EVALUATING THE EFFECTS OF THE
PACIFIC DECADAL OSCILLATION ON WINTER PRECIPITATION IN
THE CASCADES USING A MIXED-PHYSICS WRF ENSEMBLE

by

Carly S. Buxton

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Climatology

Summer 2016

© 2016 Carly S. Buxton
All Rights Reserved
EVALUATING THE EFFECTS OF THE PACIFIC DECADAL
OSCILLATION ON WINTER PRECIPITATION IN THE CASCADES USING
A MIXED-PHYSICS WRF ENSEMBLE

by

Carly S. Buxton

Approved:  ____________________________________________________________

Delphis F. Levia, Ph.D.
Chair of the Department of Geography

Approved:  ____________________________________________________________

Mohsen Badiey, Ph.D.
Acting Dean of the College of Earth, Ocean, and Environment

Approved:  ____________________________________________________________

Ann L. Ardis, Ph.D.
Senior Vice Provost for Graduate and Professional Education
I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

________________________________________
Brian Hanson, Ph.D.
Professor in charge of dissertation

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

________________________________________
Dana E. Veron, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

________________________________________
Sara Rauscher, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

________________________________________
Michael O’Neal, Ph.D.
Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed:

________________________________________
Tobias Kukulka, Ph.D.
Member of dissertation committee
ACKNOWLEDGMENTS

Thank you to the University of Delaware Department of Geography for providing me with the opportunity, funding, and resources to conduct this research. The University of Delaware IT department maintained the Mills and Farber computing clusters that were integral to my model runs and data analysis. I would like to thank my advisor, Brian Hanson, for his guidance and support throughout this project. He has been there to share his knowledge, advice, and sense of humor as I completed this research. I would also like to thank my other committee members for sharing their expertise. My friends and office mates Tricia Lawston and Joe Brodie have been there as a source of moral support and assistance while running WRF and analyzing the output. My fellow graduate students have made me feel welcome in the department and provided me with a sense of perspective. Finally, I would like to thank my family and my husband Cale for their love and support.
# TABLE OF CONTENTS

LIST OF TABLES ........................................................................................................ viii
LIST OF FIGURES ....................................................................................................... x
ABSTRACT .................................................................................................................. xiii

Chapter

1 BACKGROUND .............................................................................................................. 1

1.1 Research Question ................................................................................................ 1
1.2 Interannual and Interdecadal Ocean Variability .................................................... 2

1.2.1 The El Niño-Southern Oscillation (ENSO) ....................................................... 2
1.2.2 The Pacific Decadal Oscillation (PDO) and Pacific Decadal Variability (PDV) ......................................................................................................................... 4
1.2.3 ENSO-PDO Interactions ..................................................................................... 5

1.3 Study Area .............................................................................................................. 6

1.3.1 Weather and Climate in the Pacific Northwest .............................................. 7
1.3.2 Water Resource Issues and Future Climate Projections ................................ 8

1.4 Regional Climate Models (RCMs) ........................................................................ 10

1.4.1 Simulation of Precipitation in RCMs .............................................................. 10
1.4.2 Evaluation of RCM Simulations of Western U.S. Hydroclimate ...................... 11

1.5 This Study ............................................................................................................. 14

2 DATA AND METHODS ............................................................................................... 18

2.1 The Weather Research and Forecasting (WRF) Model ......................................... 18

2.1.1 Physics Options in WRF-ARW .................................................................. 18

2.2 WRF Initial and Boundary Conditions .................................................................. 19

2.2.1 North American Regional Reanalysis (NARR) ............................................ 20
<table>
<thead>
<tr>
<th>Section</th>
<th>Title</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.3</td>
<td>Observational Datasets</td>
<td>20</td>
</tr>
<tr>
<td>2.3.1</td>
<td>Issues with Precipitation Data</td>
<td>20</td>
</tr>
<tr>
<td>2.3.2</td>
<td>Dataset Intercomparisons</td>
<td>21</td>
</tr>
<tr>
<td>2.3.3</td>
<td>Observational Datasets used in This Study</td>
<td>22</td>
</tr>
<tr>
<td>2.3.3.1</td>
<td>University of Washington (UW)</td>
<td>23</td>
</tr>
<tr>
<td>2.3.3.2</td>
<td>Global Historical Climatology Network (GHCN)</td>
<td>23</td>
</tr>
<tr>
<td>2.3.3.3</td>
<td>Global Precipitation Climatology Project (GPCP)</td>
<td>23</td>
</tr>
<tr>
<td>2.4</td>
<td>Refining the Number of Physics Options</td>
<td>24</td>
</tr>
<tr>
<td>2.5</td>
<td>Ensemble Selection and Setup</td>
<td>27</td>
</tr>
<tr>
<td>2.6</td>
<td>Final Model Run Specifications</td>
<td>28</td>
</tr>
<tr>
<td>2.7</td>
<td>Comparison and Evaluation of Model Runs Based on MP Options</td>
<td>28</td>
</tr>
<tr>
<td>2.8</td>
<td>Evaluating the Effects of the PDO</td>
<td>29</td>
</tr>
<tr>
<td>3</td>
<td>RESULTS</td>
<td>45</td>
</tr>
<tr>
<td>3.1</td>
<td>Model Comparisons to Observations</td>
<td>45</td>
</tr>
<tr>
<td>3.1.1</td>
<td>Global Precipitation Climatology Project</td>
<td>45</td>
</tr>
<tr>
<td>3.1.2</td>
<td>University of Washington and Global Historical Climatology Network</td>
<td>45</td>
</tr>
<tr>
<td>3.1.3</td>
<td>Daily Precipitation PDFs</td>
<td>46</td>
</tr>
<tr>
<td>3.1.4</td>
<td>Model Internal Variability</td>
<td>46</td>
</tr>
<tr>
<td>3.1.5</td>
<td>Summary of Microphysics Options</td>
<td>47</td>
</tr>
<tr>
<td>3.2</td>
<td>Effects of the PDO</td>
<td>47</td>
</tr>
<tr>
<td>3.2.1</td>
<td>Latitudinal Differences in PDO Response</td>
<td>48</td>
</tr>
<tr>
<td>3.2.2</td>
<td>Effects of Elevation</td>
<td>48</td>
</tr>
<tr>
<td>3.2.2.1</td>
<td>Sensitivity to Elevation Cut-offs</td>
<td>49</td>
</tr>
<tr>
<td>3.2.3</td>
<td>700 hPa Winds</td>
<td>50</td>
</tr>
<tr>
<td>3.2.4</td>
<td>300 hPa Winds</td>
<td>51</td>
</tr>
<tr>
<td>4</td>
<td>DISCUSSION</td>
<td>71</td>
</tr>
<tr>
<td>4.1</td>
<td>WRF Physics Options</td>
<td>71</td>
</tr>
<tr>
<td>4.1.1</td>
<td>PBL Schemes</td>
<td>71</td>
</tr>
<tr>
<td>4.1.2</td>
<td>Microphysics Schemes</td>
<td>71</td>
</tr>
<tr>
<td>4.2</td>
<td>Effects of the PDO</td>
<td>73</td>
</tr>
</tbody>
</table>
4.3 Relative Effects of PDO Regime, MP Scheme, Model Noise, and Observational Data Uncertainty .......................................................... 75
4.4 Other Considerations .................................................................... 76
  4.4.1 High Precipitation Bias............................................................. 76
  4.4.2 ENSO and PDO ....................................................................... 76

5 SUMMARY ......................................................................................... 78
  5.1 WRF Simulation of Winter Precipitation ....................................... 78
  5.2 Effects of the PDO on Winter Precipitation in the Pacific Northwest .... 79
  5.3 Future Considerations ................................................................. 80

REFERENCES ....................................................................................... 82
LIST OF TABLES

Table 2.1. Fields included in the WRF boundary condition files.......................... 30
Table 2.2. The physics options used for different test runs................................. 33
Table 2.3. The physics options used in all model runs....................................... 33
Table 2.4. Variables included in each microphysics scheme. Water substances are cloud (c), rain (r), ice (i), snow (s), and graupel (g).......................... 33
Table 2.5. Years and December PDO Index values for the Positive PDO ensemble........................................................................................................ 43
Table 2.6. Years and December PDO Index values for the Negative PDO ensemble........................................................................................................ 43
Table 3.1. Regional monthly mean total precipitation (mm) for model domain 3 from the GPCP dataset and three WRF simulations. ......................... 52
Table 3.2. Coefficient of variation of regional monthly total precipitation for model domain 3 from the GPCP dataset and three WRF simulations. ... 53
Table 3.3. Regional monthly mean total precipitation (mm) for model domain 3 from the GHCN station data, UW gridded data, and the three WRF simulations. Positive PDO ensemble years are shown......................... 54
Table 3.4 Regional coefficient of variation for model domain 3 from the GHCN station data, UW gridded data, and the three WRF simulations. Negative PDO ensemble years are shown........................................ 55
Table 3.5 Coefficient of variation of regional monthly total precipitation for model domain 3 from the GHCN station data, UW gridded data, and the three WRF simulations. Positive PDO ensemble years are shown. 56
Table 3.6. Coefficient of variation of regional monthly total precipitation for model domain 3 from the GHCN station data, UW gridded data, and the three WRF simulations. Negative PDO ensemble years are shown................................................................. 57

viii
Table 3.7. Regional means and coefficient of variation in monthly total precipitation for model domain 3 from the UW gridded data, GHCN station data, and the three WRF simulations. Results for the positive PDO ensemble are shown.

