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Investigating Future Variation of Extreme Precipitation Events over the Willamette River Basin Using Dynamically Downscaled Climate Scenarios

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by

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Abstract

One important aspect related to the management of water resources under future climate variation is the occurrence of extreme precipitation events. In order to prepare for extreme events, namely floods and droughts, it is important to understand how future climate variability will influence the occurrence of such events. Recent advancements in regional climate modeling efforts provide additional resources for investigating the occurrence of extreme events at scales that are appropriate for regional hydrologic modeling. This study utilizes data from three Regional Climate Models (RCMs), each driven by the same General Circulation Model (GCM) as well as a reanalysis dataset, all of which was made available by the North American Regional Climate Change Assessment Program (NARCCAP). A comparison between observed historical precipitation events and NARCCAP modeled historical conditions over Oregon's Willamette River basin was performed. This comparison is required in order to investigate the reliability of regional climate modeling efforts. Datasets representing future climate signal scenarios, also provided by NARCCAP, were then compared to historical data to provide an estimate of the variability in extreme event occurrence and severity within the basin. Analysis determining magnitudes of two, five, ten and twenty-five year return level estimates, as well as parameters corresponding to a representative Generalized Extreme Value (GEV) distribution, were determined. The results demonstrate the importance of the applied initial/boundary driving conditions, the need for multi-model ensemble analysis due to RCM variability, and the need for further

downscaling and bias correction methods to RCM datasets when investigating watershed scale phenomena.

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Chapter 1

Introduction and Background

Investigating the potential impact of climate change on the Willamette River Basin (WRB) is an important avenue of research for water resource engineers, climate scientists, and policy makers. Through the use of dynamically downscaled climate model scenarios, this study investigates the occurrence of extreme precipitation events over the basin. This report includes background information regarding climate models, downscaling procedures, multi-model ensemble studies, extreme value analysis, and watershed scale impacts. A description of the study area and datasets used in this study follows. Next, the methods used to visualize the datasets and conduct the extreme value analysis are provided, followed by a discussion of the results. Finally, conclusions and future areas of study are drawn from these results. Overall, the results of this study demonstrate the variability among regional climate model outputs, the importance of the driving dataset, and dependence on the choice of observed dataset. The resulting analysis of the climate scenarios demonstrates the potential impact of climate change on extreme precipitation events over the WRB.

1.1 Simulating Future Climate Conditions: Climate Models

Among the many potentially significant impacts of future climate change, the variation of extreme precipitation events, in terms of magnitude as well as temporal and spatial occurrence, is a vital topic for water resources engineers, managers, and general public safety. Understanding the global impact of climate change has garnered widespread attention over recent decades, resulting in international cooperative efforts, most notably the Intergovernmental Panel on Climate Change (IPCC). Efforts at all levels of government and other organizations, from global to local, are providing funding for research of the potential impacts of climate variability.

Climate models provide one method of predicting and evaluating future climate scenarios. As noted by the IPCC, General Circulation Models (GCMs) are one of the two main approaches taken for future climate prediction, with the other being the analogue method which uses "reconstructions of past climates from paleo-climatic data" (IPCC, 1990). The origination of climate modeling approaches came in the early part of the 20th century in the form of one dimensional climate models (North et al., 1981). Due to the expense and constraints of limited computer power at the time, the formation of GCMs throughout the 60s, 70s, and 80s relied primarily on simplified energy balance models (North et al., 1981). GCMs, derived from weather forecast models traditionally focused on atmospheric circulation, have grown in sophistication to include all five components that represent the climate system: atmosphere, ocean, cryosphere (sea-ice, ice sheets, glaciers, and permafrost), biosphere, and geosphere (IPCC, 1990). Up to the end of the 1970s only two numerical models existed in the field (Kreienkamp, 2011). However, even at that time the importance of initial conditions on the non-linear differential equations that served as the basis of the models was recognized as a fundamental component (North et al., 1981). Throughout the 1980s, with rapid growth in computing power and availability, the number of GCM expanded significantly. By the end of that decade as many as 22 distinct "global mixed layer ocean atmosphere models" had been created and studied (IPCC, 1990). Furthermore, the use of coupled models such as Atmospheric-Ocean General Circulation Models (AOGCMs), which combine ocean and atmosphere component models thus yielding more comprehensive simulations, expanded (IPCC, 1990).

The basis of GCMs lies in physical conservation laws. These laws track the manner in which momentum, water vapor, and heat are distributed and influenced by movement through the atmosphere (IPCC, 1990). Each process described by a conservation law is based on first principle equations. The equations describe the behavior of a fluid, such as air or water, on a body that rotates (i.e., the globe) as they are affected by temperature variations due to the sun as an external source of heat (IPCC, 1990). These physical conservation laws are in the form of non-linear partial differential governing equations, with the only solutions brought about by numerical methods. Thus, circulation models are required to discretize the representative zones (land, ice, atmosphere, etc) into layers (IPCC, 1990). Within each layer, the variables are either determined at discretely defined grid points (as in finite difference models) or determined by a finite number of mathematical functions (as in spectral models) (IPCC, 1990). By integrating the differential governing equations forward in time in a discrete fashion, the predicted variable values for each grid point and each layer can be determined, starting from some predefined initial condition.

To ensure numerical stability of the solutions to these differential equations, both the time step and grid size play a crucial role, as does the method of integration. Due to this fact, combined with the memory capacity and speed of computers used to perform the integration steps, the spatial and temporal resolution of GCMs has historically been constrained to the order of a few degrees spatially and to days or even months temporally. According to the IPCC, as of 1990 typical GCMs had "a horizontal resolution of 300 to 1000km and between 2 and 19 vertical levels." Increasing vertical resolution requires a linear increase in computer memory, whereas the relationship is quadratic for horizontal resolution (IPCC, 1990). Due to these limitations, large-scale climate features were interpretable. However, regional-scale effects, such as those that influence a large watershed such as the Willamette River Basin (WRB), remained rather limited up to that time.

Over the last two decades, numerous improvements in the field of climate change research have bolstered confidence in the predictive capability of climate models. The IPCC Fourth Assessment Report (IPCC-AR4) in 2007 highlights some of the most significant and influential advancements that have resulted in "considerable confidence that [AOGCMs] provide credible quantitative estimates of future climate change" (IPCC, 2007). Through increased international research efforts made possible by initiatives such as multi-model ensemble investigation projects (described in greater detail in section 1.3), climate models have undergone extensive analysis by an increasing number of investigators at virtually all levels of research (IPCC, 2007). All major component phases (atmospheric, oceanic, and terrestrial) have seen improvement in terms of: model formulation (improved transport and dynamics schemes), increased resolution (vertically, horizontally, and temporally), and represented processes (such as direct and indirect aerosol effects) as well as many other aspects (IPCC, 2007). Most notably for this study, the overall distribution of precipitation and the capability of models to simulate extreme events are noted by the IPCC-AR4 as areas which have seen improvement.

The 23 AOGCMs used in the most recent IPCC assessment, which originate from multiple institutions across Europe, North America, and Asia, have undergone several evolutions and most include multiple variations (IPCC, 2007). The evolutions in the individual models can be attributed to a variety of factors, most notably the coupling dynamics have been dramatically improved, the land surface features such as soil zones and plant canopy are more adequately addressed, and the overall resolution has increased (IPCC, 2007). Given the abundance of available models, no single AOGCM stands out in terms of widespread use or simulative capabilities. The most apparent differences between current AOGCMs line in the components and coupling processes. Two such components deal with atmospheric resolution. Typical atmospheric model resolution ranges from ~1-5 degrees horizontally, as well the uppermost atmospheric level represented in the model varies, ranging from 0.01hPa to 25hPa (IPCC, 2007). The ocean resolution, generally ranging from 0.2-5 degrees horizontally, and the treatment of surface conditions are additional components that vary between models. The number of vertical levels simulated in both of these components (atmospheric and oceanic) also varies between models. The treatment of sea ice and its underlying dynamic, coupling procedures, and land surface representations are also categories that are noted by the IPCC-AR4 as contributing the most identifiable differences between commonly used AOGCMs. It is therefore common practice for multiple models to be used for evaluating potential climate change impacts, such approaches will be discussed in detail in section 1.3.

1.2 Downscaling Climate Data Scenarios

Within the climate modeling community, it has long been speculated that increasing the resolution of climate models is necessary to improve the estimates of regional-scale phenomena, such as precipitation (e.g. Giorgi, 1990; McGregor, 1997; Murphy, 1999; Di Luca et al., 2011; and Caldwell, 2010). The process of downscaling outputs from GCMs has been established as the primary approach for addressing the inadequacies of large scale resolution models. There are two main classes of downscaling procedures: statistical and dynamical. Numerous studies over the last several decades have provided detailed comparisons and exploration of both downscaling types (e.g. Hewitson and Crane, 1996; Murphy, 1999; Wood et al., 2004; Salathe et al., 2007; Fowler et al., 2007). Additional studies have focused on the success of applying various downscaling techniques combined with hydrologic modeling over particular regions within the United States including the Western U.S. (Hay and Clark, 2003), the Northeastern U.S. (Tryhorn and DeGaetano, 2010), and the Pacific Northwest (Salathe et al., 2007). Statistical approaches involve determining reliable statistical relationships between large-scale climate variables, those that are well represented by GCMs, such as pressure fields, and local scale variables, such as temperature or precipitation (Najafi et al., 2011). There is currently an extensive variety of statistically-based approaches; a general description of these groups will be provided below (for a more comprehensive review see Wilby and Wigley, (1997) and Fowler et al., (2007)). Dynamical approaches are based on the same numerical integration of differential governing equations, as in GCMs, but over a smaller spatial and temporal domain. Given recent advancements in computational efficiency and resources, dynamical downscaling, via Regional Climate Models (RCMs), has expanded to the point where numerous RCMs exist and the need for multi-model comparison is beginning to be addressed (Kendon et al., 2010; Mearns et al., 2009; van der Linden et al., 2009).

