 for Maryland and its regions.



All the models across all the regions seemed to predict average winter maximum temperatures that were much less than the actual maximum temperatures experienced for 1990-1999 (Figure 2-5). The difference between the WRF-predicted average winter maximum temperatures and the observed winter maximum temperatures was significant for all locations (Table 2-34). The range of deviation between the observed and predicted temperatures was 3.1°-7.6°C which is larger than the deviation seen for the summer minimum temperatures.

Just like the WRF predictions, the average winter maximum temperatures from CRCM underestimated the observed data for all three regions and for every location except Frostburg, which slightly overestimated the actual maximum temperatures (Figure 2-5, Table 2-34). The model-generated average maximum temperatures were 0.2°-5.3°C off from the observed data over the same period of time.

The HRM3 data followed a pattern similar to the WRF and CRCM data with every location, except Frostburg, showing average winter maximum temperatures that were less than the observed averages for the 1990s (Table 2-34). Only Catoctin and Frostburg had average maximum temperatures where a significant difference between observed and predicted values could not be concluded. For all the other locations the predicted temperature was significantly different from the observed temperature though the HRM3 data showed less deviation from the actual temperatures than the other two models (Figure 2-5).

Since all three models underestimated the winter average maximum temperatures the model average was an underestimate as well (Table 2-34). Ranging from 0.5°-5.2°C, the deviation of the model average from the observed values was much larger for winter average maximum temperatures than for summer average maximum or minimum temperature.

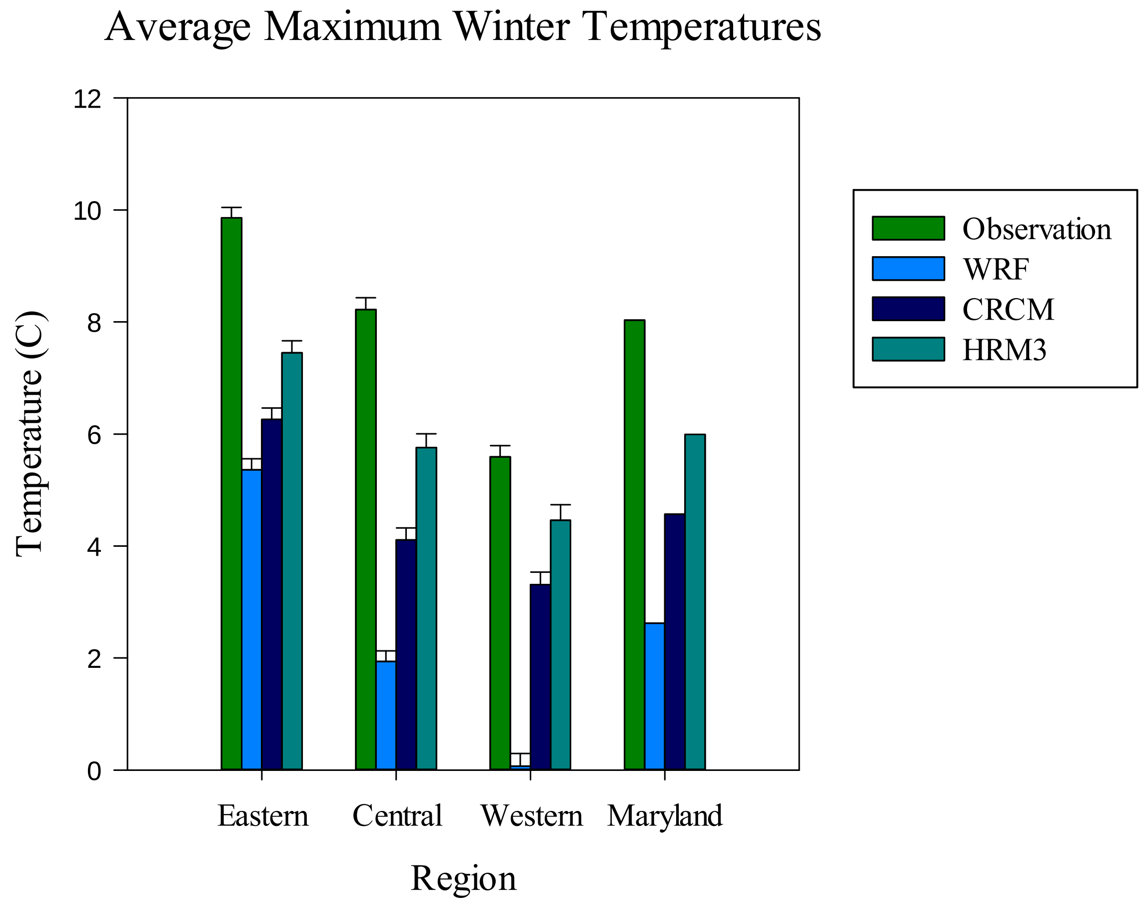
Table 2-34. Average winter maximum temperatures observed and predicted by WRF, CRCM, and HRM3, and model average for 1990-1999 for locations across Maryland.[33]

Average Winter Maximum Temperature (°C)

EASTERN	**Observation**	**WRF**	**CRCM**	**HRM3**	**Model Average**
Princess Anne	10.3	5.4	6.4	7.1	6.3
Royal Oak	8.8	4.0	5.7	7.0	5.6
Salisbury	10.3	5.5	6.4	8.0	6.6
Snow Hill	10.1	7.0	6.4	8.0	7.1
Vienna	9.8	4.9	6.4	7.1	6.1
CENTRAL					
Baltimore	7.9	2.1	3.3	5.9	3.8
Beltsville	7.9	1.9	4.8	5.9	4.2
Clarksville	8.6	1.7	3.3	5.9	3.6
Glenn Dale	9.3	3.0	5.7	6.6	5.1
Rockville	7.3	1.0	3.4	4.4	2.9
WESTERN					
Catoctin	5.2	0.2	2.4	4.4	2.4
Cumberland	6.6	-0.2	3.2	4.6	2.5
Frederick	7.9	0.3	3.4	4.4	2.7
Frostburg	3.0	-0.1	3.2	4.4	2.5
LSD (Loc*Trt)		**1.08**	**0.97**	**1.21**	

[33] Significant model overestimations of the observed temperatures are highlighted pink, significant model underestimations are highlighted in blue, and model predictions that are not significantly different from the observed are highlighted green

Figure 2-5. Average winter maximum temperatures observed and predicted by WRF, CRCM, and HRM3, for 1990-1999 for Maryland and is three regions.



Compared to the observed average winter minimum temperatures the WRF-predicted values were underestimates for all locations except Baltimore, Glenn Dale, Royal Oak, and Snow Hill (Table 2-35). Only three locations didn't have a large enough deviation between the observed and predicted values to be classified as significantly different. The range of differences between the actual 1990s temperature data and the WRF-simulated temperature data, 0.3°-5.3°C, was larger than the range seen for winter maximum temperature. The predicted average minimum temperatures from the WRF model had the smallest amount of deviation from the observed averages for the eastern and central region but for the western region exhibited a 3.6°C difference from the actual temperatures (Figure 2-6).

For all fourteen locations the CRCM predictions of average winter minimum temperature were significantly different from the observed values, exhibiting a range of 2.4°-5.3°C for the differences between the actual and modeled temperatures (Table 2-35). The underestimated average winter minimum temperatures predicted by CRCM exhibited the largest deviations from the observed values for all three regions (Figure 2-6).

The HRM3 winter average minimum temperature projections were highly variable when compared to the WRF model and CRCM results (Table 2-35). Most locations underestimated the actual temperatures while Frostburg, Princess Anne, and Snow Hill overestimated for the winter minimum temperatures. For the HRM3 there were differences between the observed and simulated data that ranged from 0°-3.8°C with predictions for the central and western region that were the closest to the actual average minimum winter temperatures of any of the models(Figure 2-6).