Table 3.8. Regional means and coefficient of variation in monthly total precipitation for model domain 3 from the UW gridded data, GHCN station data, and the three WRF simulations. Results for the positive PDO ensemble are shown.

Table 3.9. Mean monthly total precipitation (mm) at high and low elevations in the North and South boxes for both PDO ensembles. The University of Washington (UW) dataset and the three WRF MP ensembles are shown.

Table 3.10 Monthly coefficient of variation at high and low elevations in the North and South boxes for both PDO ensembles. The University of Washington (UW) dataset and the three WRF MP ensembles are shown.
LIST OF FIGURES

Figure 1.1. SST (colors), SLP (contours), and wind stress (arrows) anomalies for each phase of the PDO (JISAO, 2000). SST anomalies are in °C. 16

Figure 1.2. The study area: the Pacific Northwest, centered on the Cascade Mountain Range. Source: “Pacific Northwest.” 42° 23’ 12.9” N and 118° 32’ 4.46” W. Google Earth. Copyright 2012 TerraMetrics. 11 Aug 2012. 17

Figure 2.1. The extent of the three model domains. Domain resolutions are 27 km, 9 km, and 3 km. 31

Figure 2.2. The locations and elevations (m) of the 150 GHCN stations in model domain 3. 32

Figure 2.3. Five-day precipitation totals (mm) from each of the eight test runs. 34

Figure 2.4. Differences in total precipitation (mm) between runs with the same MP option and different PBL options for the test runs. 35

Figure 2.5. Percent change in total precipitation (mm) between runs with the same MP option and different PBL options for the test runs. 36

Figure 2.6. Differences in total precipitation (mm) between the two single-moment MP schemes (WSM6 and PL) and the two double-moment MP schemes (Thom and Morr) for each PBL scheme. 37

Figure 2.7. Percent change in total precipitation (mm) between the two single-moment MP schemes (WSM6 and PL) and the two double-moment MP schemes (Thom and Morr) for each PBL scheme. 38

Figure 2.8. Differences in total precipitation (mm) between the Thompson MP scheme and the two single-moment MP schemes for both PBL schemes. 39

Figure 2.9. Percent change in total precipitation (mm) between the Thompson MP scheme and the two single-moment MP schemes for both PBL schemes. 40
Figure 2.10. Differences in total precipitation (mm) between the Morrison MP scheme and the two single-moment MP schemes for both PBL schemes. ............................................................................................................. 41

Figure 2.11. Percent change in total precipitation (mm) between the Morrison MP scheme and the two single-moment MP schemes for both PBL schemes. ...................................................................................................................... 42

Figure 2.12. Timeseries of December PDO Index from 1900-2014 (JISAO 2014). Positive ensemble members are highlighted in red, and negative ensemble members are highlighted in blue. ........................................................................... 44

Figure 3.1. PDFs of daily precipitation totals (mm) for the University of Washington (UW) dataset and the WRF Thompson simulation for both PDO ensembles. Figures in the bottom row are an enlarged portion of figures in the top row................................................................. 58

Figure 3.2. Differences in total monthly precipitation (mm) for the month of December between the WRF run beginning on 00Z December 1, 1982 and 00Z November 31, 1982.................................................................................................................. 59

Figure 3.3. Difference in ensemble average total precipitation (mm) between the positive and negative PDO ensembles for each of the three WRF ensembles. ................................................................................................................. 61

Figure 3.4. Difference in ensemble average total precipitation (mm) between the positive and negative PDO ensembles for the UW gridded data. .......... 62

Figure 3.5. Percent precipitation change between the positive and negative PDO ensemble averages for the three WRF ensembles. ......................... 63

Figure 3.6. Locations of the north and south boxes............................................... 64

Figure 3.7. 700 hPa wind roses for the North and South boxes for both PDO ensembles. Wind speeds are shown in m/s, with the average wind speed for each direction indicated at the end of each line. ....................... 67

Figure 3.8. 700 hPa average winds (kts, shown as wind barbs), heights (m, shown as blue contour lines), and temperatures (C, shown as color contours) for the positive PDO (left) and negative PDO (right). WRF Thompson ensemble averages are shown for model domain 1.......... 68
Figure 3.9. 300 hPa wind roses for the North and South boxes for both PDO ensembles. Wind speeds are shown in m/s, with the average wind speed for each direction indicated at the end of each line. .................... 69

Figure 3.10. 700 hPa average winds (kts, shown as wind barbs), heights (m, shown as blue contour lines), and temperatures (C, shown as color contours) for the positive PDO (left) and negative PDO (right). WRF Thompson ensemble averages are shown for model domain 1. ............... 70
ABSTRACT

In most of Washington and Oregon, USA, mountain snowpack stores water which will be available through spring and early summer, when water demand in the region is at its highest. Therefore, understanding the numerous factors that influence winter precipitation variability is a key component in water resource planning. This project examines the effects of the Pacific Decadal Oscillation (PDO) on winter precipitation in the Pacific Northwest U.S. using the WRF-ARW regional climate model.

A significant component of this work was evaluating the many options that WRF-ARW provides for representing sub-grid scale cloud microphysical processes. Because the “best” choice of microphysics parameterization can vary depending on the application, this project also seeks to determine which option leads to the most accurate simulation of winter precipitation (when compared to observations) in the complex terrain of the Pacific Northwest. A series of test runs were performed with eight different combinations of physics parameterizations, and the results of these test runs were used to narrow the number of physics options down to three for the final runs. Mean total precipitation and coefficient of variation of the final model runs were compared against observational data. As RCMs tend to do, WRF over-predicts mean total precipitation compared to observations, but the double-moment microphysics schemes, Thompson and Morrison, over-predict to a lesser extent than the single-moment scheme. Two WRF microphysics schemes, Thompson
and Lin, were more likely to have a coefficient of variation within the range of observations. Overall, the Thompson scheme produced the most accurate simulation as compared to observations.

To focus on the effects of the PDO, WRF simulations were performed for two ten-member ensembles, one for positive PDO Decembers, and one for negative PDO Decembers. WRF output of total precipitation was compared to both station and gridded observational data. During positive PDO conditions, there is a strong latitudinal signal at low elevations, while during negative PDO conditions, there is a strong latitudinal signal at high elevations. This shift in where the PDO signal is most visible is due to changes in mid-level westerly winds and upper-level circulation and temperature advection. Under positive PDO conditions, wind direction and moisture transport are the most important factors, and frequent warm, moist southwesterly winds cause a PDO signal at low elevations. Under negative PDO conditions, differences in westerly wind speed, and therefore orographic precipitation enhancement, lead to a latitudinal PDO signal at high elevations. This PDO signal is robust, appearing in both the WRF simulations and observational data, and the differences due to PDO phase exceed the differences due to choice of microphysics scheme, WRF internal variability, and observational data uncertainty.
Chapter 1

BACKGROUND

1.1 Research Question

Areas of complex terrain, such as the Pacific Northwest region of the United States, present a unique challenge to climate modelers. Because the topography of this region exerts a strong influence on climate and precipitation patterns, the variations in surface roughness and elevation must be sufficiently resolved and the orographic precipitation processes sufficiently represented when modeling precipitation changes in the region. Regional Climate Models (RCMs) can typically be run at a much higher resolution than General Circulation Models (GCMs), allowing for a more accurate representation of topography. However, RCMs such as the WRF-ARW model (Skamarock et al., 2008) have added complexity due to their variety of physics parameterizations, which must be specified by the user (see section 1.4).

In most of Washington and Oregon, the dominant form of water storage is mountain snowpack. This snowpack provides water throughout spring and early summer, when water demand in the region is at its highest (Climate Impacts Group 2014). Because snowpack, and therefore winter precipitation, plays such a critical role in regional water resources, understanding the numerous factors that influence winter precipitation variability is a key component in water resource planning. In order to decouple the effects of Pacific Ocean variability, greenhouse-gas-induced climate change, and land use changes on winter precipitation, the regional model must be as accurate as possible.
In this study, I will investigate the effects of The Pacific Decadal Oscillation (PDO) on winter precipitation in the Pacific Northwest United States. This research will begin by considering the variety of available physics options in the WRF-ARW V3.5 model, attempting to determine which combination of cloud microphysics and planetary boundary layer schemes is most appropriate for simulating precipitation in this terrain. After these initial test runs, I will perform an ensemble of model simulations for different PDO conditions. Finally, I will compare these simulations to several observational precipitation datasets.

1.2 Interannual and Interdecadal Ocean Variability

The climate of the Pacific Northwest is strongly controlled by the nearby ocean surface temperatures, both by their direct temperature and moisture affects and their influence on regional wind patterns. It is useful to start with discussion of the two main variability modes by which the Pacific Ocean departs from its climatic average sea surface temperature (SST) pattern.