The multiple statistical downscaling approaches that are commonly used in recent literature have been traditionally classified into three categories: weather typing, weather generators, and regression methods. Weather typing, or weather classification schemes, establish a finite number of weather types, or classes, then group observed station data or meteorological data together based on statistically defined similarities. Such approaches include principal components, canonical correlation analyses, fuzzy rules, compositing, neural networks, correlation-based pattern recognition, and analogue procedures (Wilby and Wigley, 1997; Fowler et al., 2007). Weather generators are classified as models that deal with the statistical attributes of local climate variables. Examples of such approaches include mixture modeling, storm arrival times, spell length methods, Markov chains, and stochastic models (Wilby et al., 2004). Regression methods, among the earliest developed downscaling approaches, are based on establishing linear or nonlinear relationships between GCM output predictor variables and site specific parameters and can involve regression across multiple scales (Wilby and Wigley, 1997; Fowler et al., 2007). Among the more common regression based methods are variations based on neural networks, canonical correlation analysis, kriging, linear regression, and multiple linear regression

(Wilby et al., 2004). Since the focus of this study is related primarily toward dynamically based downscaling, the reader is encouraged to see the above references for additional information regarding statistical approaches.

The basic approach of dynamical downscaling via RCMs follows the same procedures established for GCMs, in terms of physically-based governing equations, but over a smaller scale in both time and space. GCMs evaluate climate variables over the entire globe over a multi-decade time scale, whereas RCMs focus on a regional area, on the order of a continent or single ocean body, over a more modest temporal scale, on the order of a few months or years, for analysis. Experimentation with such an approach started in the late 80s and were later summarized by McGregor (1997). A fundamental assumption of regional modeling approaches is that, over a limited area, data on large-scale climate variables can be used as initial (or driving) conditions to a RCM. The focus on a smaller domain size within the model negates the need for additional computational requirements that are often impractical.

It is accepted that climate in one particular area of the globe is influenced by the climate in all other areas across the globe. The so called 'boundary conditions' of a regional area are composed of all the climate information that will enter into or influence that particular area. For RCMs, the boundary conditions for future simulations are provided by GCMs and, for historical simulations, they can originate from GCMs or from gridded historical observation sets. The importance and influence of these boundary conditions are fundamental aspects of RCM-related research and has received a great deal of attention (e.g. McGregor, 1997; Giorgi, 1990; Murphy, 1999).

Giorgi (1990) concluded that nested models (aka RCMs) produce improved precipitation and temperature distributions at the regional-scale, compared to GCM output alone. This study represents one of the earliest applications of the dynamical downscaling approach. The study region for the article consists of the western United States and the adjacent ocean waters, selected due to the topographical complexity. As the goal of RCM approaches is to accurately reproduce large-scale climate patterns, as well as those smaller scale topographically influenced climate phenomena such as temperature, the selected study area was both large enough and entailed enough topographic variability to test both goals. The study applied a GCM, the National Center for Atmospheric Research (NCAR) Community Climate Model (CCM) version 1, and an RCM, the Penn State/NCAR Meso-scale model MM4 over the study area (Giorgi, 1990). The CCM model outputs were used to provide driving conditions to the MM4 model. As an initial step, the study used the CCM model alone to determine if large-scale January climate was simulated; this step was found to be successful. A subsequent step used the CCM model to drive the MM5 RCM in order to determine if the limited area model approach is able to improve simulation of regional climate aspects. The results demonstrate that the approach does accomplish the second goal, with the MM4 simulation producing "much more realistic regional detail of the temperature and precipitation distribution than the CCM alone" (Giorgi, 1990). Furthermore, the MM4 results were compared with high resolution station observation, in terms of temperature and precipitation mean as well as daily precipitation intensity frequency in that study.

They were found to exhibit high similarity, particularly in spatial distribution (Giorgi, 1990).

Caldwell (2010) found that RCMs tend to over-predict precipitation estimates and that, contrary to expectations, “improved resolution does not translate into improved simulation….” For this study, the author investigated performance of gridded observational datasets, RCMs, and GCMs ranging in spatial resolution from 1/12th of a degree up to 4.5 degrees in terms of their ability to reproduce wintertime precipitation (Pr) over the state of California. The author looked at the ability of the various methods to capture mean precipitation, precipitation distribution, and temporal variability. A total of 24 different models and gridded observation datasets were collected and investigated. The author concluded that all models with resolution finer than three degrees were able to accurately reflect observed conditions “in the sense that the California mean for these models is essentially independent of the averaging method” (Caldwell, 2010). The author notes that the removal of bias from the climate models is “critical” and observes that, in regards to the RCMs investigated, there exists a “wet bias [that] seems to be associated with strong Pr events, while Pr frequency is generally under-predicted” (Caldwell, 2010). The author suggests further investigation of both of these findings.

Di Luca et al. (2011) found that temporal scale is one aspect where RCMs do provide noticeable improvements compared to coarser resolution models. The central concern of that study was to identify a manner of objectively quantifying the amount of information gained from RCM efforts. The authors accurately point out that although RCM simulations may not add substantive value across all aspects of climate change prediction, identifying areas where they do add significant information should be an area of greater concern and research. Instead of concentrating on whether RCMs improve all desirable climate-related information at all locations at all time scales, it would be more beneficial for resources to be focused on identifying those aspects that are improved via RCM simulation, thereby resulting in more skillful impact and adaptation investigations. Results of that study reveal several aspects were the added value of RCMs is noticeable: shorter temporal scale, warm seasons, and in regions of complex topology (Di Luca et al., 2011).

Although the benefit of RCM-based downscaling has not been unequivocally demonstrated, the majority of results point toward marked improvements over GCM outputs. Multiple reoccurring issues tend to arise throughout recent related research. Namely the influence of the forcing/boundary conditions, the variability within the numerous available RCMs, and their applicability across different seasons, time scales, and regions are frequent focus areas. As a result, the growth of multi-model, regional, and ensemble projects has been evident in recent decades.

1.3 Multi Model Ensemble Investigation

Due to the expansion of climate modeling efforts, resulting in an abundance of distinct climate models, there is a need to evaluate how these models perform relative to one another. Multiple model inter-comparison projects have been organized to meet this need. On a global scale, the Coupled Model Intercomparison Project (CMIP) and Atmospheric Model Intercomparison Project (AMIP) are the most notable collaborations undertaken with this goal in mind. Beginning in the mid 1990s the World Climate

Research Programme (WCRP) committee, which has since evolved into the WCRP/Climate Variability and Predictability (CLIVAR) Working Group on Coupled Models (WGCM), set about to organize one of the first generations of inter-comparison projects (Meehl, 2007). Their efforts have since resulted in multiple CMIP generations, recently culminating in an open-access dataset, the WCRP CMIP3 multi-model dataset which represents "an unprecedented, comprehensive coordinated set of global couple climate model experiments" (Meehl, 2007). Among the accomplishments of this project, the ability for the climate science research community to access the results of the CMIP3 project in a comprehensive and organized fashion was of monumental importance. As a result, countless studies have been undertaken using these results, providing the climate science community with "a new era in climate science research" (Meehl, 2007).

Several regional programs have been conducted in the last decade focused on addressing the need for appropriate scale level assessment of climate change impacts. In Europe, the Prediction of Regional scenarios and Uncertainties for Defining EuropeaN Climate change risks and Effects (PRUDENCE) project described in Christensen et al. (2007), followed by the Ensembles-Based Predictions of Climate Changes and Their Impacts (ENSEMBLES) project (van der Linden et al., 2009) provided an array of regional datasets for investigating future climate variation. The STAtistical and Regional dynamical Downscaling of EXtremes for European regions (STARDEX) project focused on the frequency and intensity of twenty-first century extreme events over Europe (http://www.cru.uea.ac.uk/projects/stardex/). In South America, a coordinated effort with Europe has resulted in the Network for Climate Change Assessment and Impact Studies for South America (CLARIS) project (www.claris-eu.org). Furthermore, a worldwide project called the Coordinated Regional Climate Downscaling Experiment (CORDEX) has begun as part of the IPCC-AR5. CORDEX's goal is to combine dynamical and statistical downscaling efforts for a comparison project (Kreienkamp, 2011).

In North America, the North American Regional Climate Change Assessment Program (NARCCAP) provides data from multiple GCM-RCM coupled simulations over the majority of the continent (Mearns et al., 2009). The RCM data used in this thesis study was provided by NARCCAP efforts. NARCCAP's goal is the production of climate simulations at a resolution which allows for regional-scale investigation of future climate variation. The products are intended to be useful in generating and studying impact scenarios across much of North America. The program consists of multiple RCMs driven by multiple AOGCMs. Simulations of both future (2041-2070) and historic (1971-2004) periods were produce by the NARCCAP modelers at a spatial resolution of 50km and sub-daily temporal resolution. Future scenarios were forced for the twenty-first century using the Special Report on Emissions Scenarios (SRES) A2 emissions scenario. More information regarding the A2 emission scenario is provided in Nakicenovic et al. (2000).

To allow for additional performance evaluation of the RCMs, NARCCAP conducted a preliminary experiment in which each RCM is driven with a reanalysis dataset, specifically the National Centers for Environmental Prediction (NCEP) Reanalysis II. The reanalysis dataset, described in detail by Messinger et al. (2006), provides a "long-term, dynamically consistent, high-resolution, high-frequency, atmospheric and land surface dataset" over North America. Among other unique attributes, it utilizes the most up-to-date data assimilation techniques to bring together the vast array of observed hydrology-related data, both current and historical, made available from both in-situ and satellite-born collection devices. The goal of reanalysis datasets, which requires frequent and timely updates to previous reanalysis, is to provide an up-to-date collection of the variety of observational datasets that have been active currently and historically in order to provide a concise, accurate, and reliable comparison base for climate models. The NCEP Reanalysis II dataset represents the most recent and applicable dataset reflecting historically observed data.