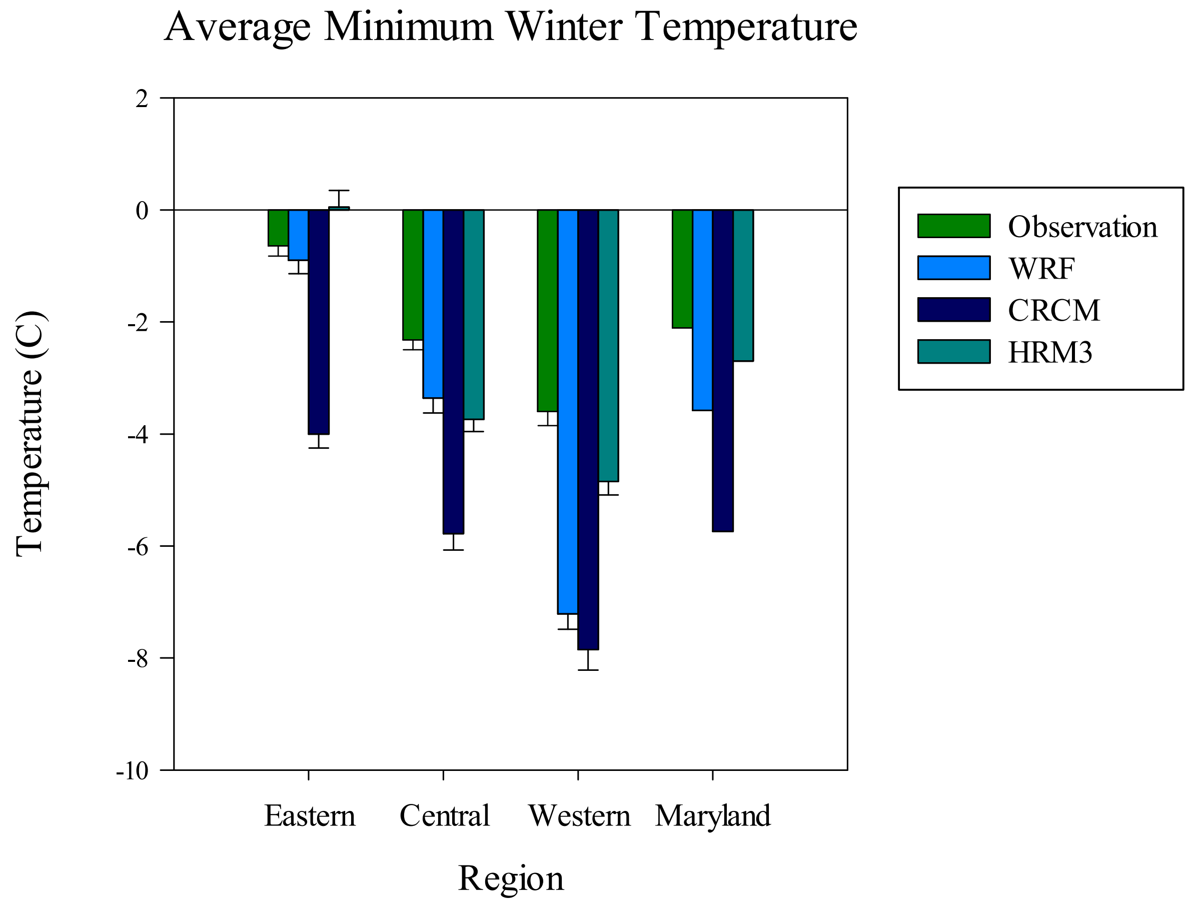
The model average encompassed the variable results for average winter minimum temperature across each model which resulted in overestimations for Salisbury and Snow Hill and underestimations for the rest of the sites (Table 2-35). The deviation between the observed data and the model average ranged from 0°-4.3°C with Frederick showing the largest differences.

Table 2-35.Average winter minimum temperatures observed and predicted by WRF, CRCM, and HRM3, and model average for 1990-1999 for locations across Maryland Table.[34]

Average Winter Minimum Temperature (°C)					
EASTERN	**Observation**	**WRF**	**CRCM**	**HRM3**	**Model Average**
Princess Anne	-1.9	-2.2	-6.1	-1.6	-3.3
Royal Oak	0.0	0.3	-5.1	-2.6	-2.4
Salisbury	0.0	-2.4	-3.7	3.1	-1.0
Snow Hill	-0.7	2.3	-3.7	3.1	0.5
Vienna	-1.0	-2.6	-3.7	-1.6	-2.6
CENTRAL					
Baltimore	-1.9	-1.3	-6.1	-3.6	-3.7
Beltsville	-2.3	-4.8	-5.7	-3.6	-4.7
Clarksville	-1.9	-4.7	-6.1	-3.6	-4.8
Glenn Dale	-2.7	-0.6	-5.1	-3.1	-2.9
Rockville	-1.6	-5.3	-6.0	-4.7	-5.3
WESTERN					
Catoctin	-3.4	-7.1	-7.3	-4.7	-6.3
Cumberland	-3.8	-7.4	-9.1	-4.9	-7.1
Frederick	-1.5	-6.8	-6.0	-4.7	-5.8
Frostburg	-5.4	-7.7	-9.1	-5.2	-7.3
LSD (Loc*Trt)		**0.87**	**1.20**	**1.13**	

[34] Significant model overestimations of the observed temperatures are highlighted pink, significant model underestimations are highlighted in blue, and model predictions that are not significantly different from the observed are highlighted green

Figure 2-6. Average winter minimum temperatures observed and predicted by WRF, CRCM, and HRM3, for 1990-1999 for Maryland and its regions.



Discussion

Examining the predictive abilities of the models for the 1990s across locations and regions as well as seasonally allowed for an examination of the model biases affecting the model's accuracy with past simulations that will also influence each model's projections for the future. While local predictions are crucial for estimating climate change and preparing for its effects at the downscaled level, these projections are often less reliable than global predictions (Schiermeier, 2010). Assessing the ability of climate models to mimic past climate patterns and regional variability is the first step towards determining which models have the potential to simulate and inform us about the future climate.

Based on the results of the statistical analysis and means comparisons, the downscaled climate change models studied (WRF, CRCM and HRM) did not accurately and consistently predict maximum or minimum temperatures at the regional level. For most of the 14 Maryland locations studied, the observed and the model projected average maximum and minimum temperatures for the 1990s were significantly different for the three climate models tested. For each model, the differences between the observed and predicted means were often large (up to 8.1°C and variable, ranging from 0.1°C to 8.1°C. Averaging the location means by region did not improve model accuracy as the treatment effect tended to increase for the analyses by region, especially when comparing the means for summer and winter maximum and minimum temperatures (Table 2-32 to Table 2-35). The large temperature differences between the observed and predicted mean temperatures for all three downscaled models were substantially more than the typical deviations seen in 160km-resolution RCMs of 2°C (Climate Change Science, 2008). For the average summer maximum temperatures, almost half of all the model projections differed significantly from the observed temperatures. The biases that made the models either significantly underestimate or overestimate the actual temperature varied by model and sometimes by region for the same model. For example, HRM3 significantly underestimated summer maximum temperatures except for two locations in the Western region (Table 2-32). For each of the models, even though the individual biases by location were observable through the means comparison, they were not predictable as the biases were not consistent across the locations or regions for summer and winter temperatures. While the WRF model underestimated summer maximum temperatures for all locations that with a significant difference between observed and predicted temperatures, it overestimated the summer minimum temperatures for five locations. Similar switches in the direction of the model (overestimating vs. underestimating) bias were seen with CRCM and HRM3 between summer maximum and minimum temperatures. While the biases for winter maximum and minimum temperature were more uniform for each model, with most locations having model-predicted temperatures that were colder than the observed temperatures, more locations differed significantly from the observed values for winter (94% and 86% respectively) than for summer. For this study, accuracy and consistency across model predictions of maximum summer temperatures and minimum winter temperatures are especially desired due to the implications of any changes of these temperatures on tree establishment, reproduction, and survival.

While scientists are hopeful that the added complexity offered by regional and local climate models will result in more realistic and accurate climate predictions, the results of this research and the literature suggest the benefit of increased resolution may only be beneficial to a certain point (Challinor et al., 2009). Studies suggest that fine-resolution regional models, like the WRF model, may not outperform coarser-scale regional models for predicting temperature and precipitation (Zhang et al., 2009). To produce downscaled forecasts scientists essentially zoom in on global models, using the same equations to make predictions at a finer-scale. This process can lead to errors and biases from the global model being compounded at the regional level (Climate Change Science, 2008; Schiermeier, 2010). Produced at such a high-resolution, some of the inadequacies of the WRF model in predicting the climate of the 1990s may, in fact, be due to issues in its parent model, the GFDL CM2.1, which provided the boundary conditions for the WRF model runs. The overall model bias of GFDL CM2.1, where temperatures in the Northern Hemisphere are simulated as too cold, could result in the cold bias found for the WRF model predictions (Strack, 2011). Though the cause of this error is unknown, it is probably related to errors in the prediction or aerosols and clouds. The role of aerosols, clouds and their interactions on the climate are just some of the many climate parameters that are not well understood and lead to uncertainty in model predictions (Schiermeier, 2010).