1.2.1 The El Niño-Southern Oscillation (ENSO)

The El Niño-Southern Oscillation (ENSO) is one of the most documented factors in interannual climate variability. The term “El Niño” was initially used to describe an anomalously warm ocean current running southward along the western coast of South America, while the Southern Oscillation was initially defined based on its influence on temperature, rainfall, and pressure (Walker and Bliss 1932). The “Southern Oscillation” can be measured using the Southern Oscillation Index (SOI), defined in Trenberth (1976) as the difference between the normalized sea level
pressure anomalies at Tahiti and Darwin, Australia. Bjerknes (1969) showed that there is a connection between Walker’s Southern Oscillation and observed SST anomalies in the eastern and central equatorial Pacific. Over the years, the definition of an El Niño event has been refined to maintain consistency when studying the effects of ENSO on global and regional interannual climate variability. Trenberth (1997) defines an El Niño event as an event where the 5-month running mean of SST anomalies in the Niño 3.4 (5°N to 5°S, 120°W to 170°W) region exceeds 0.4°C for 6 months or more.

ENSO is an important factor in interannual climate variability in the western US. Leung et al (2003c) used the PSU/NCAR Mesoscale Model (MM5) to perform a 20-year regional climate simulation with a focus on mesoscale ENSO anomalies. During ENSO years, there was an approximately 23% increase in moisture flux from the Pacific Ocean to the atmosphere. This larger moisture flux is attributed to a shift in the mean wind direction from westerly to southwesterly during El Niño years. However, this larger moisture flux does not automatically lead to higher precipitation due to interactions with topography. To the west of the Cascade Mountain Range, intense precipitation is associated with westerly flows perpendicular to the mountains. During El Niño years, large dry anomalies are typically found on the windward side of the Cascade Mountain Range.
1.2.2 The Pacific Decadal Oscillation (PDO) and Pacific Decadal Variability (PDV)

The Pacific Decadal Oscillation (PDO) is a recurring pattern of ocean-atmosphere variability centered over the mid-latitude North Pacific (Mantua et al. 1997). First discovered due to its impacts on Pacific Northwest and Alaskan salmon fisheries, the PDO also has important impacts on North American coastal SSTs and surface temperatures, as well as streamflow in many western US rivers.

The extratropical North Pacific tends to persist in one of two PDO regimes for an average duration of 23 years, though the length of any given regime can vary from a few years to decades. During the positive (warm) phase, SSTs in the central North Pacific are anomalously cool, while SSTs along the west coast of the Americas are anomalously warm. November-to-March average SLP anomalies show lower pressures over the North Pacific and enhanced counterclockwise winds associated with the Aleutian Low. During the negative (cool) phase, the opposite SST and circulation conditions exist. Figure 1.1 (JISAO, 2000) illustrates the typical SST, SLP, and wind stress anomalies for each phase of the PDO. The state of the PDO can be described using the PDO index, defined in Mantua and Hare (2002). The PDO Index is defined as the leading principle component of monthly residual SST anomalies poleward of 20°N using the 1900-1993 period of record to define the components. A positive or negative index will typically persist for 20-30 years, with an abrupt sign change indicating a regime shift. Regime shifts have occurred around 1925, 1947, and
1977. After the positive regime beginning in 1977, a shift back to the negative regime appears to have occurred in the late 1990s-early 2000s.

While the PDO Index is a useful tool for gauging the state of the Pacific and anticipating its effects on ecosystems and weather patterns, the short observational record makes it difficult to determine if the PDO truly has a robust spectral peak (Deser et al. 2012). Though some studies suggest that the PDO has a spectral peak of approximately 20-50 years (Minobe 1997, Deser et al. 2004), most of the variance is very similar to red noise.

Though the PDO is the most prominent decadal or multidecadal phenomenon in the Pacific, there are other aspects to Pacific Decadal Variability (PDV). The PDO is sometimes described as the Interdecadal Pacific Oscillation, to indicate its connection to the South Pacific, or as the North Pacific Oscillation (Minobe et al 2004). The PDO is also distinct from other forms of variability in the North Pacific, such as North Pacific Mode (Deser and Blackmon 1995) and the North Pacific Gyre Oscillation (Di Lorenzo et al 2008). This study will focus on PDV as described by the December PDO Index.

1.2.3 ENSO-PDO Interactions

There is evidence that PDO phase affects the predictability of ENSO’s effects on precipitation in the western US. Brown and Comrie (2004) found that a strong ENSO signal is evident in the Southwest only during warm PDO phases, while a strong ENSO signal is prevalent in the Northwest only during cool PDO phases. This
dipole effect on winter precipitation illustrates how ENSO and PDO interact in the region, and how this interaction affects our ability to make seasonal forecasts. The winter precipitation dipole is likely due to the movement of the jet stream and storm tracks according to PDO phase (Sung et al. 2014). Both the jet stream and storm tracks tend to move northward during negative PDO winters and southward during positive PDO winters, regardless of ENSO phase.

ENSO and PDO interactions can also affect winter precipitation variability in the Pacific Northwest. Praskievicz and Chang (2008) examined the effects of ENSO and PDO variability on winter precipitation in the Willamette Valley, Oregon, using station data. They found a negative relationship between PDO index and precipitation intensity, especially during January and March. During these months, the highest precipitation intensities are associated with the negative phase of the PDO, regardless of ENSO phase. The authors also suggest that the relative importance of ENSO and PDO may change during the cold season, with ENSO more influential in the fall and PDO more influential in midwinter.

1.3 Study Area

The study area for this research will be centered on Washington and Oregon, U.S.A. The Cascade Mountain Range, which stretches from northern California to southern British Columbia, crosses through this study area. Located approximately 140 to 200 km inland, the Cascade Mountain Range has elevations ranging from 1,200 m to 3,000 m, with isolated peaks at higher elevations, such as Mt. Rainier at
4,392 m (Western Regional Climate Center, 2012). Figure 1.2 (Google, 2012) shows the region.

1.3.1 Weather and Climate in the Pacific Northwest

Weather and climate in the Pacific Northwest are influenced by several large-scale ocean patterns. Jiang et al (2013) analyzed NOAA Climate Prediction Center (CPC) daily precipitation data for the western U.S. with the goal of examining the interactions between Atlantic and Pacific Ocean influences on precipitation. The study focused on heavy precipitation events and the influence of the Atlantic Multidecadal Oscillation (AMO), PDO, ENSO, and North Atlantic Oscillation (NAO). A combination of the PDO, NAO, and ENSO explained 49% of the variance in winter extreme precipitation in the western U.S. A dipole effect in extreme daily winter precipitation was most visible when both the PDO and NAO were in the opposite phase as ENSO, and this effect was diminished when either the PDO or NAO was in the same phase as ENSO. This suggests that the Pacific Northwest would experience fewer than normal extreme winter precipitation events in coming decades, if both negative PDO and positive NAO persist as currently expected.

The effects of the PDO, ENSO, and the Arctic Oscillation (AO) on precipitation in the conterminous US were also examined by Higgins et al. (2007). This study analyzed frequency of daily precipitation occurrence from 1948-2004 using observational data. During the period analyzed, the western U.S. experienced increases of 5% or more in the number of wet days per year, and approximately half of this increase is correlated with the PDO. The AO did not appear to be a major factor in precipitation changes for the region. Because of the importance of the PDO for this region of the country, the authors emphasize that a significant portion of climate
model skill in simulating future precipitation statistics depends on their ability to represent teleconnections and interdecadal variability like the PDO.

The Cascade Mountain Range exerts a strong influence on Pacific Northwest climate. Areas west of the Cascade Mountain Range receive higher annual precipitation than areas to the east. The region experiences a strong seasonal precipitation pattern, with most of the precipitation falling between October and March (Climate Impacts Group, 2012). The critical role of topography can create differential trends in precipitation across different elevations. Luce et al. (2013) suggest that slower westerlies may be causing a decrease in orographic precipitation in the Pacific Northwest. Their analysis of multiple datasets indicates that low-troposphere (700 hPa) winter westerlies are strongly correlated with high-elevation precipitation but weakly correlated with low-elevation precipitation. This differential trend across elevations can be difficult to detect since most observing stations are located at lower elevations.

1.3.2 Water Resource Issues and Future Climate Projections

In order to understand observed changes and variability in the Pacific Northwest during the 20th century, Abatzoglou et al (2014) examined three observational precipitation datasets. Two gridded datasets covered the period 1901-2012, while station data covered the period 1920-2012. While the observations show a long-term increase in spring precipitation, they also show a decrease in summer and autumn precipitation paired with increased potential evapotranspiration due to increasing temperatures, leading to larger climatic water deficits. During the winter season, interannual climate variability is typically the most pronounced, and contributes substantially to multidecadal trends. A multiple linear regression model,
including ENSO, PDO and the PNA, was unable to adequately explain the observed trends in seasonal precipitation, indicating that other factors need to be considered.

Because of the region’s dependence on winter precipitation and snowmelt, expected changes in precipitation quantity or type under a changing climate are important to water resource planning. Ashfaq et al (2013) examined near-term hydroclimatic change in the western U.S. using NCAR’s RegCM3 RCM forced by data from the Community Climate System Model version 3 (CCSM3) GCM. They found that over the next three decades, the western US will likely transition to a more liquid-dominated water resources regime, in contrast to the current snowpack-dominated regime.