The three RCMs selected for this study are the following: the Weather Research and Forecasting model from Pacific Northwest National Labs (WRFP), the MM5-PSU/NCAR Meso-scale Model from UC Santa Cruz (MM5I), and the Canadian Regional Climate Model from the OURANOS/UQAM group (CRCM). Detailed information regarding all RCM models used in the NARCCAP study is available from the NARCCAP website (http://www.narccap.ucar.edu/data/model-info.html). These three models were selected for comparison because they were all driven by the same AOGCM simulation which provided identical initial/boundary conditions. The specific AOGCM which provided initial/boundary conditions for each of the three RCMs is the Community Climate System Model (CCSM), ensemble member b30.030e for the historical period and b30.042e for the future period. Detailed information regarding this model is available from the following website (http://www-pcmdi.llnl.gov/ipcc/model_documentation/CCSM3.htm). The effect and importance of these initial/boundary conditions on RCM output is an ongoing area of research (e.g. Gao et al., 2011; Frei et al., 2006). By selecting these three RCMs this study attempts to look solely at the individual RCM influence compared with observed datasets. The benefit of this type of analysis is that it provides an estimate of uncertainty in future variability that is directly due to the RCM model characteristics, not a combination of AOGCM-RCM uncertainty.

1.4 Extreme Value Analysis

The evaluation of future climate scenario variation can be accomplished using common techniques from the field of extreme value analysis. Several recent studies have investigated future precipitation variability via extreme value analysis techniques (e.g. Katz et al., 2002; Tryhorn and DeGaetano, 2010; Schliep et al., 2010). If the climate signal variables can successfully be fit to known extreme value distributions, a great deal of information regarding the variable can be gained. For instance, parameters of the distribution can yield estimates of how the occurrence of extreme events may change in future periods. As such, the distributions can be used for estimating the magnitude of extreme event return values.

Katz et al. (2002) provides a detailed review of extreme value analysis techniques and their application to water resource engineering. The authors begin with a historical review of the connection between hydrologic extremes and extreme value theory. A clear description of the Generalized Extreme Value (GEV) distribution, its parameters, and the physical implications of heavy tails in the representative distribution follows, along with supporting examples. The study offers a review of how extreme value theory has been incorporated into previous research and guidance for how future studies could benefit from additional aspects established by statisticians.

Tryhorn and DeGaetano (2010) compared the results from both statistical and dynamical downscaling methods in terms of their replication and prediction of extreme precipitation events over the Northeastern United States. The study compared a bias-correction and spatial disaggregation technique (BCSD), the statistical downscaling model (SDSM) and one RCM (HadRM3). The authors used the GEV distribution approach in order to validate spatial distributions and return period estimates. Their findings demonstrate that although all methods were capable of nearly accurate reproduction of historical events, the RCM demonstrated the least skill in those simulations. However, the statistical methods were highly dependent on the historical period used to fit the models; this shortcoming is not shared by the dynamical approach.

Schliep et al. (2010) used spatial hierarchical modeling to compare six different RCMs generation of extreme precipitation. A significant benefit of the hierarchical approach taken by the authors is that it allowed for analysis covering the entirety of the NARCCAP study region. The GEV distribution served as the “foundation” of the authors’ hierarchical model (Schliep et al, 2010), providing additional evidence that its application toward extreme precipitation analysis is beneficial. The results of the study demonstrate that the RCMs produce similar spatial patterns of extreme event occurrence, however the individual models demonstrate noticeable differences in the details of these occurrences.

1.5 Watershed Scale Impact Analysis

The influence of future climate variation on individual watershed characteristics is a topic of numerous recent research studies which have included both statistical and dynamical downscaling approaches. Gao et al. (2011) used RCM simulations to investigate climate variation impacts on the Colorado River Basin. They found that although RCMs do not provide significant improvements to simulation of precipitation estimates, the increased resolution of RCMs compared with their host GCMs do provide a better representation of the overall influence of future climate change. Chang and Jung (2010) estimated possible variability in runoff over Oregon's Willamette River Basin using multiple GCM and emission scenario combinations. Their results demonstrated that the main source of variability in future projections is due to the climate model choice rather than emission scenario or parameter choice within the hydrologic model. A related study by Najafi et al. (2011) investigates the uncertainty due to both GCM and hydrologic model selection by using four hydrologic models and eight statistically downscaled GCM simulations, each with two emissions scenarios, over Oregon's Tualatin River Basin. Their results demonstrate an effective implementation of Bayesian Model Averaging (BMA) toward quantifying the uncertainty due to various aspects of climate change impact assessment, whether it be related to the choice of hydrologic model, emission scenario, or GCM (Najafi et al., 2011).

Further studies, such as Mote and Salathe (2010) have found, over the Pacific Northwest US, climate model (specifically GCM) simulations predict a rather modest one-two percent increase in precipitation accompanied with a more profound change in the seasonal cycle of precipitation. Hay and Clark (2003) compare five separate datasets, applied to a hydrologic model, over three distinct Western US mountainous basins. The five datasets include a reanalysis dataset, an RCM downscaled and statistically downscaled version of that same reanalysis data, and two derived observed datasets (Hay and Clark, 2003). Results of that study indicate the importance of bias correction (discussed in section 3.3) of all downscaling procedures, particularly for dynamically downscaled datasets. Najafi et al. (2011) applied three statistical downscaling approaches to describe precipitation occurrence over the upper WRB, with a focus on the selection of appropriate GCM predictors. Their results demonstrate that an efficient downscaling procedure based on selecting appropriate GCM variables and Multi-Linear Regression (MLR) analysis is achievable. Moradkhani et al. (2010) applied the Bias-Corrected Spatial Downscaling (BCSD) method of Wood et al. (2004) to multiple GCM datasets over the Lower Tualatin basin in Oregon. Their focus was on the impact to floodplains and eco-hydrologic factors resulting from climate change, as predicted by multiple GCMs and emissions scenarios. Results of that study indicate that the emission scenario has a profound impact on return period flow levels in the basin, as modeled by the Soil and Water Assessment Tool (SWAT) hydrologic model (Moradkhani et al., 2010). Further investigation of the extent of this variation, as well as the impact on extreme precipitation events, is required in order to provide confidence in future predictions that will impact water managers, public safety concerns, and water-related structural designs.

Chapter 2

Study Area and Datasets

2.1 Willamette River Basin

Oregon's Willamette River basin (WRB), see figure 1, covers 29,728 square kilometers (11,478 square miles), roughly twelve percent of the entire state, and intersects or contains thirteen of the thirty-six counties in the state (Hulse et al., 2002). It is home for more than two-thirds of Oregon's population and serves urban, agricultural, wildlife and recreational land use interests (Hulse et al., 2002; Chang and Jung, 2010). According to the US Census Bureau, Oregon's population grew approximately twelve percent from 2000-2010, reaching a total of 3.8 million people statewide. The 1990 population within the WRB, roughly 2 million people, is predicted to double by the year 2050 (Hulse et al., 2002). The Willamette River, 13th largest in the continental US in regards to stream flow, captures more runoff than its higher ranked counterparts, per unit of land area (Hulse et al., 2002).

The temperate marine climate of the basin translates into cool wet winters, with 80 percent of annual precipitation occurring between October and May, and warmer mostly dry summers (Lee and Risley, 2001). Average annual temperatures in the region depend primarily on elevation and range from forty to sixty-five degrees Fahrenheit (F), with the lower valley elevations experiencing January's daily minimum at thirty degrees F and July's daily maximum at eighty degrees F (Lee and Risley, 2001). Annual mean precipitation also varies with elevation, from about forty inches at the lowest elevations up to 175 inches at the highest elevations. Precipitation in the form of snow at the higher elevations within the basin is an influential component of the overall water cycle. Recent studies estimate that as much as seventy-five percent of precipitation falls as snow at or above 6500 feet (Change and Jung, 2010). Above 4000 feet, thirty-five percent of precipitation falls as snow (Lee and Risley, 2001). Snowfall, and subsequent snowmelt, provides an estimated thirty-five percent of annual flow in the Willamette, directly as surface flow or indirectly through the subsurface (Lee and Risley, 2001).

Given the projected population growth and influence of precipitation on the WRB, understanding the effect of future climate variability on the region is of crucial importance for all stakeholders in the region. The range of land uses within the basin all rely heavily on the Willamette River and the watershed basin itself, even small alterations in the form or timing of precipitation events may have monumental impacts on the region as a whole. Understanding how the WRB may change given the potential of future climate variation is therefore a crucial study question and exploratory analysis of climate models yields one approach for addressing this issue.

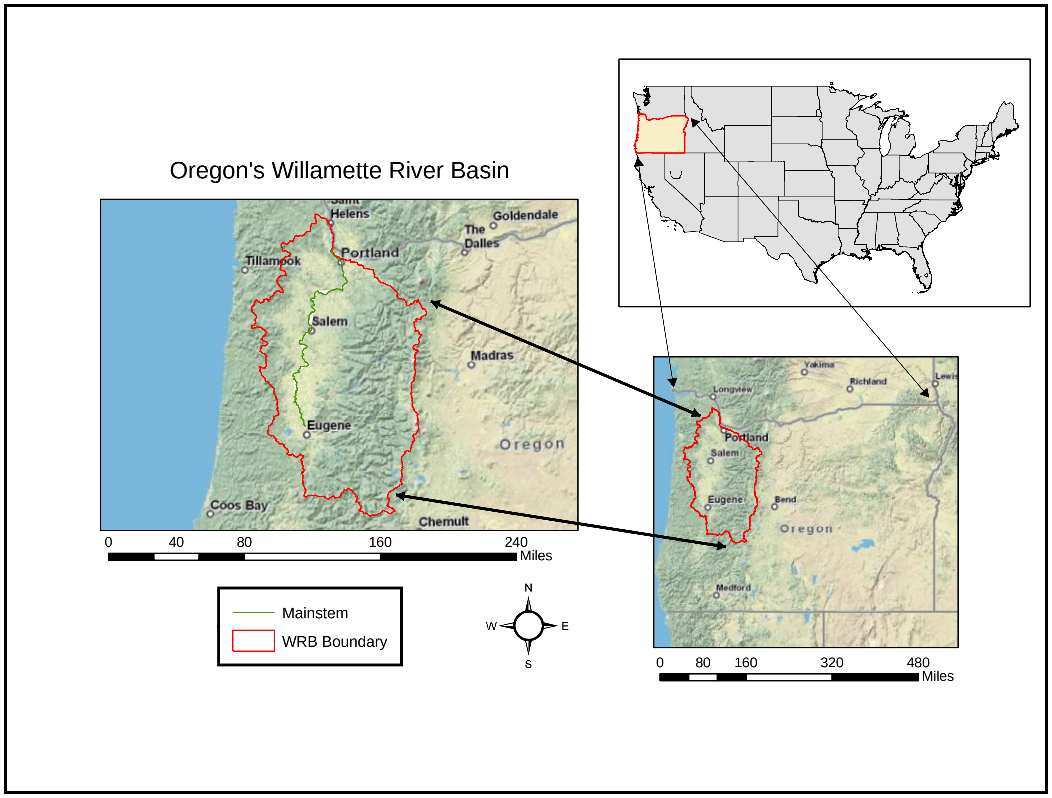

Figure 1 Study Area: The Willamette River basin in Oregon outlined in red with the mainstem Willamette River outlined in green.