The same issues surrounding model uncertainty for the WRF model have affected CRCM and HRM3 predictions to a lesser degree. While downscaled models typically exacerbate any inadequacies in their parent global models, it is important to realize that there is no model currently available that can simulate our natural climate system completely. This problem is deemed model inadequacy and can seriously impact the use of model data for decision support. However, models being developed continue to incorporate more aspects of the climate for a more holistic look at the global and regional climate processes. Although downscaling allows regional models to include aspects of the environment, such as hydrology, vegetation and topography at a finer-scale than global models (Climate Change Science, 2008; Stainforth et al., 2007a), other aspects that can be important to climate variation and change may not be included, even at the regional scale. One such model inadequacy is that the effect of urbanization on regional climates is often not considered in models even though it can be substantial and will become increasingly important as cities grow and expand. The distribution of urban areas in Maryland is unequal across the three physiographic regions, with the major urban and adjacent suburban areas within the central region. In the current study, the central region did not display a substantially greater difference between observed and predicted values, the influence of urbanization on climate is likely to increase and may need to be considered when utilizing future climate predictions.

In addition to model inadequacy, model uncertainty can also weaken regional climate change predictions. Much is still uncertain about how aspects of our climate function and interact to create changes to temperature and precipitation. Often, even less is known about these processes at the regional level. When looking at the past climate and trying to project for the future, it is difficult to tell the difference between actual patterns in our climate and the stochastic variability for numerous factors, especially precipitation (Stainforth et al., 2007a). While it is acknowledged that climate change will significantly affect the hydrological cycle with expected increases in precipitation for the eastern part of North America, the ability of models to predict how and when this precipitation will fall is unsure. Models typically differ on how the amount of snow and rainfall will change in the future since these factors are the most difficult to predict. This is a contributing factor to the high error rate (typically around 50%) associated with precipitation predictions for regional climate change models. The error rate is particularly high for predicting winter precipitation (Climate Change Science, 2008; Schiermeier, 2010). In the current study, coefficients of variation estimated from the analyses of variance ranged from 42%- 64% for precipitation compared to a range of 3%-9% for temperature across all the models. This corroborates that the uncertainty surrounding precipitation forecasts is very high, which is not the case for temperature.

The potential caveats of using regional models have led to attempts to improve forecasting accuracy through other methods. A multi-model approach attempts to strengthen predictive power by sampling a wide range of models, which reduces the influence of the systematic errors of individual models (Challinor et al., 2009). These inherent errors as well as choices made about how to represent physical processes, climate dynamics and the forcing for future change can lead to drastically different regional model predictions. By averaging over these individual uncertainties and inaccuracies a more accurate portrayal of the predicted climate (Collins et al., 2011). The benefit of using a multi-model ensemble can be seen in the model averages for average summer and winter maximum and minimum temperatures (Table 2-32 –Table 2-35). While the WRF model, CRCM, and HRM3 tended to significantly overestimate or underestimate the predicted temperatures for most locations, the average of all the models generally led to more accurate predictions. The utility of climate models can be severely compromised by uncertainties or errors that affect model predictions. In a world where information about climate change is needed now to inform policy and planning, the ensemble approach may be our best estimate of the climate to come. In addition, the ensemble approach also allows for the identification of model uncertainties that need to be targeted for future research to improve our understanding of the climate and make accurate predictions (Collins et al., 2011).

Climate change predictions will be most useful if conducted at the regional level. While the level of confidence with regional predictions is not as high as global predictions estimates, projections of the future climate at the downscaled level are necessary for determining adaptation and mitigation strategies. While scientists work to formulate climate models that realistically simulate our complex climate and increase model reliability, regional models may be one of the best strategies for predicting an uncertain future that can be used to investigated the emergent and future risks to specific locations (Challinor et al., 2009). Recently, fine-resolution, regional climate models are being developed but for future climate projections to be useful, their limitations must be recognized and used to develop more accurate models. The limitations illustrate the need for studies that evaluate the simulated data with observational data. Using weather records from land-based weather stations to determine a model's ability to predict local conditions is an essential component of the validation process. Although land-based weather data can be difficult to obtain and time-intensive to format and standardize, these data are essential for assessing and improving climate models to be used for projections of climate at a regional scale.

Chapter 3: Impact on Bioclimatic Factors

Introduction

Climate models like WRF, CRCM, and HRM3 produce approximate renditions of the actual climate and how it may change over time. Since no model can accurately and completely simulate Earth's complex climate, the limitations of specific model outputs must be considered before using the results for any application. Comparing observation data to model data from 1990-1999 allowed for the biases of each model to be identified. To produce future forecasts that are meaningful and useful for applications these biases must be taken into account (RÄIsÄNen, 2007). The most widely used method for model bias removal is called the "delta" method. The future change in climate is calculated by looking at the difference in temperature and precipitation between some past or current time period and the future (Climate Change Science, 2008). By calculating the adjusted temperatures that remove the individual model biases, predictions that are useful and can be understood in the context of our current climate are made. These predictions are useful for investigating the impact of the projected climate change on a number of species. Being able to identify the future issues and risks for forests in Maryland under a changing climate will allow for the development of more effective management strategies.

Data Description and Analysis

The average monthly maximum and minimum temperatures and the monthly total accumulated precipitation forecasted by the WRF model, CRCM, and HRM3 for

2050-2059 were obtained for the same grid cells used in the comparison of observed and model predicted values for the 1990s.

Using the delta method, the difference between the model-predicted maximum and minimum temperatures for the 1990s was subtracted from the model-predicted temperatures from the 2050s to determine the temperature change predicted by each model.

Using monthly temperature predictions the delta was calculated as:

$\Delta = T_{max50} - T_{max90}$

This change was added to the 1990-1999 observation values for maximum and minimum temperature to adjust the individual model's biases and obtain the future predicted temperatures.

The adjusted predicted values for the 2050s were then calculated as:

$T_{maxadj50} = T_{max90} + \Delta$

Model projections for the daily maximum and minimum temperatures for the 2050s were also acquired and used to predict changes in yearly average growing degree days (GDD) and frost days (FD) and extreme weather events. Changes in these bioclimatic factors will significantly influence the reproductive capacity of tree species which will contribute to changes in forest structure and function (Gu et al., 2008). Investigating how these factors will be impacted by a changing climate in the future will hopefully lead to more accurate predictions that will aid in the management of forests across the state.

It is assumed that the earlier assessments of the accuracy of the monthly temperatures and precipitation are applicable to these daily values. Thus, only the model predicted data was used to investigate the decadal changes in GDD, FD, and extreme weather events from the 1990's to the 2050's. However, a potential minor source of variation between the models is the fact that different AOGCMs, which are used to drive the regional model predictions, use different calendars to determine the number of timesteps in a run of the model. Both the WRF model, forced by the GFDL global climate model, and CRCM, forced by the CGCM3 global climate model, use a 365-day "no leap" calendar which is the same as the standard Gregorian calendar, but does not include leap-years. The HRM3 model driven by the HadCM3 model uses a 360-day calendar where there are 12 months of 30 days each (citation needed). This difference in model parameterization must be taken into account when looking at the results for these daily measures.

Daily temperature predictions were used to calculate:

$GDD = \sum \frac{T_{max}+T_{min}}{2} - T_{base}$: where T_{base} =10°C and T_{max} does not exceed 32.2°C

Total FD = $\sum$ days: where $T_{min} < 0$°C.

Average yearly extreme heat events were calculated as:

Days above 32.2°C = $\sum$ days where $T_{max} > 32.2$°C/ $\sum$ days in a year.

Days above 37.8°C = $\sum$ days where $T_{max} > 37.8$°C/$\sum$ days in a year.

Using climate models to project decadal average temperature changes has become a fundamental tool broadly used for anticipating and preparing for general trends of climate change (Climate Change Science, 2008). However, the utility of these models is dependent on their accuracy and reliability. Because their predictive powers of climate models cannot be directly evaluated until the predicted times have occurred. Thus, climate models are assessed indirectly by comparing past time slices of observed weather with model-simulated weather. However, without direct validation, the projections simulated by climate models contain unknown uncertainties and are extremely controversial. Nonetheless, climate models can be useful and informative when their limitations are acknowledged and considered in their interpretation.