Mote et al. (2003) used a combination of interannual and interdecadal climate variations and output from eight GCMs included in the IPCC Third Assessment Report to identify potential resource management challenges in the Pacific Northwest under a changing climate. The eight models used in the study project 0.5 to 2.5° C of warming by the 2040s. The foremost impact of a warming climate is expected to be a decrease in snowpack, due mainly to increased temperatures. Warmer, drier years are typically associated with the positive phase of the PDO and with El Niño, while cooler, wetter years are associated with the negative PDO and La Niña. Continuous 20-to-30 year periods of warmer-drier or cooler-wetter conditions produce a different response than single anomalous years, so variability associated with the PDO can provide some insight into changes that may take place under climate change.

Mote et al. (2003) also examined data from the U.S. Historical Climate Network, which show that the Pacific Northwest has exhibited a trend toward warmer, wetter conditions over the 20th century. However, while the temperature increase has
been fairly uniform throughout the year, the precipitation increase is concentrated in a few months: April, July, August, and December. In many river basins to the west of the Cascade Mountain Range, the largest impacts under a changing climate will likely stem from changes in flow during certain seasons, rather than changes in total annual flow. Areas west of the Cascade Mountain Range are particularly vulnerable to flooding during warm, wet winters, a risk that can be expected to increase if current trends continue.

The observed and projected changes mentioned above feed into a larger discussion of water resource planning and climate vulnerability in the Pacific Northwest. Nolin (2011) explores this range of factors and the connections between them that must be considered in western water resources planning, as well as assessing climate vulnerability and adaptive capacity in the region. In the western U.S., interannual variability in precipitation can be an important factor in climate vulnerability. Areas with high interannual variability may be more resilient to changing precipitation patterns, because they are already accustomed to deal with large differences in precipitation from year-to-year, whereas areas with low variability are accustomed to more consistent annual precipitation and may be less resilient.

1.4 Regional Climate Models (RCMs)

1.4.1 Simulation of Precipitation in RCMs

Regional Climate Models (RCMs) such as WRF-ARW allow for a much finer spatial resolution when compared to Global Circulation Models (GCMs). This finer spatial resolution can allow for more accurate precipitation simulations in mountainous areas. RCMs can be used to dynamically downscale input data from
GCMs: Guttman et al. (2011) showed that dynamical downscaling was better at predicting the spatial variation of changes in precipitation under a warming climate when compared with statistical downscaling. Zhang et al. (2009) showed that higher spatial resolution could improve the simulation of orographic precipitation by reducing dry biases on the windward side of the Cascade Mountain Range and wet biases on the lee side. Precipitation forecasts in the Eastern Pyrenees improved with finer spatial resolution down to a grid spacing of 3km (Trapro et al, 2012). Salathe et al. (2010) showed that feedbacks between precipitation, snowpack, and temperature must be represented in order to accurately simulate winter precipitation in the Cascade Mountain Range, and that snowpack can be underestimated at middle elevations if the horizontal resolution of the model cannot accurately resolve the topography.

Resolution is not the only factor to consider. Caldwell (2010) found that most RCMs over-predicted winter precipitation in California and over the western coast of the U.S., and that some evidence indicates that this over-prediction increases with higher resolution. This result suggests that while model resolution is important, other factors like the sensitivity of the physical parameterizations are also playing a role in model performance.

1.4.2 Evaluation of RCM Simulations of Western U.S. Hydroclimate

Large differences currently exist between different regional model simulations and different reanalysis datasets. Leung et al (2003a) present an intercomparison of reanalysis data and RCM simulations for the western US. NCEP-NCAR Reanalysis 1, NCEP-DOE Reanalysis II, and ECMWF Reanalysis were used to drive MM5 and the Regional Spectral Model (RSM), and the results were compared with a 2.5° and a 1/8° dataset. In general, both regional models produced too much cold-season
precipitation, regardless of the driving data. Moisture flux from the Pacific Ocean, wind direction, and interactions with topography may be an important factor in cold-season precipitation, and differences in these factors can lead to differences between precipitation simulation. The results of the RCM simulations by Leung and colleagues indicate that topography, spatial resolution, and model treatment of precipitation and clouds were responsible for differences in moisture transport and precipitation between datasets. The relatively low rawinsonde density and complex topography of the western U.S. present a challenge when creating realistic boundary conditions for forcing the RCM, and larger differences between reanalysis data are found over the oceans and the complex topography of the West than over the Eastern U.S. Topographic gradient appeared to be important for the simulation of orographic precipitation, as shown by the comparison of MM5 (which represented the Cascade Mountain Range with a steep gradient) and RSM (which represented the Cascade Mountain Range with a more smoothed gradient).

Because of these issues with RCMs and reanalysis data, it is important to evaluate how RCMs add value when downscaling GCM data. Caldwell et al. (2009) performed a 40-year WRF experiment forced by CCSM3 output, using a domain centered on California, USA. The CCSM3 output had a resolution of 1° latitude by 1.25° longitude, which was dynamically downscaled by WRF to a 12 km grid. WRF captured the spatial distribution of precipitation better than CCSM3. The more realistic topography of WRF caused more precipitation to fall as snow over high-elevation areas, leading to more realistic snowpack simulations. However, the WRF simulation did have some biases when compared to observations. For example, during the cold season, WRF overpredicted precipitation intensity, but underpredicted
precipitation frequency. In regions of high topography, WRF overpredicted precipitation, but then underpredicted mean precipitation in the rainshadow of the Sierra Nevada mountains. Because the moisture flux from the Pacific appeared to be well-represented, the precipitation biases were likely due to processes internal to WRF. The authors also mention that overprediction of winter precipitation seems to be a general trait of dynamical downscaling, as this bias has been observed in other regional models.

Leung and Qian (2003) investigated the added value of RCMs by examining the effects of model resolution via nesting on the simulation of precipitation in MM5, focusing on complex terrain in the Pacific Northwest and California. The study used a 20-year simulation of the western U.S. at 40 km resolution and a 5-year simulation of the Pacific Northwest and California at 13 km resolution. While higher horizontal resolution generally improved the spatial distribution of precipitation compared to observations, increasing resolution did not automatically improve simulation of precipitation intensity or frequency. Along the Cascade Mountain Range and Sierra Nevadas, precipitation was strongly amplified at higher resolution, with the increase in precipitation associated with an increased frequency of heavy precipitation events. Changes in precipitation also depended on synoptic conditions such as wind direction and moisture transport. In the Cascade Mountain Range, the 13 km simulation showed an increase in precipitation for heavy precipitation events associated with westerly flows, when winds are coming in roughly perpendicular to the mountain chain.

Further evidence of the importance of model representation of topography and large-scale circulation is found in Leung et al (2003b). A 20-year simulation was
performed using the MM5 model forced by the NCEP-NCAR Reanalysis at 40 km resolution for a domain centering on the Western U.S. The Cascade Mountain Range region had a broad frequency distribution of orographic precipitation during winter, while the Columbia River Basin had a narrower frequency distribution of precipitation. This difference in precipitation patterns on the windward and leeward side of the Cascade Mountain Range agrees with observations. At the 40 km resolution used, the Olympics were smoothed to be too low and their rain shadow was not accurately represented. However, the Cascade Mountain Range was much better represented, likely due to their steeper elevation gradient. Because of the influence of the Aleutian Low on the region, both large-scale circulation and model topography must be accurately represented to simulate seasonal variations in the region.

1.5 This Study

The PDO has been identified as an important factor in interannual climate variability in the western United States. Because of the importance of mountain snowpack to regional water resources, understanding the factors that influence winter precipitation variability is crucial to future water resource planning. In order to investigate the effects of the PDO on winter precipitation in the Pacific Northwest, and particularly in the Cascade Mountain Range, I will be performing a series of simulations using the WRF-ARW regional climate model.

In order to determine the PDO’s effect on winter precipitation, it is important the precipitation be modeled as accurately as possible. WRF-ARW comes equipped with a number of cloud microphysics options, which the user can choose between for a given simulation. As part of this study, I will be running the same simulations with each of three cloud microphysics options, and will use observational data to determine
which option produces the most realistic simulation in the complex terrain of the Pacific Northwest.

While there is a body of existing research concerning the effects of the PDO on the Pacific Northwest, these studies tend to neglect the possibility that the PDO has different effects at different elevations. Because of the importance of orographic processes to the climate of the region, and the importance of mountain snowpack to the region’s water resources, understanding the effect of the PDO across elevation gradients is an important gap in our current knowledge. This study will seek to fill that gap by examining the effects of the PDO on total precipitation and precipitation variability across a variety of elevations in the complex terrain of the Pacific Northwest.
Figure 1.1. SST (colors), SLP (contours), and wind stress (arrows) anomalies for each phase of the PDO (JISAO, 2000). SST anomalies are in °C.
Figure 1.2. The study area: the Pacific Northwest, centered on the Cascade Mountain Range. Source: “Pacific Northwest.” 42° 23’ 12.9” N and 118° 32’ 4.46” W. Google Earth. Copyright 2012 TerraMetrics. 11 Aug 2012.
Chapter 2
DATA AND METHODS

2.1 The Weather Research and Forecasting (WRF) Model

The Weather Research and Forecasting Version 3.5 model is a fully compressible, nonhydrostatic regional climate model with a hydrostatic option designed for both research and operational numerical weather prediction. For this study, the Advanced Research WRF (WRF-ARW) option was used. The ARW dynamics solver uses a terrain-following hydrostatic pressure coordinate to integrate the compressible, nonhydrostatic Euler equations in flux form. Detailed documentation regarding the WRF version 3 model can be found in Skamarock et al. (2008).