2.2 Observed Dataset

To provide a comparison with observed precipitation over the WRB the University of Washington (UW) gridded dataset, described by Maurer et al. (2002), was used. This dataset covers the time period 1950-2000 and provides surface level information regarding numerous climatic variables at three-hourly time intervals. Specifically for this study, the UW dataset provides values of total daily precipitation over the continental United States obtained from the National Oceanic and Atmospheric Administration's (NOAA) Cooperative Observer (Co-op) stations (Maurer et al., 2002). The precipitation data over the WRB used in this study was obtained at 1/8th degree resolution and served as an observational benchmark upon which the dynamically downscaled NARCCAP datasets were compared. This dataset was downloaded in NetCDF form and converted to spatially referenced point values using ESRI ArcMap 9.3. A description of this process is located in the methods section of this paper.

2.3 Dynamically Downscaled Datasets

As described in the introduction in chapter 1, the NARCCAP project provides dynamically downscaled GCM outputs at a spatial resolution averaging 50km. Data from three distinct RCMs were selected for this study. This selection provided a means of investigating the variation due to the RCMs themselves, since they were driven using the same GCM initial/boundary conditions. Precipitation rate data [$kgm^{-2}s^{-1}$], at a temporal resolution of three hours, was obtained over both a historical period (1979-2004 for the NCEP reanalysis driven data and 1976-2000 for the GCM driven data) as well as a future period (2038-2069). The spatial location of each RCMs grid points within the WRB is displayed in figure 2. The number and location of grid points within the WRB varies between RCMs, owing to inherent design differences of each model. The CRCM model provided 14 grid points within the study area where as the MM5I and WRFG models each had 11 grid points within the WRB. Although the amount of RCM grid points within the study region is rather sparse, it still represents an improvement upon the spatial resolution of GCMs. As with the UW dataset described above, the NARCCAP RCM datasets were downloaded from the NARCCAP project website in NetCDF form and converted to spatially referenced point values using ESRI ArcMap 9.3 as described below in the methods section.

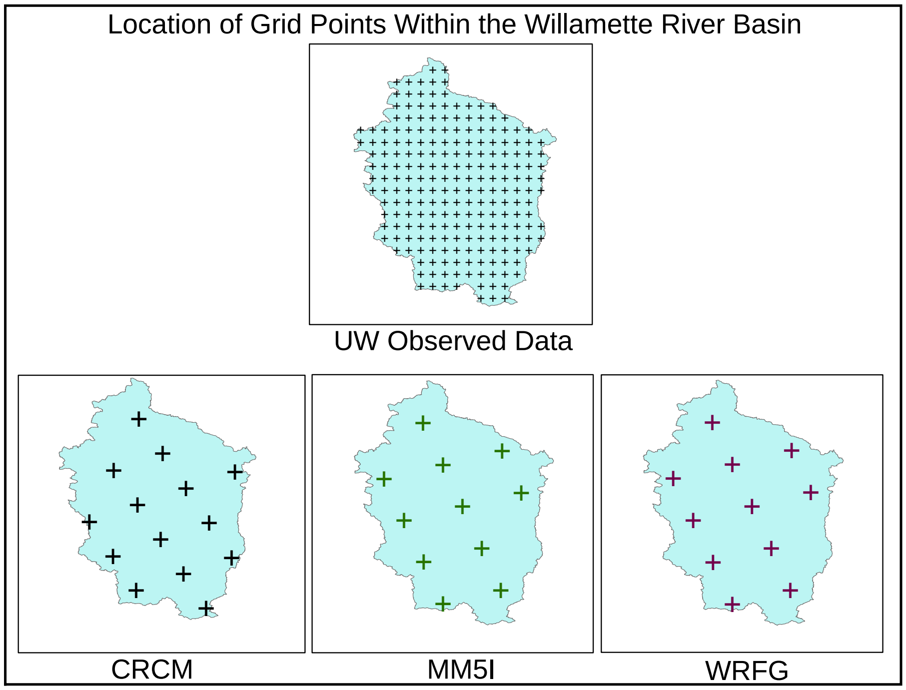

Figure 2 Grid Points: Location of grid points within the WRB study area for both the observed UW dataset and each RCM (location indicated by a '+' sign).

Chapter 3

Methods

The majority of analysis in this study was intended to provide initial exploratory analysis of the NARCCAP RCM datasets. In order to accomplish this goal, all datasets were converted into ESRI ArcMap 9.3 for visual depiction, interpolation, and spatial analysis. In addition to ESRI's ArcMap 9.3, additional analysis of extreme precipitation values was carried out using the R language extension package 'extRemes'. This section will provide a description of the tools and procedures implemented that provides the means for visual comparison and exploratory analysis of the RCM data.

3.1 Visual Data Depiction

To provide a visual basis for comparing the NARCCAP RCM datasets with observed historical datasets, both datasets were converted from NetCDF format into spatially referenced point values using ArcMap 9.3. As mentioned in chapter 2, the observed UW gridded dataset has a spatial resolution of $1/8^{th}$ of a degree, or approximately 12km. The NARCCAP RCM datasets have a spatial resolution of approximately 50km.

To provide a means of visual comparison between the datasets, a linear interpolation scheme was implemented on the RCM data points in order to achieve the UW spatial scale of 12km. The interpolation scheme implemented converted the point values, spatially referenced to the grid locations identified in chapter 2, into raster grid approximations with an individual grid cell size set at 12km using an inverse distance weighted (IDW) scheme. Although multiple interpolation schemes are preprogrammed into ArcMap (including IDW, Spline, and Kriging) the IDW scheme was selected since it is the simplest and most straightforward approach therefore providing an initial basis for dataset comparison.

In order to visually identify the influence of the driving data (or initial conditions) of RCM simulations this study used multiple approaches. First a comparison between each RCM, driven by NCEP Reanalysis initial conditions, and the observed UW dataset was performed. This comparison will provide initial estimates of how RCM simulations, even when driven by a dataset representing real-world observed conditions, compare to other gridded observed datasets. The goal of this comparison is demonstrate the fact that the choice of observed dataset used for comparison to climate model output has a profound impact on any visual analysis and comparison between climate models.

A second approach will compare RCM simulations, driven by GCM derived initial/boundary conditions, with RCM simulations driven by the NCEP Reanalysis initial/boundary conditions. This comparison will provide a visual depiction of the influence of the driving characteristics on the RCM simulations. As mentioned in chapter 1 this influence is currently a topic of study for researchers and modelers using any climate model outputs.

3.2 Extreme Value Analysis

3.2.1 GEV Distribution

For this study, precipitation values obtained from the NARCCAP datasets for the historic and future periods were fit to a Generalized Extreme Value (GEV) distribution.

Parameters of the GEV distribution, which is a combination of the Gumbel, Frechet and Weibull extreme value families, were then calculated based on maximum likelihood estimation. Mathematically, the GEV distribution is:

$$F(x;\, \mu, \sigma, \gamma) = \exp\{-[1+\gamma(x-\mu)/\sigma]^{-1/\gamma}\}, \tag{1}$$

$$\text{If } \gamma \neq 0 \text{ then: } F(x;\, \mu, \sigma, \gamma) = 1+\gamma(x-\mu)/\sigma>0, \tag{2}$$

$$\text{If } \gamma = 0 \text{ then: } F(x;\, \mu, \sigma, \gamma) = \exp\{-\exp[-(x-\mu)/\sigma]\}, \tag{3}$$

where μ is termed the location parameter, σ is the scale parameter, and γ is the shape parameter of the representative distribution (Katz et al., 2002). In order to determine the distribution values given the observed precipitation dataset, the maximum likelihood (ML) estimation method was employed. The observed precipitation datasets for each model were exported from ArcMap shapefiles into .dat data files for implementation into the R language software package extension 'extRemes' for extreme value analysis. The 'extRemes' package then computed the GEV distribution parameters based on the ML estimation procedure.

Of particular importance for this study, the shape parameter of the estimated GEV distribution provides valuable information regarding the historic and future occurrence of extreme events. When the shape parameter is positive, the presence of a heavy leading tail in the representative GEV distribution is indicated (Katz et al., 2002). The presence of a heavily tailed distribution indicates that a quantifiable likelihood of events with large magnitudes exists in the representative distribution. If instead the shape parameter is less than zero, the GEV distribution is said to have a bounded upper tail (Katz et al., 2002). The presence of a bounded tail in a distribution indicates that there is defined event magnitude above which there is no statistical likelihood of any larger magnitude events occurring. If the shape parameter is equal to zero, the GEV distribution simplifies to the Gumbel EV distribution; this distribution is representative of an unbounded but thin tail (Katz et al., 2002). An unbounded but thin tailed distribution indicates that although no upper bound exists, the likelihood of events with large magnitudes is small compared to those distributions with heavy tails. It is important to mention that the width of the GEV distribution indicates the level of uncertainty present in the distribution. Wider distributions, for example those that are unbounded and have either heavy or thin tails, indicate that a higher level of uncertainty accompanies that distribution. Narrower distributions, for example those that are bounded, indicate a lower level of uncertainty in the assignment of the distribution. Therefore, although the presence of an unbounded heavy or thin tail indicates the potential likelihood of larger magnitude events, these distributions are also more uncertain compared to those that include a bounded tail distribution.