Climate variables that are of primary importance to tree growth and survival were predicted for the 1990's and compared to weather station data for that decade. Thus, the average monthly minimum and maximum temperatures projections are discussed in the context of the limitations and uncertainties discussed in the model assessment section of this thesis. However, in addition to the monthly temperature, other dependent variables related to daily temperatures, such as growing degree days, FD's, and number of extremely hot days also have major impacts on forests, trees and other vegetation. These variables were also simulated for the 1990's and 2050's using the climate change models.

Results

For each of the climate models and the model averages, the predicted location means for the 2050s are presented along with the 1990's observed means in Tables 3-1 to 3-4 for summer maximum and minimum temperatures and winter maximum and minimum temperatures, respectively. The predicted values were adjusted for biases using the delta method described previously. The means for the predicted temperatures are presented and compared for each location within a region with the 1990s observed temperatures listed in the tables as a reference. The location means are organized by region in Figures 3-1 to 3-4 to facilitate comparisons between regionals and the average delta for each model for summer and winter maximum and minimum temperatures is listed.

Based on the scientific climate literature, the average global temperature is expected to increase over the next half-century, although the magnitude of the increase is predicted to vary among regions based on factors such as latitude, topography, hydrology, urbanization, etc.(IPCC, 2007) Although the WRF model predicted a statewide increase in average summer maximum temperatures of 1.3°C from the 1990's to the 2050's (Table 3-1), the overall change was not consistent across Maryland's three physiographic regions (Figure 3-1). Unexpectedly, the WRF model actually predicted that two locations within the Eastern region would experience a decrease in average summer maximum temperatures over the next 50 years. Summer maximum temperatures were projected to decrease 6.0° and 2.2 ° C for Princess Anne and Salisbury, respectively, and a subsequent mean decrease of 1.0° C for the overall Eastern Region. On the other hand, the WRF model 2050's projections for the Central and Western Regions showed increasing summer maximum temperatures that were only slightly less than the CRCM and HRM3 projections. Interestingly, the WRF model predicted that Baltimore, the largest city in Maryland, would experience a 7.6 °C increase in summer maximum temperature, which is the largest predicted change for any of the locations. This radical increase in summer maximum temperature was not predicted by either the CRCM or HRM3, which may be related to the scale of resolution of grid size.

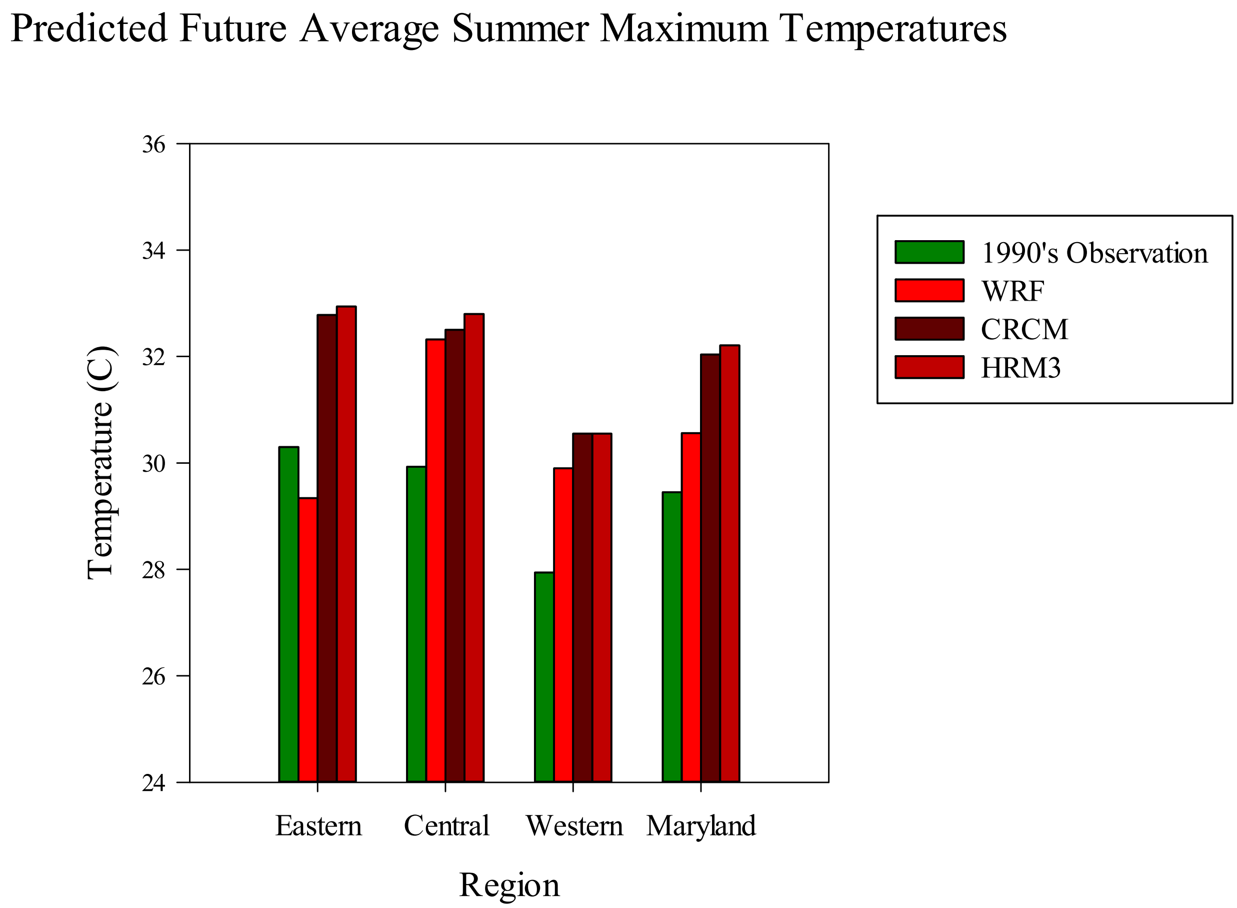
The CRCM average summer maximum temperatures for the 2050s were much more consistent than the WRF predictions across all the regions, which is almost certainly related to the larger grid size and multiple locations being represented by the same grid. CRCM maximum summer temperatures projected an increase of 2.5°-2.6° C for each region. (Table 3-1, Figure 3-1).

HRM3 predicted the largest increases for the average summer maximum temperatures for the 2050s statewide and for all three regions (Table 3-1, Figure 3-1). Like CRCM, HRM3 used a coarser resolution than WRF and predicted temperature changes that were almost constant across the state, with a slightly higher increase in temperatures expected for the Central region.

Table 3-1.Comparison of 1990s observed and 2050s predicted average summer maximum temperatures for locations across Maryland.

2050-2059 Average Summer Maximum Temperature (°C)					
EASTERN	**1990s Observation**	**WRF**	**CRCM**	**HRM3**	**Model Average**
Princess Anne	30.4	24.4	33.3	33.1	30.3
Royal Oak	29.9	30.1	32.3	33.1	31.8
Salisbury	30.1	27.9	32.3	32.2	30.8
Snow Hill	30.1	31.3	32.5	32.3	32.0
Vienna	31.0	33.0	33.5	34.0	33.5
CENTRAL					
Baltimore	30.1	37.7	32.8	32.9	34.5
Beltsville	29.9	31.9	32.4	32.6	32.3
Clarksville	30.1	31.0	32.7	32.8	32.2
Glenn Dale	30.7	31.3	33.1	34.0	32.8
Rockville	28.9	29.7	31.5	31.7	31.0
WESTERN					
Catoctin	26.6	28.5	29.4	29.4	29.1
Cumberland	30.0	32.0	32.5	32.2	32.2
Frederick	30.2	32.0	32.8	33.0	32.6
Frostburg	25.0	27.1	27.5	27.6	27.4
Average Δ		**1.32**	**2.53**	**2.72**	

Figure 3-1. Average summer maximum temperatures observed for the 1990s and predicted for the 2050s by WRF, CRCM, and HRM3 for Maryland and its regions.



More expectedly, the WRF model predicted average summer minimum temperatures increases by the 2050s for all locations (Table 3-2, Figure 3-2). However, the change in summer minimum temperature varied by region. The projected increases for the Eastern and Western regions were a 2.1°C and 2.5°C, respectively, while the Western region was projected to increase only 0.3°C. The Western Region included the Rockville location, where the summer minimum temperature was projected to decrease 1.4 ° C by 2050. .