Nested domains of increasing resolution can be utilized, with options for one-way nesting, two-way nesting, or a moving nest. In both one-way and two-way nesting, coarse grid conditions are used to create the fine grid boundary conditions, but in two-way nesting, the fine grid solution replaces the coarse grid solution in locations where the grid points overlap. The simulations presented here utilize two-way nested runs. Figure 2.1 shows the model domains used in all simulations in this study. The three nested domains have horizontal resolutions of 27 km, 9 km, and 3 km.

2.1.1 Physics Options in WRF-ARW

In addition to high spatial resolution, WRF-ARW also contains a variety of physics packages for cloud microphysics (MP), turbulence and flux parameterizations for the planetary boundary layer (PBL), radiative transfer, and land surface processes, so that the user can choose the best options for their needs. Several studies have
demonstrated that the user’s choice of physics options is important when simulating precipitation. For example, Otkin and Greenwald (2008) showed that changing the MP and PBL options in WRF strongly influenced both the spatial distribution and properties of simulated clouds in a mid-latitude cyclone. Awan et al (2011) found that changing physics options produced differences in precipitation variability when simulating precipitation over the Alps. Studies like this suggest that further investigation is needed to determine which combination(s) of physics options will best simulate orographic precipitation.

Following the example of Otkin and Greenwald (2008), I investigated which combination of the available physics options in WRF-ARW leads to the best simulation of winter precipitation in the Pacific Northwest, specifically in the complex terrain surrounding the Cascade Mountain Range, when compared with available observations. My analysis will focus on total monthly precipitation and precipitation variability.

2.2 WRF Initial and Boundary Conditions

The WRF Preprocessing System (WPS) takes large-scale Gridded Binary (GriB) input data and converts it into a format suitable for use by the ARW solver by using the user-specified domain and resolution. Because our simulations used real data as input, the initial and boundary conditions are generated from this data by WPS. WPS horizontally interpolates input data onto the model domain at the specified resolution for each domain, and vertically interpolates input data onto a number of vertical levels specified by the user. WRF then specifies boundary conditions for the outer domain based on the processed input data, while the outer domains provide boundary conditions for any inner domains. A lateral boundary condition file is
generated that supplies boundary conditions for the beginning of each timestep, as well as a tendency term to move toward the next timestep. Table 2.1 contains a list of fields included in the WRF boundary files.

2.2.1 North American Regional Reanalysis (NARR)

North American Regional Reanalysis (NARR) data were obtained from NCAR as input for the WRF model. NARR data have a spatial resolution of 32 km, data for 30 vertical levels, and a temporal resolution of 3 hours. NARR combines surface and upper-air observations from a variety of sources from 1979-present and assimilates them into one dataset using NCEP’s Eta model and Regional Data Assimilation System (Shafran et al., 2005). NARR uses assimilation of observed precipitation and was created with the goal of addressing the variability of precipitation patterns in the U.S. NARR was also determined to be better than global reanalyses at simulating the regional hydrologic cycle and diurnal cycles (Mesinger et al 2005). A more detailed description of this dataset can be obtained from NCEP (2012).

2.3 Observational Datasets

2.3.1 Issues with Precipitation Data

In order to get a complete picture of the accuracy of a model simulation, it is advisable to use multiple sources of observational precipitation data. Xie and Arkin (1995) outline several known issues with common precipitation data sources. Rain gauges tend to underestimate total precipitation, primarily because of wind. In addition, rain gauge data can be problematic when creating areal averages, due to the greater number of gauges located in more populated areas and away from areas of high elevation or complex terrain. Satellite IR imagery can provide a good
combination of resolution and coverage, but may have issues with accuracy due to the indirect relationship between the measured quantity and precipitation. Satellite observations may also have poorer correspondence with land observations during the cold season.

Gonzalez et al (2012) assessed the coherence between station data and regional averages of Global Precipitation Climatology Centre gridded data in southeastern South America, an area with relatively sparse coverage of observing stations. They found that station data were consistent with GPCC regional averages for both mean precipitation and area-weighted average precipitation. There was also reasonable agreement on interannual and decadal variability. However, there is evidence that for statistics other than annual totals and averages, differences can exist between station and gridded data. Ensor and Robeson (2008) examined the characteristics of the Climate Prediction Center’s Unified Rain Gauge Dataset, a 0.25-degree gridded dataset, as compared to station observations. They found that gridded datasets can have different statistical characteristics from station observations for the same point. While the annual totals in the datasets they compared were not generally different, gridded data often had a higher frequency of light precipitation, and a lower frequency of heavy precipitation when compared to station observations.

2.3.2 Dataset Intercomparisons

Two studies by Guirguis and Avissar (2008) compared observational datasets in the Western United States. Guirguis and Avissar (2008a) includes a precipitation climatology and dataset intercomparison for the region. The authors compared nine precipitation datasets covering a period from January 1986 - July 2000 by re-scaling all data to a 2.5° by 2.5° grid. Five precipitation regions in the Western U.S.,
including a Pacific Northwest region consisting of Washington and Oregon and bounded to the east by the Rocky Mountains, were identified using principal component analysis. Congruence coefficients were calculated for all dataset pairs for each of the five regions. For the Pacific Northwest, a high level of similarity exists among datasets, with the differences among datasets occurring primarily in the eastern part of the region along the Rockies.

Guirguis and Avissar (2008b) use the same nine datasets from Guirguis and Avissar (2008a), but focus on precipitation variability, persistence, and uncertainty of observational datasets. The inclusion of nine datasets means there are 72 possible pairs of datasets to compare. All datasets represented general large-scale climate features, but high biases exist among datasets. While the ensemble spread for winter precipitation was relatively large in the Pacific Northwest, the differences between datasets do not represent a large percentage of the mean due to high winter precipitation in the region. However, variations still exist between datasets, with statistically significant differences existing between 58 of the 72 dataset pairs for the Pacific Northwest in winter, and 80% of the dataset pairs overall. The precipitation anomaly fields are more similar, with significant differences between only 40% of the dataset pairs.

2.3.3 Observational Datasets used in This Study

To examine regional-scale spatial patterns in precipitation differences, I will compare my WRF output to several observational datasets. Multiple datasets have been chosen to give a more complete picture of the strengths and weaknesses of the WRF simulations.
2.3.3.1 University of Washington (UW)

A monthly 1/8-degree gridded precipitation dataset (Maurer et al 2002) was obtained from the University of Washington’s Surface Water Modeling Group. This dataset is based on daily totals from National Ocean and Atmospheric Administration (NOAA) Cooperative Observer (COOP) stations, gridded and then scaled to according to the long-term averages of the parameter-elevation regressions on independent slopes model (PRISM) dataset (PRISM Climate Group). Because PRISM data account for topography, as well as lower station density in complex terrain, these data address some of the key issues involved in studying precipitation in a mountainous area like the Cascade Mountain Range. Further details on this dataset can be obtained from the University of Washington (2013).

2.3.3.2 Global Historical Climatology Network (GHCN)

The Global Historical Climatology Network (GHCN) dataset combines station observations from various global, national, and continental-scale datasets. This project was undertaken by the Carbon Dioxide Information Analysis Center (CDIAC) and National Climatic Data Center (NCDC) and is described in more detail in Vose et al (1992). All precipitation observations are monthly totals in tenths of millimeters. One hundred fifty GHCN stations are located in model domain 3 (Figure 2.2). Stations in Figure 2.2 are binned by elevations, with 114 stations at elevations lower than 500 m, 21 stations at elevations between 500 and 1000 m, and 15 stations at elevations greater than 1000 m.

2.3.3.3 Global Precipitation Climatology Project (GPCP)

The Global Precipitation Climatology Project (GPCP) one-degree daily (1DD) dataset combines two sources of satellite observations to create a gridded precipitation
product (Huffman et al 2001). From approximately 40°N to 40°S, IR brightness temperatures from geostationary satellites are used, while at higher latitudes, soundings from low-Earth polar orbiting satellites are used. The precipitation estimates from these satellite data are then scaled to match the totals from the GPCP version 2 satellite-gauge precipitation dataset (Huffman et al. 1997). While mean absolute errors can be high on fine spatial and temporal scales, errors decrease with averaging.

2.4 Refining the Number of Physics Options

In order to determine which WRF-ARW physics options to use in the final simulations, a total of 8 test runs were performed, each using a different combination of planetary boundary layer (PBL) and cloud microphysics (MP) options. The physics options used are described in further detail below and outlined in Table 2.2. All simulations use the domain configuration shown in Figure 2.1, and a vertical resolution of 30 vertical levels. Physics options that remained unchanged for all test runs can be found in Table 2.3. All runs simulate the period from 00Z on January 1, 1996, through 21Z on January 5, 1996, a period during which the monthly PDO index was 0.59.