In terms of the simulated historic and future period precipitation datasets, an unbounded tail indicates that larger magnitude precipitation events are possible, or at least that the representative GEV distribution indicates there exists a quantifiable likelihood of their existence. A bounded upper tail in the distribution indicates that there is a maximum precipitation level above which the likelihood of larger magnitude events is not statistically likely.

3.2.2 Return Level Analysis

As well, the return level of extreme storm events can then be calculated by combining the GEV distribution with desired non-exceedance probability values. Given the GEV distribution above, the quantile function yields estimates of the return levels that exceed a desired return period. Mathematically this quantile function is:

$$F^{-1}(1\text{-}p;\, \mu, \sigma, \gamma) = \mu + (\sigma/\, \gamma)\{[-\ln(1 - p)]^{-\gamma} - 1\},\ \gamma \neq 0, \tag{4}$$

$$F^{-1}(1\text{-}p;\, \mu, \sigma, \gamma) = \mu + \sigma\{-\ln[-\ln(1 - p)]\},\ \gamma=0. \tag{5}$$

As in section 3.2.1, μ is termed the location parameter, σ is the scale parameter, and γ is the shape parameter of the representative GEV distribution, p is the desired return period, and (1-p) is the computed non-exceedance probability. For this study, two, five, ten and twenty-five year return levels, in units of mm/day, were determined for both the historic and future periods. As was the case with the ML estimation of the GEV distribution, the 'extRemes' package, using the shape, location and scale parameters combined with user specified return periods, yielded estimates of the return levels for each RCM simulation dataset. Return level magnitudes serve as the basis for many aspects of water resource design and management, the ability to accurately predict how these values may change in the future due to climate variability may provide valuable insight and information that leads to increased economic and public safety.

3.3 Bias Correction

In order to more accurately compare historic and future climate model simulations, current research studies suggest the use of bias correction techniques such as the delta change procedure (e.g Fowler et al., 2007; Mote and Salathe, 2010; Shrestha, R.R. et al., 2011). The need for bias correction of climate model simulations over future periods is widely accepted throughout the community of researchers who use climate model outputs for hydrologic impact studies (Wood et al., 2004), however the relative strengths and weaknesses of each individual correction technique is still a focus of research (Johnson and Sharma, 2011). Model bias exists within climate models for multiple reasons. Commonly identified causes of bias are attributed to model structure and initial/forcing condition treatment. The delta change approach represents a particularly straight forward bias correction technique that has been extensively researched within the field. This approach involves identifying the difference between observed and model simulated historical conditions, quantifying this difference for a specified grid location, and then applying this knowledge to future period climate model simulations. The major advantage of this approach is its ease of implementation and that it is commonly used in current research. A common criticism of this approach is that it is not able to account for the non-stationarity aspect of future climate variability (Johnson and Sharma, 2011).

Chapter 4

Results

Several methods exist for displaying, comparing, and evaluating climate model variables. One approach is to spatially plot the data values within a particular study region using color variation to highlight the differences between individual simulations and models. Such an approach has multiple benefits. First, it involves relatively few post processing steps, thereby reducing the possibility of errors due to improper mathematical transformation or other user-specific contributions. Second, the products tend to require little accompanying information. The figures are essentially self explanatory and appeal to a variety of viewers, not just experts in the field. In order to avoid a common pitfall to this approach, data misrepresentation associated with the choice of classification scheme, an equal interval scale was applied to all of the output graphics. The interval extent will vary depending on the type of comparison being presented, however within each individual figure the color scheme and corresponding interval range will be similarl. Each figure will be displayed with a corresponding scale bar informing the viewer of the range of possible values.

4.1 Initial Condition Dependence

As mentioned in the methods section, two approaches were taken to demonstrate the importance of the initial conditions (or driving dataset). Figure 3 demonstrates the first approach, comparing the UW gridded precipitation dataset against the simulations produced by each RCM simulation forced using the NCEP reanalysis dataset as initial/boundary conditions. The first row of figure 3 shows the interpolated values of the average of extreme value precipitation over the historical period (1979-1999) as given by the UW gridded dataset. The second row of figure 3 shows the same quantity as derived from each of the RCMs. The average of extreme precipitation values range from 31mm/day to 48mm/day. Comparing the RCMs with one another (figure 3, row 2) reveals that the CRCM model has notably lower simulated values versus both the WRFG and MM5I models, which are comparable with each other. Row 3 of figure 3 displays the bias between the observed UW gridded dataset and each RCM simulation, where bias is defined as the difference (RCM-UW) between the interpolated pixel values. Larger magnitudes in bias indicate areas of large disagreement between observed and RCM simulation. Negative bias values represent RCM simulation values lower than observed and positive values indicate RCM over-prediction of precipitation. The range of bias present between each RCM and UW gridded data indicate as much as 20% disagreement between simulated and observed values. Comparing the bias present within each RCM reveals that the WRFG and MM5I models tend to over-predict precipitation over much of the central WRB where as the CRCM model tends to slightly under-predict precipitation over the higher elevations surrounding the central WRB valley.

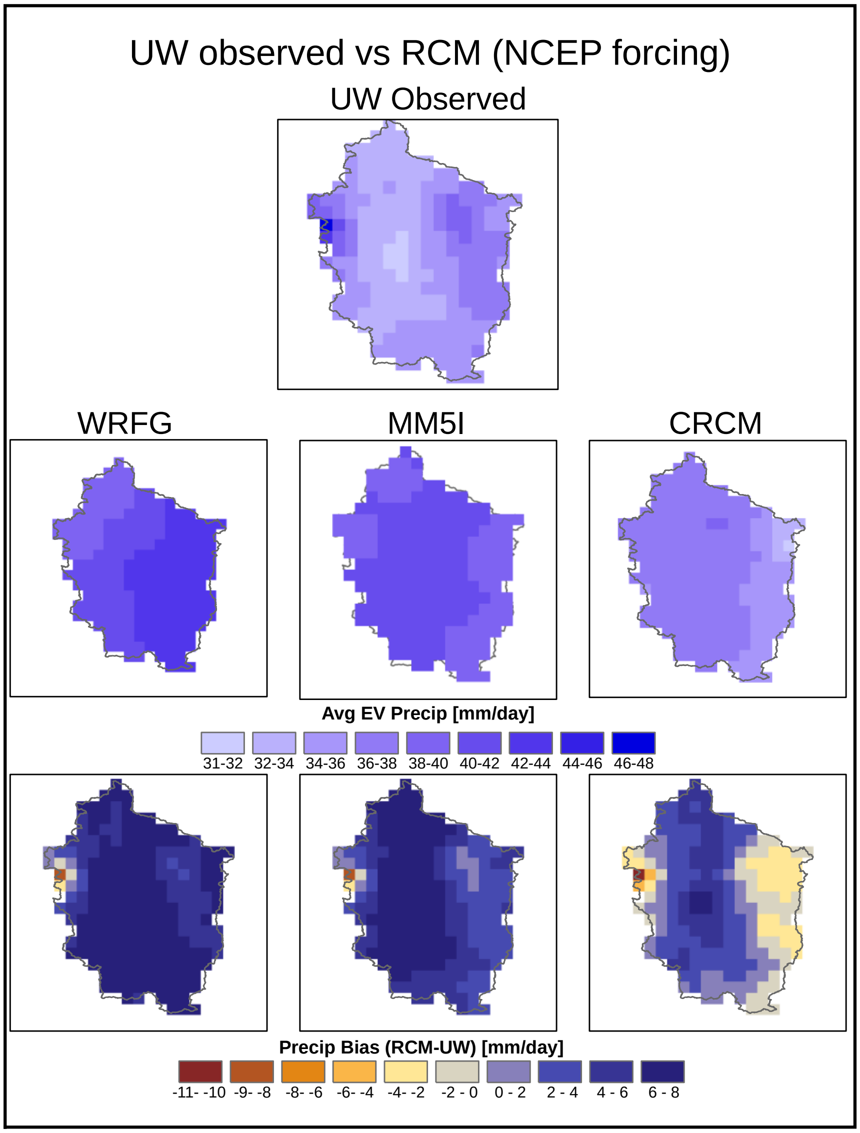

Figure 3 UW vs NCEP: UW observed data compared with each RCM (forced with NCEP Reanalysis) along with bias (RCM – UW) (Larger magnitude bias indicates larger disagreement, negative bias indicates RCM under-predicting precipitation and positive bias indicates RCM over-predicting precipitation).

The second comparison approach, as described in the methods section, further demonstrates the importance of the initial conditions/forcing dataset. Figure 4 compares each RCM driven by the NCEP Reanalysis dataset (row 1) as well as an AOGCM dataset (row 2). As mentioned above this AOGCM, the CCSM model, provided the same initial/boundary conditions to the RCMs. Therefore figure 4 demonstrates the difference between each RCM driven by two forcing datasets and is not complicated by the inclusion of multiple AOGCMs, which would contribute an additional level of error and uncertainty attributed to the AOGCM and is not the focus of this study. This comparison is not aimed at identifying an optimal AOGCM for providing initial/boundary conditions, but rather the difference between the RCMs as well as the influence of the forcing dataset.

Row 1 of figure 4 shows the interpolated average of extreme precipitation values over the historical period (1979-1999) resulting from each RCM when driven by the NCEP Reanalysis dataset as initial/boundary conditions. Row 2 of figure 3 shows the result when the RCMs are driven by an AOGCM (CCSM). As in figure 3, the CRCM model tends to predict slightly smaller magnitudes of precipitation compared to the MM5I and WRFG models, as demonstrated by the presence of lighter color shades throughout the WRB.