CRCM 2050 projections for summer minimum temperatures were similar to the CRCM average summer maximum temperature projections (Table 3-2, Figure 3-

2). The statewide increase in average summer minimum temperature predicted by CRCM was 2.5° C larger than the change predicted by the WRF model.

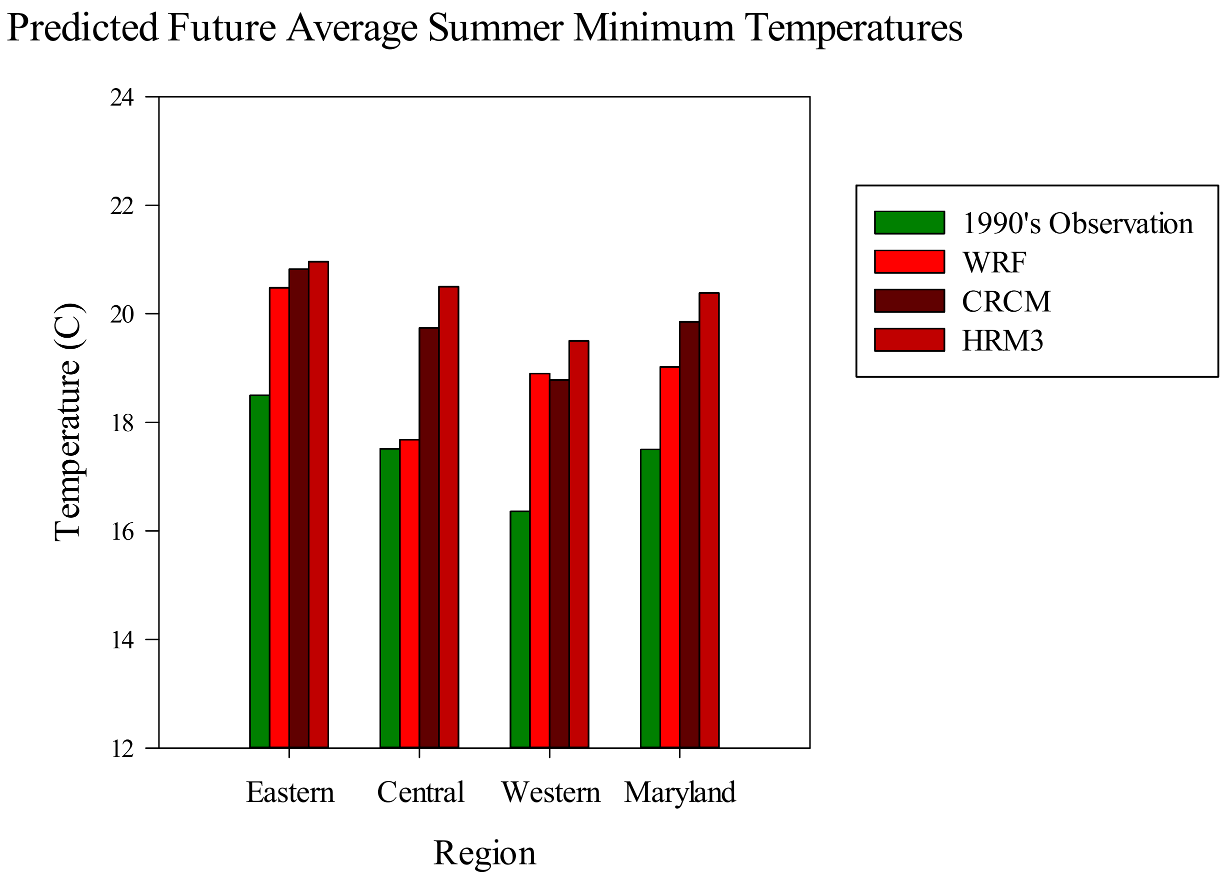
HRM3 projections for the 2050's again predicted the largest increases in summer minimum temperatures by region; although some individual location had predictions were slightly less than those predicted by the WRF model or CRCM (Table 3-2, Figure 3-2).

Acting like a model ensemble, the predicted minimum temperature averaged over all three models probably provided a projected increase in temperature that would be the most credible for impact studies (Table 3-2).

Table 3-2.Comparison of 1990s observed and 2050s predicted average summer minimum temperatures for locations across Maryland.

2050-2059 Average Summer Minimum Temperature (°C)					
EASTERN	**1990s Observation**	**WRF**	**CRCM**	**HRM3**	**Model Average**
Princess Anne	16.6	19.9	19.1	18.7	19.2
Royal Oak	19.4	20.1	21.7	22.6	21.5
Salisbury	19.2	23.2	21.7	21.6	21.2
Snow Hill	17.9	19.9	20.4	20.3	20.2
Vienna	18.6	19.3	21.2	21.6	20.7
CENTRAL					
Baltimore	18.3	18.2	20.7	21.4	20.1
Beltsville	17.7	19.2	20.0	20.7	20.0
Clarksville	15.5	15.9	17.7	18.5	17.4
Glenn Dale	17.0	18.0	19.4	20.2	19.2
Rockville	18.5	17.1	20.9	21.7	19.9
WESTERN					
Catoctin	16.8	19.4	19.3	19.9	19.5
Cumberland	16.1	18.3	18.4	19.2	18.6
Frederick	18.4	20.8	20.9	21.6	21.1
Frostburg	14.2	17.0	16.5	17.3	16.9
Average Δ		**1.73**	**2.45**	**3.02**	

Figure 3-2. Average summer minimum temperatures observed for the 1990s and predicted for the 2050s by WRF, CRCM, and HRM3 for Maryland and its regions.

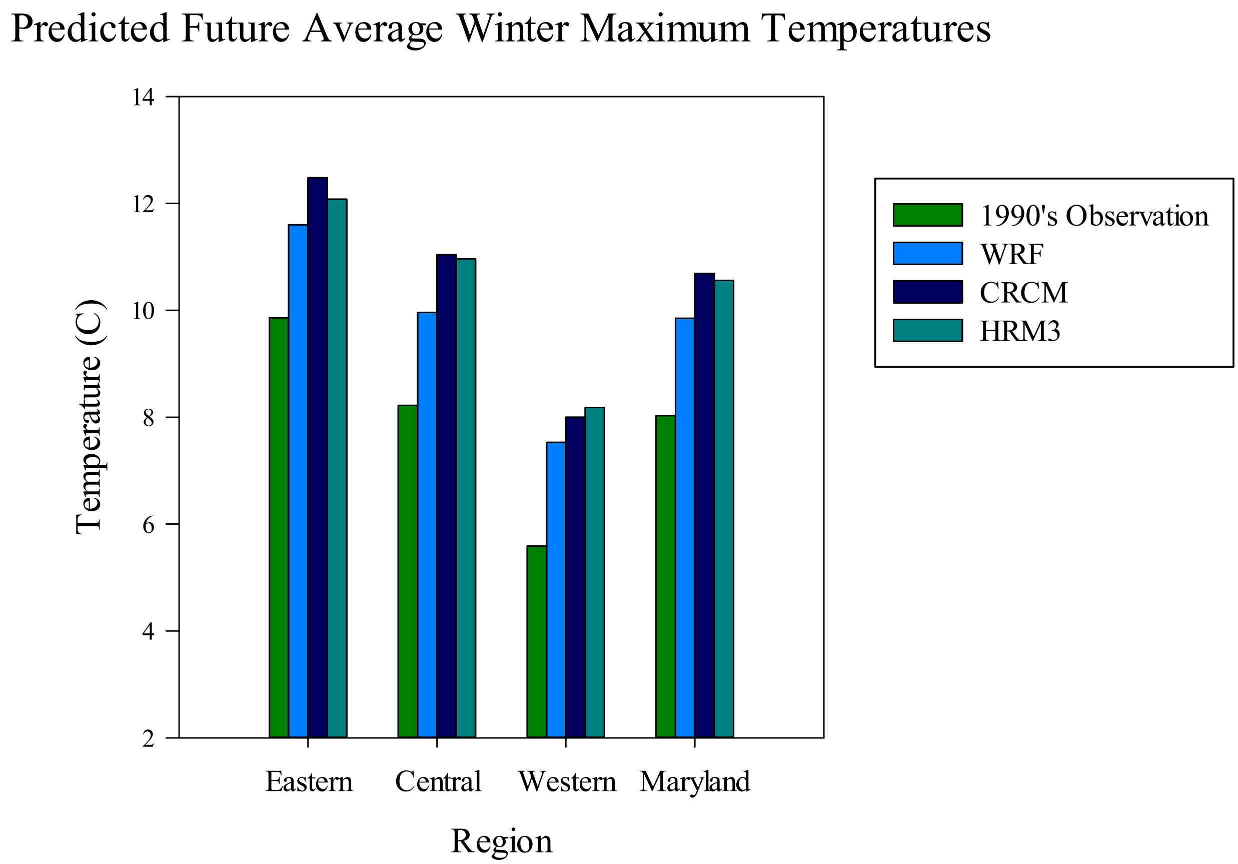


The projected average winter minimum temperatures for the 2050s and relative differences between models for the decade were similar to those noted for average summer maximum and average summer minimum temperatures (Table 3-3, Figure 3-3). However, for the Eastern and Central region the CRCM exhibited slightly greater increases in average winter minimum temperature than the predictions for HRM3.