Four MP options and two PBL options were used in the simulations. PBL schemes used were the YSU and MYJ schemes. The YSU scheme (Hong, Noh, and Dudhia 2006) produces a well-mixed boundary layer and defines the PBL top based on critical bulk Richardson number. The MYJ scheme (Janjic, 1994) focuses on the production and dissipation of turbulent kinetic energy, and also includes a deep convection scheme that incorporates cloud efficiency – the ability of a convective column to transport enthalpy upward while producing as little precipitation as
possible. The four MP schemes all simulate mixed-phase clouds and are recommended by NCAR for high-resolution simulations (NCAR 2010). The four MP options used were the Purdue Lin (Lin et al. 1983), WSM6 (Hong and Lim 2006), Thompson (Thompson et al. 2008), and Morrison (Morrison et al. 2009) schemes. The four MP options can be broken into two main categories based on which moisture variables are included. Single-moment MP schemes only include mixing ratio variables, while double-moment schemes also include number concentration for at least some of the moisture variables. Table 2.4 lists the mixing ratio and number concentration variables included in the four MP schemes. The Purdue Lin and WSM6 schemes are single-moment, while the Thompson and Morrison schemes are double-moment, with the Thompson scheme including number concentration for only some moisture variables, and the Morrison scheme including number concentration for all variables.

Comparisons between the test runs are for the period from 00Z on January 2 through 21Z on January 5. The first 24 hours have been excluded from the analysis to allow for model spin-up. Figure 2.3 shows the total five-day precipitation in millimeters for all eight test runs. While all eight physics combinations produce a similar general pattern, differences are evident between the simulations. The test run results indicate that the largest precipitation differences are between MP options, and not between PBL options. Figure 2.4 shows the difference in total precipitation between the two different PBL scheme runs for each MP scheme, and Figure 2.5 shows these differences as percent changes. For all MP schemes, changing the PBL scheme has relatively little effect on simulation of total precipitation. While the percent changes are large in some areas, they are typically largest in areas of very low
total precipitation, and there is no clear spatial pattern. The differences between the two single-moment MP schemes (Purdue Lin and WSM6) and the two double-moment MP schemes (Thompson and Morrison) for a given PBL scheme, shown in Figure 2.6, are larger than the differences from changing the PBL scheme. Percent changes between the two single-moment and the two double-moment schemes are shown in Figure 2.7. Figures 2.8 and 2.9 show the total precipitation differences and percent changes between the Thompson MP scheme and the two single-moment MP schemes, while Figures 2.10 and 2.11 show the differences and percent changes between the Morrison MP and the two single-moment schemes. The differences between any combination of a single-moment and a double-moment scheme are larger than those between the two single-moment or the two double-moment schemes. Percent changes between a single-moment and a double-moment scheme are also high in northern Washington around the Cascade Mountain Range.

The most striking result of the test runs is the difference between single-moment and double-moment MP options. While there were differences between the two single-moment schemes and the two double-moment schemes, the largest differences occurred between the two types of MP schemes. This suggests that the added complexity of the double-moment schemes does make a meaningful difference in the simulation of total precipitation.

Because changing the PBL option has such a small effect for this application, only one PBL option will be used in the final simulations. According to Otkin and Greenwald (2008), the MYJ scheme’s treatment of turbulent mixing in the boundary layer may make it more suitable to high-resolution simulations. The MYJ PBL scheme will be used for all final model runs, along with three different MP schemes.
One single-moment MP scheme, Purdue Lin, and both double-moment schemes will be used in the final simulations. This will allow comparison between a single-moment scheme and both double-moment schemes, and will also allow comparison between the two double-moment schemes. The Morrison scheme includes more number concentration variables than the Thompson scheme (see Table 2.4), while the Purdue Lin scheme contains no number concentration variables, so this comparison will shed light on whether these additional variables make for a more realistic simulation.

2.5 Ensemble Selection and Setup

The month of December was used for our simulations because the Pacific Northwest receives its highest monthly precipitation during this time (OCCRI 2010; Climate Impacts Group 2009). Ten Decembers with a positive PDO index were chosen for the positive ensemble, and ten Decembers with a negative PDO index were chosen for the negative ensemble. Tables 2.5 and 2.6 show the years and PDO index values for both ensembles. Figure 2.7 shows a timeseries of December PDO index values, with ensemble years highlighted (JISAO 2014). Input data for all model runs were obtained from the North American Regional Reanalysis (see section 2.3.1).

Because there is some evidence that longer-term PDO regime, not just monthly PDO index (Gutzler et al 2002), affects precipitation in the Pacific Northwest, positive PDO ensemble members are from years with a positive December PDO index that also fall inside the positive PDO regime from approximately 1977 through the mid-90s, while negative PDO ensemble members are chosen from the mid-90s through the 2000s, where possible. However, due to data constraints (NARR data are only available from 1979 onward), not all years fit these conditions.
2.6 Final Model Run Specifications

WRF ensemble members, described in Section 2.5, were performed for the month of December, with simulations running from 00Z on December 1 through 21Z on December 31. All runs used the nested domains illustrated in Figure 2.1 and described in Section 2.1. The model domains have horizontal spatial resolutions of 27 km, 9 km, and 3 km, with 30 vertical levels and a timestep of 162 seconds. This timestep is in keeping with the WRF User’s Guide suggestion of six seconds per kilometer of horizontal resolution of the outermost domain (NCAR 2010). The MP options and other physics options mentioned in Section 2.4, and described in Tables 2.3 and 2.4 were used for the final runs.

2.7 Comparison and Evaluation of Model Runs Based on MP Options

Regional means and coefficients of variation based on the gamma distribution were calculated for monthly total precipitation from both the WRF model output and the observational data. The gamma distribution was used for these statistics because of its positively skewed shape and proven value for climate variables with a lower bound of zero (Thom 1958). The gamma distribution also provides some flexibility in its shape, allowing it to fit a variety of distributions, including those for monthly precipitation (Husak et al 2006). Precipitation statistics are based on model domain 3, shown in Figure 2.1 and described in section 2.6. For comparison with the GPCP data, I regridded the WRF output to the GPCP 1° grid using conservative remapping, then calculate statistics for the regridded data. For comparison with the UW and GHCN data, the WRF output were regridded to the UW 1/8° grid. Comparisons of means and coefficients of variation between WRF output and observational data will then be performed for individual years.
2.8 Evaluating the Effects of the PDO

The differences between the positive and negative PDO ensembles show the effects of the PDO on winter precipitation in the Pacific Northwest. First, means and coefficients of variation based on the gamma distribution (as described for the WRF MP options in Section 2.7) will be calculated for each ensemble. A graphical comparison of the difference between the mean total precipitation for the positive and negative PDO will also be used to identify spatial patterns in precipitation difference between PDO regimes. These results can guide the rest of the analysis by highlighting regions of interest within the study area.

Statistics will also be calculated for “high elevations” and “low elevations” within the domain in order to determine the effects of the PDO at different elevations. “High elevation” will be defined as 1300 m or higher, while “low elevations” will be defined as 500 m or lower. See section 3.2.2.1 for further discussion on elevation cut-offs.
Table 2.1. Fields included in the WRF boundary condition files.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$u$</td>
<td>Horizontal component of velocity in x-direction</td>
</tr>
<tr>
<td>$v$</td>
<td>Horizontal component of velocity in y-direction</td>
</tr>
<tr>
<td>$\theta$</td>
<td>Potential temperature</td>
</tr>
<tr>
<td>$q_v$</td>
<td>Water vapor mixing ratio</td>
</tr>
<tr>
<td>$\phi'$</td>
<td>Perturbation geopotential</td>
</tr>
<tr>
<td>$\mu_d'$</td>
<td>Dry hydrostatic pressure difference between surface and top of model – perturbation from reference state</td>
</tr>
</tbody>
</table>
Figure 2.1. The extent of the three model domains. Domain resolutions are 27 km, 9 km, and 3 km.
Figure 2.2. The locations and elevations (m) of the 150 GHCN stations in model domain 3.
Table 2.2. The physics options used for different test runs.

<table>
<thead>
<tr>
<th>Microphysics Options</th>
<th>Planetary Boundary Layer Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thompson (Thompson et al., 2008)</td>
<td>YSU (Hong et al., 2006)</td>
</tr>
<tr>
<td>Morrison (Morrison et al., 2009)</td>
<td>MYJ (Janjic, 1994)</td>
</tr>
<tr>
<td>WSM6 (Hong and Lim, 2006)</td>
<td></td>
</tr>
<tr>
<td>Purdue Lin (Lin et al., 1983)</td>
<td></td>
</tr>
</tbody>
</table>

Table 2.3. The physics options used in all model runs.

<table>
<thead>
<tr>
<th>Unchanged Physics Options</th>
</tr>
</thead>
<tbody>
<tr>
<td>LW Radiation</td>
</tr>
<tr>
<td>SW Radiation</td>
</tr>
<tr>
<td>Land Surface Model</td>
</tr>
<tr>
<td>Cumulus Parameterization</td>
</tr>
</tbody>
</table>

Table 2.4. Variables included in each microphysics scheme. Water substances are cloud (c), rain (r), ice (i), snow (s), and graupel (g).