However the disagreement between the NCEP and CCSM simulations is small compared to the difference between the NCEP driven RCMs and the UW gridded dataset. Several factors will influence this difference; however the most notable factor is the resolution of the UW dataset compared to the RCM resolution. Although an interpolation scheme, IDW, was implemented on the RCM data to achieve the resolution of the UW gridded dataset, this interpolation scheme does not take elevation variation into account. Since precipitation magnitude varies with elevation, it would be prudent for further studies to apply an interpolation scheme, such as the hypsometric method, that accounts for elevation changes when providing precipitation estimates.

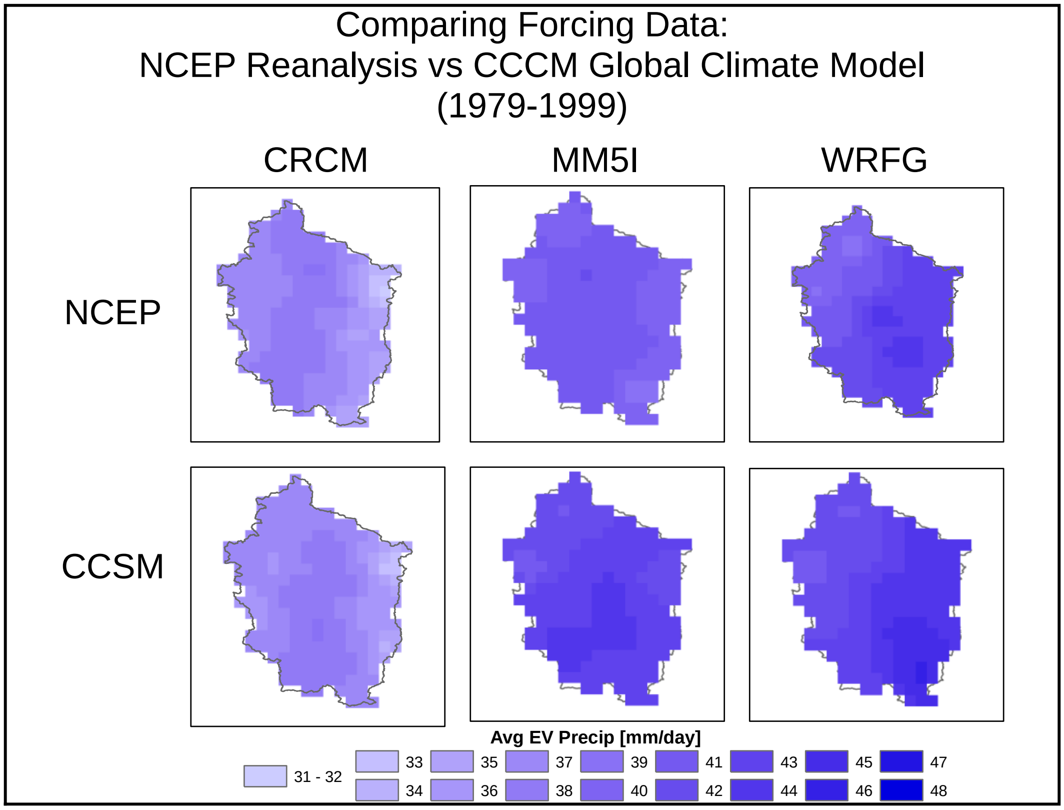

Figure 4 NCEP vs GCM: Illustrating the influence of the forcing dataset on the RCM results (darker shades represent greater magnitudes of average extreme value precipitation). Note: the NCEP reanalysis produces lower values of average extreme precipitation and the CRCM RCM produces noticeably lower values than both MM5I and WRFG.

4.2 Extreme Value Analysis

The shape parameter obtained from the GEV distribution analysis reveals a number of important aspects about the historic and future RCM datasets. As mentioned in section 3.2.1, the value of the GEV distribution shape parameter yields valuable information regarding extreme events. In terms of the simulated precipitation events over the WRB, a positive shape parameter indicates the presence of a heavy upper tail (higher likelihood of extreme magnitude events), a negative shape parameter indicates a bounded distribution (an identifiable upper limit to those extreme events), and when the shape parameter is equal to zero the distribution is unbounded but has a thin upper tail. However, when the distribution is wider, or unbounded, the uncertainty in the distribution increases.

Figure 6 displays the value of the shape parameter interpolated over the study area. Darker shades represent positive shape parameter values and lighter shades represent negative values. Evidently the CRCM model consistently simulates precipitation values that can be represented by bounded GEV distributions. The large negative magnitude of the shape parameter indicates a narrower representative GEV distribution. Therefore the CRCM notably carries the lowest uncertainty in terms of the estimated GEV distribution due to the fact that during both historic and future simulations the representative GEV distribution is bounded since the shape parameter is negative. The MM5I model also exhibits solely negative shape parameters, however compared to the CRCM model they are smaller in magnitude indicating slightly wider, although still bounded, representative distributions.

The WRFG model demonstrates the largest positive magnitude shape parameter values, thereby indicating the presence of heavily tailed representative GEV distributions as well as the high uncertainty. It is noteworthy that the spatial location of the positive shape parameter shifts from the Western edge of the study area in the historic period to the Eastern edge of the study area in the future period and becomes larger in magnitude. The Western edge of the study area shifts from a slightly positive shape parameter in the historic period to a negative value in the future period, indicating that the distribution representing the simulated events switches from unbounded to bounded. In terms of precipitation events, this could be interpreted as an increase in the occurrence of extreme events over the Cascade Range on the Eastern edge of the WRB in the future period accompanied by a decrease in the occurrence of extreme events over the Coastal Range in the Western extents of the WRB. Given that the Cascade Range is higher in elevation and as a result currently receives more precipitation in the form of snowfall this shift may result in increased snowpack. However the temporal distribution of the precipitation events would yield more insight into the possibility of this actually being the case.

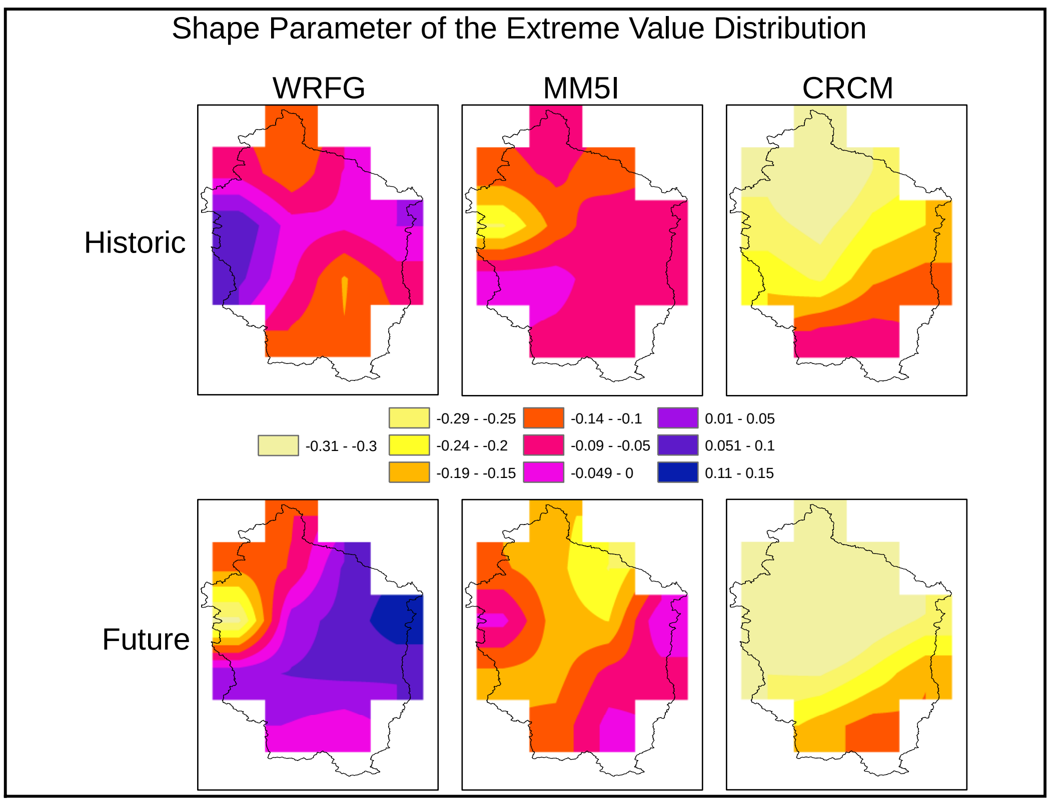

Figure 5 Distribution Shape Parameter: Value of the extreme value distribution shape parameter for historic and future datasets provided by each RCM (Greater positive numbers of the shape parameter indicate a more sizeable tail in the distribution, indicating more extreme values).

4.3 Return levels

A particularly influential value for water resource engineers and other professionals charged with the design, management, and control of water systems is the return level. Combining the GEV distribution information derived from the NARCCAP datasets with various exceedance probabilities (or non-exceedance probabilities) different historic and future return level estimates were obtained. Values of return levels, as simulated by each RCM, for specified return periods of 2, 5, 10 and 25 years were obtained. These estimates were then interpolated to represent the original grid size of the RCMs (50km) and were plotted over the WRB. Figure 6a represents 2 year return levels, 6b 5 year return levels, 6c 10 year return levels, and 6d 25 year return levels associated with a 2, 5, 10 and 25 year return period, respectively. Again the CRCM model simulations tended to have markedly lower estimated magnitudes compared to the WRFG and MM5I models. The differences required that the CRCM results be assigned a separate color scheme in order to provide a comparable display. For the historic 2 year return period, figure 6a, levels [mm/day] ranged from 77 to 102 for the WRFG and MM5I models and from 39 to 65 for the CRCM model. For future simulations the 2 year return period, figure 6a, levels [mm/day] ranged from 74 to 96 for the WRFG and MM5I models and from 43 to 70 for the CRCM model. From figure 6a it is notable that the future WRFG and MM5I simulations tended to decrease 2 year return level magnitude over the southern portion of the WRB. As well, the magnitude of the 2 year return level over the higher elevations of the WRB, the Eastern and Western edges, decreased in the future period almost universally, the only exception being CRCM. A decrease in high elevation return levels indicates a potential decrease in snowpack, as the percentage of precipitation that falls at these higher elevations tends to be snowfall. Given the importance of snowpack indicated in section 2, any changes in snowpack levels would have noticeable impacts throughout the basin. However additional research into the temporal occurrence of extreme precipitation events, as well as investigation into the variation in temperature would yield more detailed information regarding any potential changes.