Table 3-3.Comparison of 1990s observed and 2050s predicted average winter maximum temperatures for locations across Maryland.

2050-2059 Average Winter Maximum Temperature (°C)					
EASTERN	**1990s Observation**	**WRF**	**CRCM**	**HRM3**	**Model Average**
Princess Anne	10.3	12.0	13.8	13.4	13.1
Royal Oak	8.8	9.4	11.6	11.5	10.8
Salisbury	10.3	12.8	13.3	12.6	12.9
Snow Hill	10.1	12.0	13.2	12.4	12.5
Vienna	9.8	11.8	10.5	10.5	10.9
Baltimore	7.9	9.4	10.8	10.7	10.3
Beltsville	7.9	9.7	10.6	10.7	10.3
Clarksville	8.6	10.5	11.4	11.0	10.9
Glenn Dale	9.3	10.5	12.2	12.1	11.6
Rockville	7.3	9.7	10.2	10.3	10.1
Catoctin	5.2	7.1	7.8	8.1	7.7
Cumberland	6.6	8.5	9.3	9.5	9.1
Frederick	7.9	10.2	9.3	9.6	9.7
Frostburg	3.0	4.3	5.6	5.5	5.1
Average Δ		**1.73**	**2.9**	**2.70**	

Figure 3-3. Average winter maximum temperatures observed for the 1990s and predicted for the 2050s by WRF, CRCM, and HRM3 for Maryland and its regions.



The WRF model’s 2050’s projections for average winter minimum temperature followed a pattern similar to the WRF-predicted average summer minimum temperature. The Central region exhibited a very small increase in temperature when compared to the Eastern and Western regions (Table 3-4, Figure 3-4). The average increase expected in the Eastern region, according to the WRF model simulation, was the largest of any model for average winter minimum temperature, predicting an increase of 3.1°C regionally.

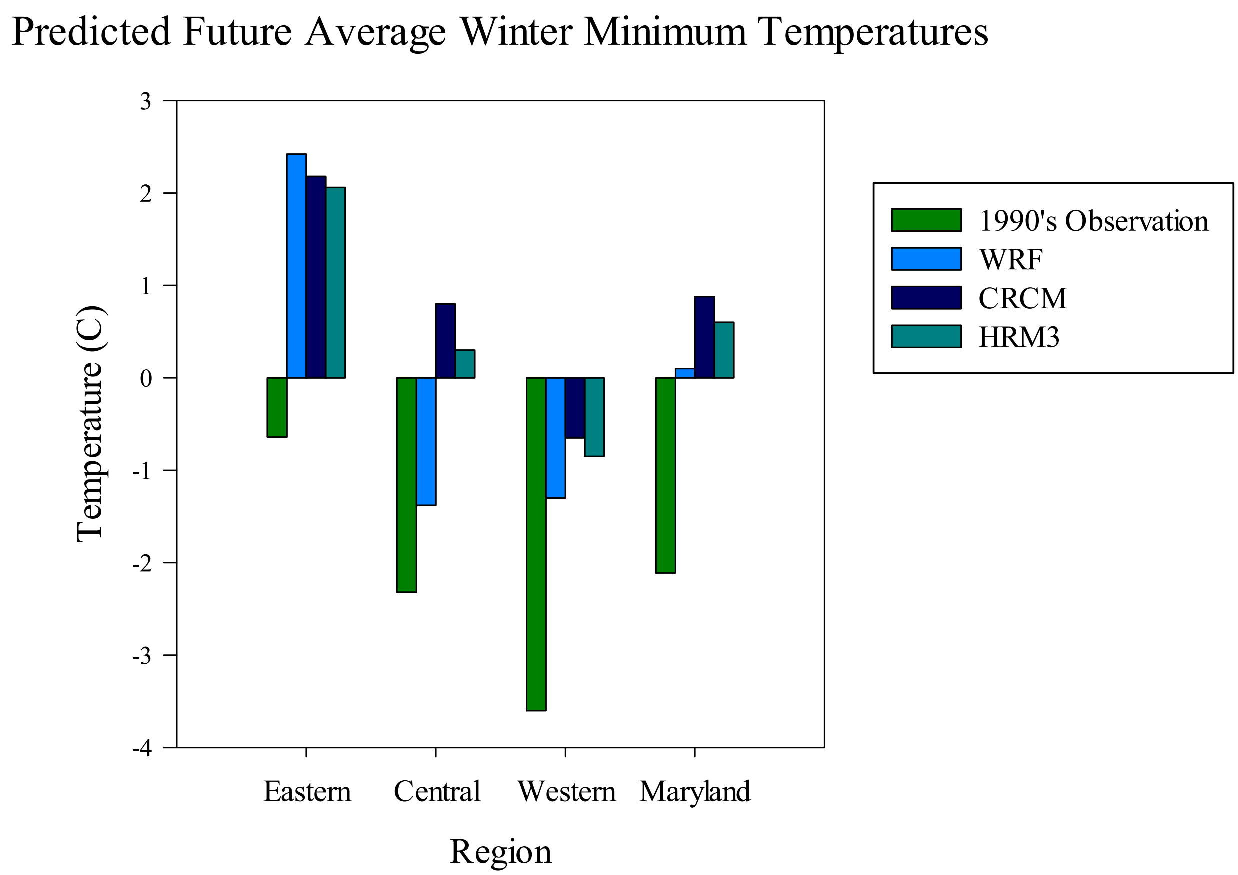
CRCM predictions for the future average winter minimum temperatures were slightly higher than any other seasonal CRCM predictions with increases of 2.9°C for all three regions (Table 3-4, Figure 3-4).

The statewide HRM3-predicted increase in average winter minimum temperature from the 1990s to the 2050s was equal to the overall increase of HRM3-predicted average winter maximum temperatures and slightly smaller than the increases in average summer maximum and minimum temperatures (Table 3-4, Figure 3-4). The change in average winter minimum temperature was fairly consistent across the three physiographic regions with a 2.8° C increase projected for the Eastern region, a 2.4° C increase for the Central region and a 2.7° C increase for the Western region.

Table 3-4. Comparison of 1990s observed and 2050s predicted average winter minimum temperatures for locations across Maryland.

2050-2059 Average Winter Minimum Temperature (°C)					
EASTERN	**Observation**	**WRF**	**CRCM**	**HRM3**	**Model Average**
Princess Anne	-1.9	3.2	1.3	1.3	1.9
Royal Oak	0.0	1.0	3.1	2.8	2.3
Salisbury	0.0	5.8	2.8	2.5	3.7
Snow Hill	-0.7	1.7	2.1	1.9	1.9
Vienna	-1.0	0.4	1.6	1.8	1.3
CENTRAL					
Baltimore	-1.9	-3.7	1.3	0.8	-0.5
Beltsville	-2.3	-0.6	0.8	0.3	0.2
Clarksville	-1.9	-1.1	0.0	-0.8	-0.6
Glenn Dale	-2.7	-1.2	0.4	0.1	-0.2
Rockville	-1.6	-0.3	1.5	1.1	0.8
WESTERN					
Catoctin	-3.4	-1.1	-0.4	-0.7	-0.7
Cumberland	-3.8	-2.0	-0.5	-0.9	-1.1
Frederick	-1.5	1.1	0.5	1.0	0.9
Frostburg	-5.4	-3.2	-2.2	-2.8	-2.7
Average Δ		**2.18**	**3.05**	**2.70**	

Figure 3-4. Average winter minimum temperatures observed for the 1990s and predicted for the 2050s by WRF, CRCM, and HRM3 for Maryland and its regions.



Similar to the model-predicted temperature data for the 1990s and the 2050s, the projected number of yearly growing degree days differed between models and by region. Just as the average temperatures increase as you move eastward across the state of Maryland, so do the GDD's. The predicted and projected GDD's for all models accurately simulated this regional trend.