<table>
<thead>
<tr>
<th>MP Scheme</th>
<th>Mass Mixing ratio variables</th>
<th>Number Concentration Variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>Purdue Lin</td>
<td>$Q_c, Q_r, Q_i, Q_s, Q_g$</td>
<td>None</td>
</tr>
<tr>
<td>WSM6</td>
<td>$Q_c, Q_r, Q_i, Q_s, Q_g$</td>
<td>None</td>
</tr>
<tr>
<td>Thompson</td>
<td>$Q_c, Q_r, Q_i, Q_s, Q_g$</td>
<td>$N_r, N_i$</td>
</tr>
<tr>
<td>Morrison</td>
<td>$Q_c, Q_r, Q_i, Q_s, Q_g$</td>
<td>$N_r, N_i, N_s, N_g$</td>
</tr>
</tbody>
</table>
Figure 2.3. Five-day precipitation totals (mm) from each of the eight test runs.
Figure 2.4. Differences in total precipitation (mm) between runs with the same MP option and different PBL options for the test runs.
Figure 2.5. Percent change in total precipitation (mm) between runs with the same MP option and different PBL options for the test runs.
Figure 2.6. Differences in total precipitation (mm) between the two single-moment MP schemes (WSM6 and PL) and the two double-moment MP schemes (Thom and Morr) for each PBL scheme.
Figure 2.7. Percent change in total precipitation (mm) between the two single-moment MP schemes (WSM6 and PL) and the two double-moment MP schemes (Thom and Morr) for each PBL scheme.
Figure 2.8. Differences in total precipitation (mm) between the Thompson MP scheme and the two single-moment MP schemes for both PBL schemes.
Figure 2.9. Percent change in total precipitation (mm) between the Thompson MP scheme and the two single-moment MP schemes for both PBL schemes.
Figure 2.10. Differences in total precipitation (mm) between the Morrison MP scheme and the two single-moment MP schemes for both PBL schemes.
Figure 2.11. Percent change in total precipitation (mm) between the Morrison MP scheme and the two single-moment MP schemes for both PBL schemes.
Table 2.5.  Years and December PDO Index values for the Positive PDO ensemble.

<table>
<thead>
<tr>
<th>Year</th>
<th>December PDO Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981</td>
<td>0.67</td>
</tr>
<tr>
<td>1982</td>
<td>0.26</td>
</tr>
<tr>
<td>1983</td>
<td>1.69</td>
</tr>
<tr>
<td>1984</td>
<td>0.82</td>
</tr>
<tr>
<td>1985</td>
<td>0.38</td>
</tr>
<tr>
<td>1986</td>
<td>1.77</td>
</tr>
<tr>
<td>1987</td>
<td>1.27</td>
</tr>
<tr>
<td>1993</td>
<td>1.07</td>
</tr>
<tr>
<td>1997</td>
<td>0.67</td>
</tr>
<tr>
<td>2003</td>
<td>0.33</td>
</tr>
</tbody>
</table>

Table 2.6.  Years and December PDO Index values for the Negative PDO ensemble.

<table>
<thead>
<tr>
<th>Year</th>
<th>December PDO Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1988</td>
<td>-0.43</td>
</tr>
<tr>
<td>1989</td>
<td>-0.21</td>
</tr>
<tr>
<td>1990</td>
<td>-2.23</td>
</tr>
<tr>
<td>1994</td>
<td>-1.79</td>
</tr>
<tr>
<td>1998</td>
<td>-0.44</td>
</tr>
<tr>
<td>1999</td>
<td>-1.63</td>
</tr>
<tr>
<td>2001</td>
<td>-0.93</td>
</tr>
<tr>
<td>2007</td>
<td>-0.58</td>
</tr>
<tr>
<td>2008</td>
<td>-0.87</td>
</tr>
<tr>
<td>2010</td>
<td>-1.21</td>
</tr>
</tbody>
</table>
Figure 2.12. Timeseries of December PDO Index from 1900-2014 (JISAO 2014). Positive ensemble members are highlighted in red, and negative ensemble members are highlighted in blue.
Chapter 3
RESULTS

3.1 Model Comparisons to Observations

3.1.1 Global Precipitation Climatology Project

Tables 3.1 and 3.2 show monthly statistics for the three WRF MP options compared to the GPCP 1° daily data. All simulated years for which GPCP data were available are shown. For these comparisons, WRF output was regridded to the GPCP 1° grid using conservative remapping. All three WRF configurations over-predict the mean monthly total precipitation (Table 3.1), but the double-moment schemes (Thompson and Morrison) over-predict to a lesser extent than the single-moment scheme (Lin). All three WRF configurations produce more precipitation variability, as represented by the coefficient of variation, than the GPCP data (Table 3.2), though no one scheme is consistently closer to observations than the others.

3.1.2 University of Washington and Global Historical Climatology Network

Tables 3.3 through 3.6 show monthly statistics for all model ensemble years for the three WRF MP options compared to the UW 1/8° data and the 150 GHCN stations. For these comparisons, WRF output was regridded to the UW 1/8° grid using conservative remapping. Like with the comparison to GPCP data, relative to the UW and GHCN data, all three WRF configurations over-predict mean monthly total precipitation, with the SM scheme over-predicting by the largest amount. For most years, the coefficient of variation of the WRF simulations fall in or below the range of coefficient of variability from the UW and GHCN datasets. The Lin and Thompson
simulations falls within the range of observations more frequently than the Morrison scheme.

### 3.1.3 Daily Precipitation PDFs

Many climate models produce accurate monthly or annual precipitation, but overestimate precipitation frequency, especially for light precipitation events of 1-10 mm/day (Dai 2006; Sun et al. 2006; Stephens et al. 2010). Figure 3.1 shows PDFs of daily precipitation totals for both PDO ensembles from the WRF Thompson simulation and the UW gridded dataset. The WRF Thompson simulation has a higher frequency of 30-60mm/day precipitation events compared to the UW data. In contrast to models that overestimate frequency of light precipitation, the WRF Thompson configuration overestimates the frequency of moderate-to-heavy precipitation relative to the UW data.

### 3.1.4 Model Internal Variability

To provide more context for the magnitude of the differences between MP options, a measure of WRF internal variability is needed. To estimate this internal variability, an additional model run for one ensemble member was performed. 1982 was chosen because it had a PDO index close to neutral with a value of 0.26. The additional run was initialized at 00Z on November 30, 1982. Total precipitation for the period from 00Z December 1 through 21Z December 31 was compared with the original ensemble member run initialized on 00Z on December 1, 1982. Figure 3.2 shows the differences between the run initialized on November 30 and the run initialized on December 1. Some of the differences between the two runs are
substantial, with values up to 100 mm of total precipitation. However, there is a lack of any spatial pattern to the differences.

3.1.5 Summary of Microphysics Options

Based on the comparisons to observations, the double-moment MP schemes produce more accurate simulations of both total monthly precipitation and monthly standard deviation. However, the DM schemes still consistently over-predict mean precipitation. The coefficient of variation, on the other hand, is frequently lower for the WRF simulations than for the observational data. The coefficients of variation fell within the range of observations more frequently for the Lin and Thompson schemes. Overall, the Thompson scheme had the most accurate combination of mean precipitation and coefficient of variation.

3.2 Effects of the PDO

Tables 3.7 and 3.8 show the ensemble mean and coefficient of variation for both phases of the PDO as simulated by all three MP options across model domain 3. The three MP options show similar differences relative to each other as they did in the statistics for individual years. The SM scheme, Lin, produces higher total precipitation, while the two DM schemes, Thompson and Morrison, produce very similar totals to one another. For any given MP option, total regional precipitation across model domain 3 does not vary greatly between PDO phases. However, the coefficient of variation is slightly higher for both the model and observational data under the negative PDO. Though the overall mean precipitation values are not very different between PDO phases, we wish to investigate difference within the region and across different elevations.
3.2.1 Latitudinal Differences in PDO Response

Figure 3.3 shows the difference in total monthly precipitation between the average of the 10 positive PDO Decembers and 10 negative PDO Decembers. From these difference maps, it is clear that there is a latitudinal pattern to the PDO response. Under positive PDO conditions, the southern portion of the domain receives more precipitation, while under the negative PDO, the northern portion of the domain receives more precipitation. This pattern appears regardless of which WRF MP option is used, and also appears in observational data. The ensemble differences for the UW data are shown in Figure 3.4, and exhibit the same pattern as the WRF output. Figure 3.5 shows the percent difference in ensemble average total precipitation between the positive and negative PDO WRF ensembles. The Lin scheme shows larger changes at high elevations, especially in northern Washington, while the Thompson and Morrison schemes show larger changes in eastern Washington and Oregon.

To further investigate this latitudinal trend, two boxes within the domain, one in the north and one in the south, were chosen for further analysis (Figure 3.6). These boxes were chosen because they are representative of the areas with the largest differences in PDO related precipitation changes. They also contain a range of elevations, which are shown in the sections below to be important.

3.2.2 Effects of Elevation

To examine differences in PDO response based on elevation, monthly statistics were calculated for “high elevation points,” defined as points with an elevation over 1300 m, and “low elevation points,” defined as points with an elevation below 500 m. Tables 3.9 and 3.10 show ensemble monthly mean total precipitation and coefficient of variation for north and south boxes based on elevation and PDO phase. Statistics
are shown for the University of Washington dataset and for all three WRF simulations. Under positive PDO conditions, a stronger signal in total mean precipitation between north and south is present at low elevations, while under the negative PDO, a stronger signal between north and south is present at high elevations. These patterns appear in both the observational data and model simulations.

### 3.2.2.1 Sensitivity to Elevation Cut-offs

Initially, statistics were calculated using 500 m and below as the cut-off for “low elevation,” and 1000 m and above as the cut-off for “high elevation,” as in Karmalkar et al. (2008). However, the cut-offs for these categories were changed in an effort to keep approximately 25-30% of the gridpoints in the “high elevation” and “low elevation”. In the northern and southern boxes, respectively, 28% and 24% of the gridpoints fall into the “low elevation” category, while 28% and 33% fall into the “high elevation” category.