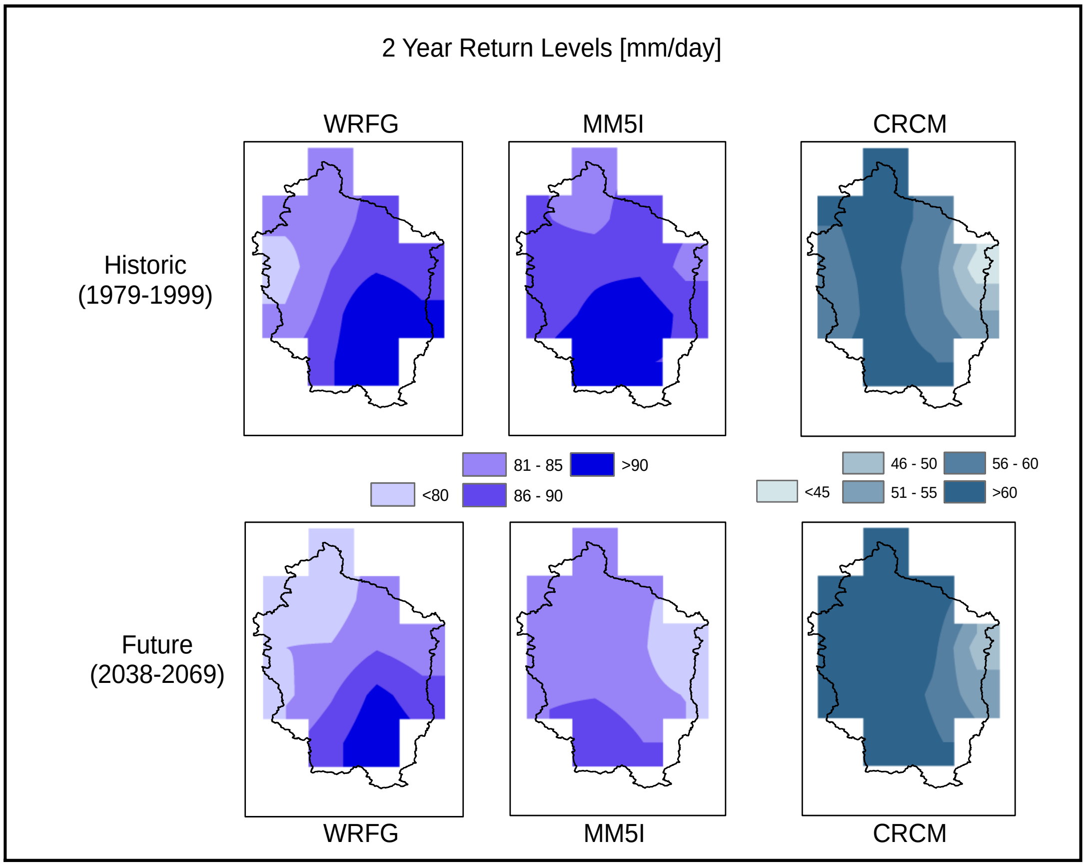

Figure 6a Return Levels: 2 year return levels [mm/day] for each RCM over both historic and future periods. Darker shades indicate higher magnitudes [note: CRCM is displayed with a separate color scheme as values were distinct from WRFG and MM5I models].

For the historic 5 year return period, figure 6b, levels [mm/day] ranged from 97 to 123 for the WRFG and MM5I models and from 46 to 76 for the CRCM model. For future simulations the 5 year return period, figure 6b, levels [mm/day] ranged from 88 to 120 for the WRFG and MM5I models and from 53 to 80 for the CRCM model. The overall spatial pattern of each model is consistent between figures 6a and 6b, so similar conclusions can be drawn. Again both the WRFG and MM5I models exhibit reduced magnitudes over the extent of the WRB in future simulations, particularly over the snowpack dominated higher elevations. Again, the CRCM model displays the opposite effect, with an increase in return levels at the higher end of the scale. Since the CRCM model demonstrates the lowest level of uncertainty, in terms of the GEV distribution shape parameter analysis given in section 4.2, the resulting changes in return levels are also less uncertain, as they are derived from the GEV distribution.

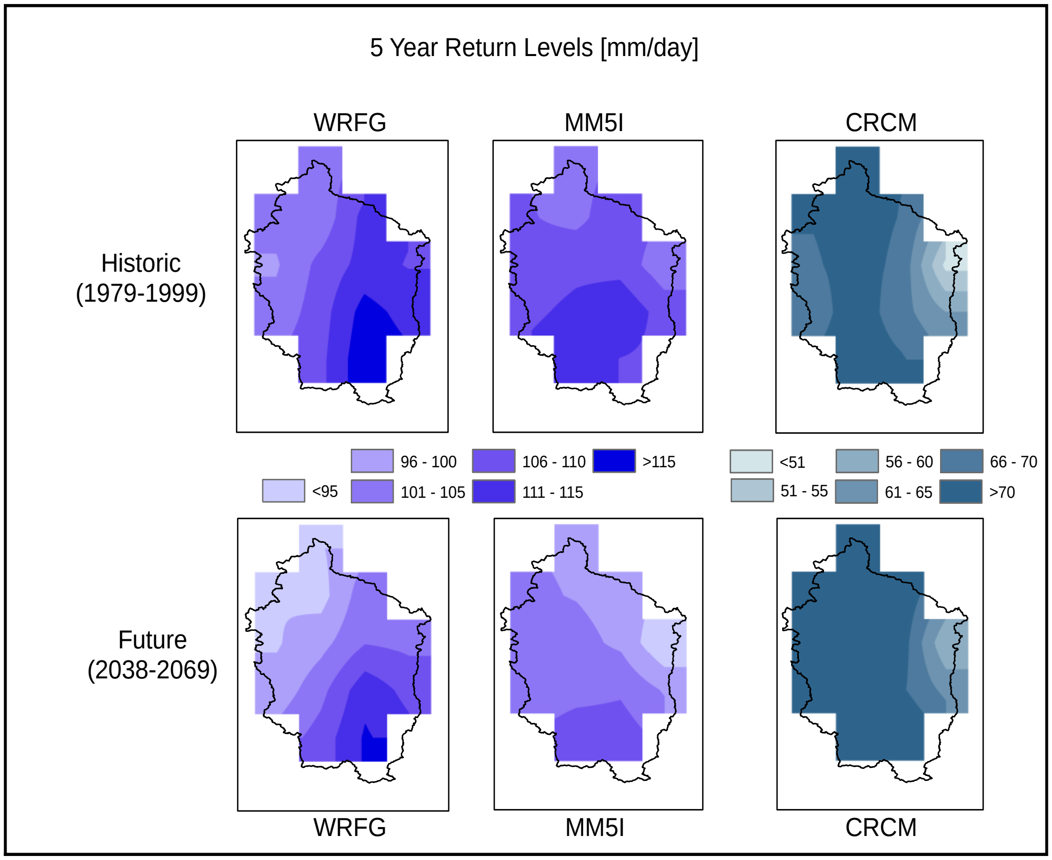

Figure 6b Return Levels: 5 year return levels. Similar to figure 6a but with different value ranges plotted

For the historic 10 year return period, figure 6c, levels [mm/day] ranged from 106 to 136 for the WRFG and MM5I models and from 49 to 82 for the CRCM model. For future simulations the 10 year return period, figure 6c, levels [mm/day] ranged from 96 to 135 for the WRFG and MM5I models and from 57 to 87 for the CRCM model. Again, the WRFG and MM5I simulations show similar results and both conflict with the CRCM results. For WRFG and MM5I the return level magnitudes tend to decrease over the region, demonstrated by the presence of lighter shades in the future period. However for the CRCM model the opposite is true, evidence of increased magnitudes of return levels are identifiable in a strip that runs through the study area from the northwest corner down to the southern extents.

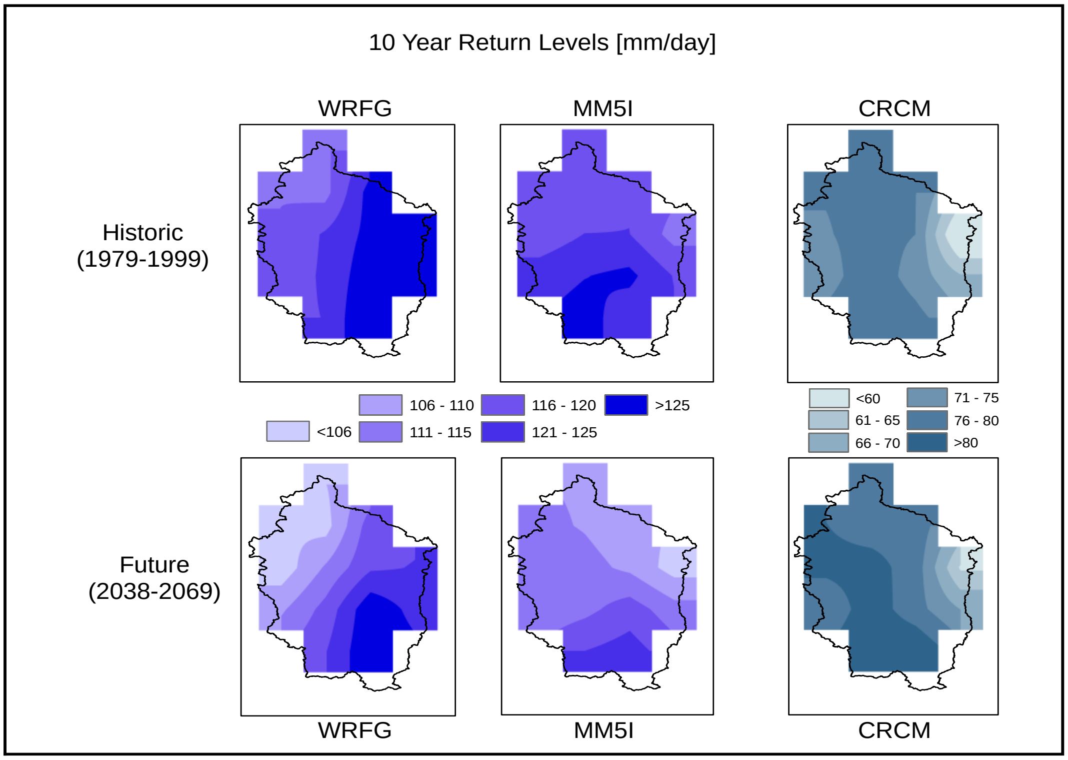

Figure 6c Return Levels: Similar to figure 6a but for 10year return level magnitudes. Again a different range of values is plotted.