The WRF model estimates of the yearly growing degree days were generally less than the predictions from the other two models (Table 3-6). While the average number of GDD was lower for the WRF model, the percent change expected in the Western region was comparable to the percent change predicted by CRCM and

HRM3. However, the WRF-predicted percent change for the Eastern and Central regions was 6%-13% less than the amount simulated by CRCM and HRM3.

CRCM predicted an average statewide increase of 971 GDD from the 1990s to the 2050s with fairly consistent changes expected in the GDD's across Eastern, Central, and Western Maryland (Table 3-6).

Compared to CRCM, the HRM3 predicted more substantial gains in the GDD per year statewide with an increase of 1051 GDD by the 2050s (Table 3-6). While the GDD's were higher for HRM3, the percent change between the 1990s and the 2050s was equal to or slightly less than the change predicted by CRCM.

Table 3-5. Change in the average yearly number of growing degree days from the 1990s to the 2050s predicted by the WRF model, CRCM, and HRM3 for the three regions of Maryland[35].

Predicted Yearly Growing Degree Days									
	WRF			**CRCM**			**HRM3**		
Region	**1990's**	**2050's**	**Δ**	**1990's**	**2050's**	**Δ**	**1990's**	**2050's**	**Δ**
Eastern	3346	3983	637	3496	4629	1132	4086	5119	1032
Central	3040	3630	590	3210	4129	919	3763	4857	1093
Western	2452	3224	772	2859	3718	860	3396	4426	1030
MD Avg	2946	3612	666	3188	4159	970	3749	4800	1052

The changes in temperature that contribute to an increase in GDD's will also influence the predicted yearly FD's. However, unlike the GDD's which are expected to increase with a global climate change, the number of FD's is expected to decrease between the 1990s and 2050s. The overall trend of all three models to underestimate the average winter minimum temperatures for most locations for the 1990s could be influential in the number of FD's predicted and the amount of change expected (Table 2-35).

[35] Blue bars represent the predicted average number of yearly GDD for the 1990's and 2050's for each model while the red bars represent the change in GDD over the half-century for each model.

For the Central and Western regions, the WRF model predicted the least amount of FD's for the 1990s and expected the least amount of change from 1990-2059 for the number of FD's (Table 3-6). The Eastern region was an anomaly with the number of FD's for the 1990s and the 2050s being less for HRM3 than for WRF. While the CRCM exhibited a strong bias to underestimate the average winter minimum temperatures for the 1990s (Table 2-35) it also predicted the largest amount of change in the average winter minimum temperatures from the 1990s to the 2050s (Table 3-4). The cumulative effect of both of these factors could explain the large number of FD's predicted and the large amount of change expected in the number of FD's according to CRCM.

Table 3-6. Change in the average yearly number of frost days from the 1990s to the 2050s predicted by the WRF model, CRCM, and HRM3 for the three regions of Maryland[36].

Predicted Yearly Frost Days									
	WRF			CRCM			HRM3		
Region	**1990's**	**2050's**	**Δ**	**1990's**	**2050's**	**Δ**	**1990's**	**2050's**	**Δ**
Eastern	69	56	-18	118	87	-26	58	38	-35
Central	88	75	-14	136	106	-23	99	75	-24
Western	134	121	-10	153	119	-22	110	85	-23
MD Avg	97	84	-13	136	104	-24	89	66	-26

The number of extreme weather events, like heat waves, can be very influential on plant survival and are expected to change due to anthropogenic climate change. The WRF model predicted very few days over 32.2°C during the 1990s, which could be attributed to significant underestimations of the WRF model for summer maximum temperature during that time for all three regions (Table 2-32,

[36] Blue bars represent the predicted average number of yearly FDs for the 1990's and 2050's for each model while the red bars represent the change in FDs over the half-century for each model.

Table 3-7). This clear underestimation of the number of days over 32.2°C for the 1990s may be a consistent model bias that

The CRCM exhibited a pattern that was the reverse of the WRF differences, with many days over 32.2°C predicted for the 1990s. For CRCM a state average of 45 days a year over 32.2°C was projected to increase to 67 days a year by the 2050s (Table 3-7). As with the WRF model, the comparatively high number of days over 32.2°C predicted by CRCM could be influenced by the model's inherent bias to overestimate summer maximum temperatures in the 1990s (Table 2-32) and high projections for the average 2050's temperatures (Table 3-1).

While the HRM3 projections of average summer maximum temperature represented a large change from the 1990s predictions (Table 3-1), the tendency for the HRM3 to underestimate summer maximum temperatures (Table 2-32) probably balanced this effect, leading to predictions of the yearly number of days over 32.2°C between the number of days predicted by the WRF model and CRCM (Table 3-7).

Table 3-7. Change in the average yearly number of days over 32.2°C from the 1990s to the 2050s predicted by the WRF model, CRCM, and HRM3 for the three regions of Maryland[37].

Predicted Yearly Days Over 32.2°C									
	WRF			**CRCM**			**HRM3**		
Region	**1990's**	**2050's**	**Δ**	**1990's**	**2050's**	**Δ**	**1990's**	**2050's**	**Δ**
Eastern	2	10	8	50	72	22	10	24	15
Central	5	17	12	45	68	22	21	43	22
Western	2	11	9	39	61	21	17	35	18
MD Avg	3	13	10	45	67	22	16	34	18

The changes and patterns seen in the predicted yearly days over 32.2°C (Table 3-7) were also seen with the predicted yearly days over 37.8°C. While the CRCM

[37] Blue bars represent the predicted average number of days over 32.2°C annually for the 1990's and 2050's for each model while the red bars represent the change in the days over 32.2°C over the half-century for each model.

predicted the greatest number of days over 37.8°C, the largest percent change in the number of extreme heat days was projected for HRM3 (Table 3-8). Once again, the WRF model appeared to grossly underestimate the days over 37.8°C for both the 1990s and the 2050s.

Table 3-8. Change in the average yearly number of days over 37.8°C from the 1990s to the 2050s predicted by the WRF model, CRCM, and HRM3 for the three regions of Maryland[38].

Predicted Yearly Days Over 37.8°C									
	WRF			**CRCM**			**HRM3**		
Region	**1990's**	**2050's**	**Δ**	**1990's**	**2050's**	**Δ**	**1990's**	**2050's**	**Δ**
Eastern	0	1	1	16	27	11	2	6	4
Central	0	1	1	12	25	13	4	12	8
Western	0	1	1	9	20	11	3	7	4
MD Avg	0	1	1	12	24	12	3	8	5

Discussion

Determining the deficiencies and limitations of regional climate models by identifying and quantifying their inherent biases and random error by using historical data, allows for the change between past and future model predictions to be used to forecast the future. The predicted temperature changes from the WRF model, CRCM, and HRM3 simulations from a recent decade, the 1990s, to a decade 50 years in the future (2050s) seems to mostly agree with the IPCC A2 projections of a 3.4^{0}C (with a likely range of 2.0°- 5.4^{0}C) increase in temperature by the end of the century (IPCC, 2007). However, these predictions are highly subjective and dependent on the IPCC emissions scenario employed. Using other IPCC emissions scenarios for the future would predict GDD's, FD's and extreme heat days different from the

[38] Blue bars represent the predicted average number of days over 37.8°C annually for the 1990's and 2050's for each model while the red bars represent the change in the days over 37.8°C over the half-century for each model.

projections presented here. Thus, rather than focus on the actual values predicted, emphasis should be placed on the predicted change in these factors over time as well as the general trends in each model's future projections.