For the historic 25 year return period, figure 6d, levels [mm/day] ranged from 116 to 154 for the WRFG and MM5I models and from 53 to 92 for the CRCM model. For future simulations the 25 year return period, figure 6d, levels [mm/day] ranged from 105 to 157 for the WRFG and MM5I models and from 60 to 97 for the CRCM model. Figure 6d demonstrates more pronounced but altogether similar results with the previous return level figures. The WRFG and MM5I models exhibit an overall decrease in return level magnitude across the region where as the CRCM model demonstrates an increase in return levels, particularly in the Southern extents of the basin.

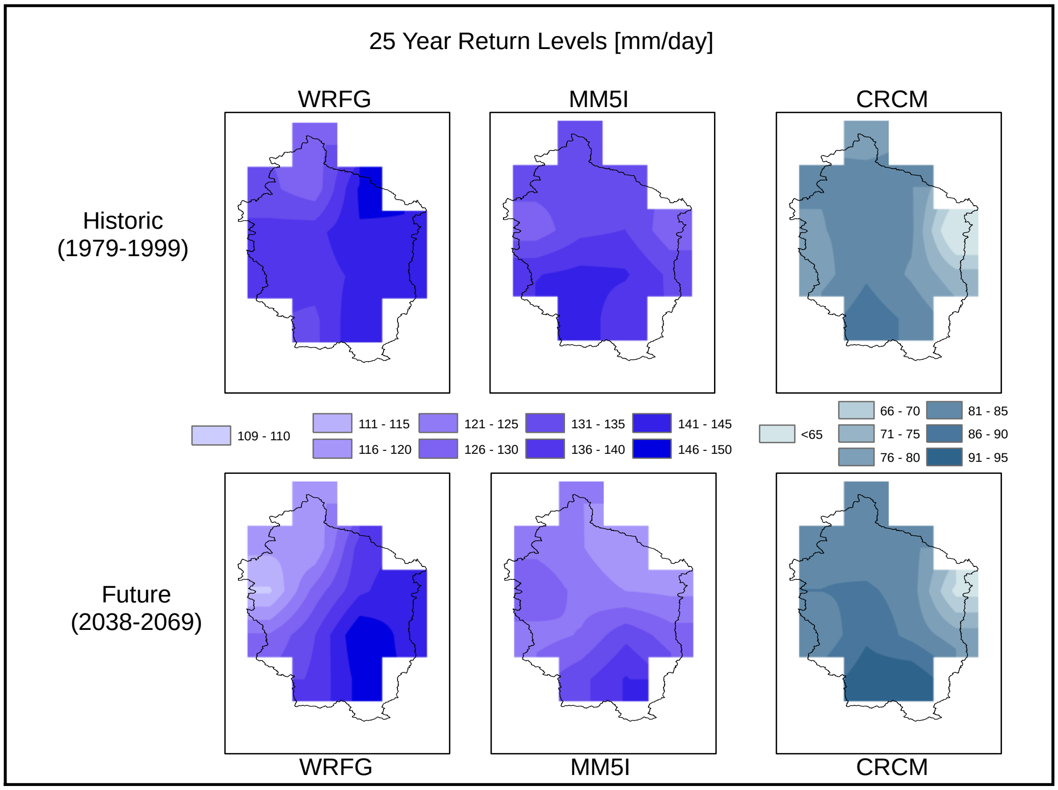

Figure 6d Return Levels: 25 year return levels plotted similar to figure 6a-c but with different range of values.

Chapter 5

Conclusion

Understanding the impact of future climate variation on all aspects of global weather patterns is a rapidly growing area of research of fundamental importance to water resource engineers, climate scientist, policy makers, and public safety in general. The development of climate models as a primary approach to predicting future climate scenarios provides researchers with one avenue for evaluating the impact of potential variation on various stages of the water cycle. For water resource engineers, the development of climate models with finer spatial and temporal resolution allows for impact analysis on scales that are of essential importance.

Gaining a deeper and more accurate understanding of watershed scale responses to future climate change is made practical through further enhancement of climate modeling capabilities and by projects such as NARCCAP. The impact of climate change on the WRB is important not only for the population that lives within its borders, but for all those who utilize the agricultural and timber products that are manufactured and produced in the region. Developing watershed scale impact analysis studies of the potential changes in the water cycle due to predicted climate change is an area of research that is has grown rapidly in recent years. This study explores the applicability of RCM output on the WRB and is only one step toward gaining a robust understanding of the potential changes the watershed may face in the future.

The results presented in this study further demonstrate the challenge of identifying the appropriate dataset for comparison to observed conditions. The UW dataset was selected for comparison in this paper, however multiple other gridded observed datasets exist and, as demonstrated by Caldwell (2010), these datasets highlight the lack of universal agreement. Furthermore, the fundamental importance of driving or forcing conditions on RCM simulations is reflected in this paper, as well as in many of those mentioned in the Chapter 1. Due to the structure of the models, which are based on numerical approximations to non-linear differential equations, very small variations in the forcing conditions dramatically impact the resulting simulation. The subject of ongoing research in the field, multi-model ensembles of RCM simulations, driven by multiple AOGCMs, have demonstrated promise in terms of understanding at least the range of possible scenarios.

Evaluating precipitation intensity, temporal and spatial occurrence, and future variability in these aspects is a challenging area of research. Multiple studies have indicated that although this topic has extensive impacts, the ability of climate models to accurately simulate even historic precipitation aspects has traditionally been rather limited. It is therefore no surprise that there is an abundance of recent research literature on the topic.

This study focused on providing a visual and qualitative-based comparison of historic and future climate simulations, thus contributing an initial exploratory data analysis step illustrating the applicability of RCM output as applied directly over a watershed scale study area. In addition to demonstrating the importance of the boundary condition dataset and the need for further investigation regarding comparison with gridded observed data, the results provide introductory analysis into the occurrence of extreme precipitation events in the WRB. Analysis of both historic and future conditions demonstrate that return levels simulated by the selected RCMs do not vary dramatically between the periods investigated. This is not to say that these results are definitive or all-inclusive. Rather, they outline one approach that provides a visual depiction of future scenarios that relies primarily on the output from RCMs without extensive post processing. If RCMs can therefore demonstrate quantifiable skill in producing or reproducing climate signals, then this approach may offer insight into the occurrence of extreme precipitation events.

The extreme value analysis does yield interesting results concerning the three RCMs investigated in this study. First, the WRFG model alone demonstrates extreme value precipitation events that can be represented by an unbounded, heavy tailed distribution. The MM5I and CRCM model simulations are best represented, in terms of the extreme value analysis, by bounded distributions. Since the width of the distribution gives an indication of the uncertainty in that representation, the WRFG model, with its heavy and unbounded upper tail, yields the highest level of uncertainty, whereas the CRCM model demonstrates the least uncertainty.

The return period analysis also yields some informative results. The WRFG and MM5I simulations consistently demonstrate decreased return level magnitudes across the basin in the future period. The CRCM model demonstrates the opposite effect, with increased return level magnitudes throughout much of the basin. Further analysis of this change, including temporal aspects of precipitation occurrence and considerations regarding temperature (which controls precipitation levels as well as form), is necessary in order to provide more robust conclusions regarding the possibility of future changes in the WRB.

Several avenues of future study and research are possible as a result of this study. The first additional step is to consider a wider scope of GCM-RCM simulations. The data available from NARCCAP is frequently updated, with new GCM-RCM combination simulations being made available. It would be prudent to explore all possible combinations in order to establish a more complete range of historic and future simulations for climate change analysis. Including additional model simulations would yield an enhanced estimation of the range of possible future climate characteristics and would provide a more in-depth look at the potential for future change over the WRB.

Providing impact analysis by using the dynamically downscaled climate scenario datasets to drive a hydrologic model, calibrated to represent the characteristics of the WRB, would also be advisable. The ability to investigate hydrologic parameters such as streamflow, infiltration, and storage that come as the result of hydrologic modeling would provide a more detailed exploration of the impact of climate change on the WRB.

A more robust statistical analysis of the dataset would also provide valuable information to both climate and hydrologic scientists. For example, comparing additional bias-correction techniques, evaluating the added value of RCM simulations via a metric such as the Added Value Index (AVI), including statistical methods for evaluation, and looking at other influential climate model parameters have all been included in recent studies. Each of these research topics would add valuable information and would create stronger confidence in the results obtained. The methods performed in this work represent an initial exploration of the results obtained from dynamically downscaled climate scenarios. Further investigations incorporating more robust techniques and impact analysis are required to more thoroughly address the potential for variation in extreme precipitation events as a result of climate change over the WRB.

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