Long-term and extensive impending changes in numerous and interconnected bioclimatic factors in the future are expected to impact vegetation in a variety of ways. One of these factors that would influence changes in geographic range shifts as well as plant phenology is the GDD. To accomplish some basic physiological functions, like budburst, many tree species need at least a particular number of GDD. Having an insufficient number of GDD often limits the northern or high-elevation expansion of a species or significantly impairs the competitive ability of the plant through limited growth (Shafer et al., 2001). While the lack of GDD may become less limiting for tree species with the increases in temperatures expected in certain regions due to climate change, the upper limit of GDD may also impose restrictions on habitat expansions through competitive exclusion (Shafer et al., 2001). The competitive interactions that will take place under a changing climate may be difficult to predict as changes in tree species distributions will occur independently and lead to the formation of new communities that have different species interactions than the current environment (Iverson et al., 2008). The increases in GDD predicted by all three models will likely cause significant and long-term changes in Maryland's forest communities. These models predicted increases in GDD between 23% and 30% over the next half-century. Range expansions and restrictions should be expected in the future as evidence is mounting that these shifts are already taking place in response to warmer overall temperatures and extended growing seasons. One study suggests that under a high emissions scenario (IPCC scenario A1fi (part of the A1 family) and a higher emissions scenario than A2) by the end of the 21st century, the most common forest tree species in Maryland; *Acer rubrum* (Red maple), *Quercus bicolor* (Swamp white oak) and *Maculura pomifera* (Osage orange) will experience a loss in importance value which might contribute to those species having their ranges shift outside the state or become competitively excluded from their current habitat. While modeling can predict the future suitable habitat of species under a variety of conditions, it is unknown how species will fulfill their realized niche, adapt to their current niche, or create a new niche. With tree species, which often take a long time to reach maturity, changes in habitat will likely impact the regeneration portion of a tree's life cycle in the future (Iverson et al., 2008).

Additionally, changes in GDD that correspond to changes in the reproductive phenology of tree species have already been documented worldwide as further evidence of the effects of a changing climate (Orlandi et al., 2005). Flowering dates are occurring earlier in most regions of the world than in the past. Since flowering phenology is linked to other life-history traits, flowering times indicate larger changes in the timing of multiple events that will influence how ecological relationships and processes occur in the future (Miller-Rushing et al., 2008). Most research suggests longer growing seasons and extended life cycles for most plants under predicted climate change which is supported by all three model predictions for future GDD (McMahon et al., 2010; Peñuelas et al., 2009). However, the individual responses of plant species to climate change may lead to the development of divergent strategies. Field and satellite data at the community level suggest a lengthening of the growing season while observations for individual species indicate shortening of life cycles due to warming. Both strategies could prove advantageous. Advancing the time of events in a plant's life cycle could reduce loss of reproductive tissues to drought but extended life cycles could be beneficial for the production of more offspring. These divergent responses to a warming climate stress the importance of investigating climate change at the species level to provide useful suggestions for environmental management (Körner and Basler, 2010; Steltzer and Post, 2009).

While all three models predicted reductions in the number of frost-days for the 2050s, as would be expected under a warming climate, the timing of frost events could also be altered due to climate change as more erratic weather is predicted (IPCC, 2007). Having warmer temperatures occur earlier, as projected by the climate models assessed in this study, can actually increase the risk of frost damage to plants. An extreme freeze event after a period of warm temperatures can be extremely detrimental to plant development (Gu et al., 2008; Santiestevan, 2010). The abnormal spring freeze in 2007, which lasted only a few days, killed newly formed leaves, shoots, fruits, and flowers and left entire forests damaged throughout the Eastern United States. For Eastern deciduous forests, including those in Maryland, the 2007 freeze demonstrated that swings between warm and cold temperatures are much more destructive to plants than consistent warm or cold temperatures. Further investigation to determine the timing of the FD's predicted by the models is needed to identify shifts in the freezing patterns expected for Maryland. Like the impacts of changing GDD's, changes to the number and duration of frost days can also have long-term impacts on forest structure. While different species are differentially equipped to handle the impacts of freezing temperatures, studies suggest that increasing global temperatures due to elevated CO_2 may be reducing many plant species' ability to tolerate freezing temperatures (Gu et al., 2008).

The general consensus that climate change will alter the intensity and frequency of extreme events has led to an interest in forecasting cold spells, precipitation-induced floods and heat waves for the future. However, achieving accurate predictions for these rare events is problematic (IPCC, 2007). Climate models use statistics to forecast trends based on established patterns. Extreme events that could occur from once every 30 years to once every 100 years make estimates of the real risk of such an event highly uncertain. When multiple models were run to see if they could simulate heat waves that match the duration and intensity of the heat episode of 1995 only a few models had predictions that came even close (Climate Change Science, 2008).

Temperatures above 32.2 ° C do not contribute to GDD's and these excessively high temperatures can negatively impact tree growth and survival. The model projections for the 2050's indicate substantial increases in the number of heat events, although the magnitudes of these increases are substantially different. While it is expected that the number of extreme heat events will continue to rise in the coming years, the uncertainty around exact predictions of such events comes from the fact that changes in the mean climate conditions do not apply equally to changes in extremes. The warmest summers may not coincide with the years when heat waves occur. Therefore, increasingly warmer summers do not necessarily correspond with increasing frequency of days with excessive heat (Climate Change Science, 2008).

The ability to accurately predict the occurrence and frequency of climatic extremes would be a very useful tool for managing natural areas for the future. While increases in the number and duration of heat waves could have direct consequences for plants, the most significant impacts are expected to be due to the interactive effects of heat waves and other changes to the climate, particularly precipitation. While in general precipitation is expected to increase in North America, the predictions are too uncertain to suggest whether there may be seasonal effects with this increased rainfall occurring at particular times of the year. This information would be useful as the interactive effects of heat waves and drought are detrimental for plants, especially in summer. Excessive temperatures combined with low soil moisture causes extreme stress to plants which may result in die-back and leaf-shedding (De Boeck et al., 2011). The frequency of concurrent extreme heat events and drought may be altered additionally by the change in duration of growing season. If plants experience a lengthened growing season the time available for drought and heat waves to coincide may increase and could lead to reproductive loss due to these conditions (Steltzer and Post, 2009).

Recognition of how bioclimatic variables will be impacted by climate change is necessary for addressing the changes that will possibly occur in forests and generating management techniques for the future. While the regional changes in temperature predicted by the three models for Maryland may differ slightly from other model projections, the general trends seen for temperature, GDD, frost-days, and extreme weather events are all corroborated by the literature. These predicted changes, if correct, could have a substantial influence on Maryland's forests in the future and will need to be addressed as our climate continues to change.

Chapter 4: Conclusions

Strategic planning and sustainable management of forests depend on understanding potential impacts of climate change on forests. Climate change models that forecast impending climate changes and recognize regional features that will influence how climate change will unfold across an area are becoming increasingly important tools. While regional climate models offer the most detailed predictions currently available, these simulations will only be useful if they are deemed accurate and provide a considerable improvement over coarse-resolution global models.

For this study, three regional climate models were used to investigate their downscaled accuracy for predicting the recent past, which will influence their assumed accuracy for projecting into the future. Weather station observations from decade of the 1990s were compared to the predicted model data for the WRF model, CRCM, and HRM3. Predicted monthly minimum and maximum temperatures for winter and summer seasons differed significantly from the observed monthly temperatures. Substantial model biases differentially affected the predictive abilities of each model. Though the models could mimic the general regional temperatures patterns of Maryland, predictions at the location level (8km or 50 km) were much less accurate and did not show consistent biases. These biases persisted when regional means were calculated by averaging over the locations in each region, but tended to diminish when averaging the three model's predictions together to form a model ensemble.

While models should not be expected to perfectly replicate a past climate, the significant differences between the observations and model predictions for all three models suggest that there are remain unanswered questions surrounding model uncertainty. The downscaled nature of the models, especially with the 8km resolution for the WRF model, might be exacerbating problems inherent in the global parent models. For cumulative precipitation, deviations between the observed and predicted values were especially large and inconsistent. This result was expected as a consequence of model inadequacy. Precipitation patterns are extremely variable and difficult to predict in Maryland. The parameters influencing precipitation are complex and difficult to understand and model, especially for Maryland regions which span different physiographic provinces.

A research goal was to use projected temperatures and precipitation to predict the impact of climate change on Maryland forests in the next half-century based on the best available climate projections. After determining that model biases were highly significant for all models tested, a "delta" method was used to adjust model projections for the 2050's decade. The average decadal specific model biases found for the 1990's were taken into account and their "deltas" were used to adjust the 2050's projections, which should be more accurate than the original model-projected means. Additionally, the models were used to project growing degree days, frost days, and extreme heat events, which are climate variables that also have major impacts on forest composition. The models predictions for the next half-century include changes that will have profound effects on the structure and function of Maryland's forests. Increases in GDD could influence range shifts for species and alter established forest communities while fewer frost days combined with erratic temperature swings could leave plants susceptible to reproductive damage. More summer days with extreme heat events would also have direct detrimental effects on trees and possibly cause changes in forest composition long-term as species adapt or migrate due to these conditions. These consequences of climate change found in the literature are supported by the changes projected for bioclimatic factors by each of the downscaled models.

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