Statistics for the WRF output were re-calculated for different cut-offs of “low” and “high” elevations to examine their sensitivity to these cut-offs. The low-elevation results are not sensitive to changes in the cut-off, with a strong signal under the positive PDO and weak signal under the negative PDO regardless. The high-elevation signal, however, does show some sensitivity to the cut-off value. For cut-off values from 1000 to 1300 m, a strong high-elevation signal is present under the negative PDO, with a weak signal under the positive PDO. For cut-off values of 1400 or 1500 m, a strong high-elevation signal is seen under both phases of the PDO. Under the positive PDO, more high-elevation precipitation falls in the southern part of the domain, while during the negative PDO, more high-elevation precipitation falls in the north.
3.2.3 700 hPa Winds

Previous work by Luce et al. (2013) suggests that the strength of westerly winds is an important influence on high-elevation precipitation in the Pacific NW. To assess the strength of westerly winds in the WRF simulations, 700 hPa wind roses were created for the positive and negative PDO ensembles. Wind roses for the north and south boxes during both phases of the PDO are show in Figure 3.7. During the negative PDO, there is a larger contrast in average westerly wind speed between the north and south boxes compared to the positive PDO. This relatively small north-south contrast in westerly wind speed during the positive PDO could be why a high-elevation signal is only detectable at the highest elevations (1400 m and above), as described in section 3.2.2.1.

The wind roses also clearly illustrate a difference in frequency of northwesterly and southwesterly winds between the positive and negative PDO. During the positive PDO, both the northern and southern boxes experience frequent southwesterly winds, while under the negative PDO, northwesterly winds are more common.

Figure 3.8 shows ensemble average 700 hPa wind speed and direction, temperature, and heights for both PDO ensembles. The wind direction shift shown in the wind roses is also evident in these figures. Under the positive PDO, southwesterly winds are common across the domain, while northwesterly winds are common under the negative PDO. This shift in wind direction can be attributed to the movement of a ridge, located inland over central Washington and Oregon during the positive PDO, and located slightly offshore during the negative PDO.
3.2.4 300 hPa Winds

Wind roses at 300 hPa for the north and south boxes during both phases of the PDO are shown in Figure 3.9. Under the positive PDO, winds are consistently from the west and northwest in both the north and south boxes. Under the negative PDO, winds are more variable, though still confined mainly to the westerly, northwesterly, and northerly directions. This larger variability in wind direction is consistent with the higher standard deviation in precipitation totals under the negative PDO discussed in section 3.2.

Figure 3.10 shows ensemble average 300 hPa wind speed and direction, temperature, and heights, as in Figure 3.5. Several differences in these variables exist between the positive and negative PDO. A shift in the area of maximum wind speeds, corresponding to the latitudinal precipitation response to PDO phase, is one of the most striking results. During the positive PDO, the highest wind speeds are located near Oregon, corresponding to higher precipitation amounts seen in Figure 3.1. During the negative PDO, the highest wind speeds occur over Washington, again corresponding with higher monthly precipitation.

Under both PDO regimes, a ridge is visible over the domain. Under the positive PDO, this ridge is located over the western U.S. and Canada, and as a result much of the study area experiences southwesterly flow. Under the negative PDO, the ridge is located over the Pacific Ocean, leading to northwesterly flows in much of the study area. These changes in wind direction, when combined with the temperature contours, show mainly warm air advection (WAA) in WA and OR during the positive PDO, and mainly cold air advection (CAA) during the negative PDO. During the positive PDO, there is a stronger temperature gradient off the California and Oregon coasts compared the negative PDO, further enhancing this WAA.
Table 3.1. Regional monthly mean total precipitation (mm) for model domain 3 from the GPCP dataset and three WRF simulations.

<table>
<thead>
<tr>
<th>Year</th>
<th>PDO Phase</th>
<th>GPCP</th>
<th>WRF Lin</th>
<th>WRF Thompson</th>
<th>WRF Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>+</td>
<td>119</td>
<td>140</td>
<td>122</td>
<td>123</td>
</tr>
<tr>
<td>1998</td>
<td>-</td>
<td>222</td>
<td>295</td>
<td>262</td>
<td>262</td>
</tr>
<tr>
<td>1999</td>
<td>-</td>
<td>165</td>
<td>200</td>
<td>173</td>
<td>173</td>
</tr>
<tr>
<td>2001</td>
<td>-</td>
<td>215</td>
<td>264</td>
<td>235</td>
<td>237</td>
</tr>
<tr>
<td>2003</td>
<td>+</td>
<td>202</td>
<td>219</td>
<td>196</td>
<td>198</td>
</tr>
<tr>
<td>2007</td>
<td>-</td>
<td>198</td>
<td>248</td>
<td>216</td>
<td>220</td>
</tr>
<tr>
<td>2007</td>
<td>-</td>
<td>137</td>
<td>196</td>
<td>177</td>
<td>177</td>
</tr>
</tbody>
</table>
Table 3.2. Coefficient of variation of regional monthly total precipitation for model domain 3 from the GPCP dataset and three WRF simulations.

<table>
<thead>
<tr>
<th>Year</th>
<th>PDO Phase</th>
<th>GPCP</th>
<th>WRF Lin</th>
<th>WRF Thompson</th>
<th>WRF Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>1997</td>
<td>+</td>
<td>0.52</td>
<td>0.79</td>
<td>0.78</td>
<td>0.76</td>
</tr>
<tr>
<td>1998</td>
<td>-</td>
<td>0.52</td>
<td>0.78</td>
<td>0.75</td>
<td>0.74</td>
</tr>
<tr>
<td>1999</td>
<td>-</td>
<td>0.68</td>
<td>0.81</td>
<td>0.83</td>
<td>0.81</td>
</tr>
<tr>
<td>2001</td>
<td>-</td>
<td>0.44</td>
<td>0.63</td>
<td>0.55</td>
<td>0.55</td>
</tr>
<tr>
<td>2003</td>
<td>+</td>
<td>0.43</td>
<td>0.64</td>
<td>0.59</td>
<td>0.59</td>
</tr>
<tr>
<td>2007</td>
<td>-</td>
<td>0.43</td>
<td>0.76</td>
<td>0.72</td>
<td>0.71</td>
</tr>
<tr>
<td>2007</td>
<td>-</td>
<td>0.46</td>
<td>0.66</td>
<td>0.59</td>
<td>0.59</td>
</tr>
</tbody>
</table>
Table 3.3. Regional monthly mean total precipitation (mm) for model domain 3 from the GHCN station data, UW gridded data, and the three WRF simulations. Positive PDO ensemble years are shown.

<table>
<thead>
<tr>
<th>Year</th>
<th>Observations</th>
<th>Model</th>
<th>WRF Lin</th>
<th>WRF Thompson</th>
<th>WRF Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981</td>
<td>249</td>
<td>288</td>
<td>355</td>
<td>318</td>
<td>321</td>
</tr>
<tr>
<td>1982</td>
<td>205</td>
<td>225</td>
<td>272</td>
<td>251</td>
<td>254</td>
</tr>
<tr>
<td>1983</td>
<td>163</td>
<td>209</td>
<td>233</td>
<td>211</td>
<td>213</td>
</tr>
<tr>
<td>1984</td>
<td>116</td>
<td>113</td>
<td>158</td>
<td>140</td>
<td>140</td>
</tr>
<tr>
<td>1985</td>
<td>55</td>
<td>61</td>
<td>89</td>
<td>80</td>
<td>81</td>
</tr>
<tr>
<td>1986</td>
<td>101</td>
<td>97</td>
<td>131</td>
<td>120</td>
<td>121</td>
</tr>
<tr>
<td>1987</td>
<td>210</td>
<td>221</td>
<td>279</td>
<td>255</td>
<td>256</td>
</tr>
<tr>
<td>1993</td>
<td>140</td>
<td>152</td>
<td>226</td>
<td>208</td>
<td>209</td>
</tr>
<tr>
<td>1997</td>
<td>100</td>
<td>115</td>
<td>141</td>
<td>124</td>
<td>124</td>
</tr>
<tr>
<td>2003</td>
<td>186</td>
<td>210</td>
<td>233</td>
<td>209</td>
<td>211</td>
</tr>
</tbody>
</table>
Table 3.4  Regional coefficient of variation for model domain 3 from the GHCN station data, UW gridded data, and the three WRF simulations. Negative PDO ensemble years are shown.

<table>
<thead>
<tr>
<th>Year</th>
<th>GHCN</th>
<th>UW</th>
<th>WRF Lin</th>
<th>WRF Thompson</th>
<th>WRF Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>1988</td>
<td>114</td>
<td>112</td>
<td>175</td>
<td>163</td>
<td>164</td>
</tr>
<tr>
<td>1989</td>
<td>85</td>
<td>80</td>
<td>97</td>
<td>87</td>
<td>88</td>
</tr>
<tr>
<td>1990</td>
<td>123</td>
<td>106</td>
<td>161</td>
<td>141</td>
<td>142</td>
</tr>
<tr>
<td>1994</td>
<td>164</td>
<td>178</td>
<td>222</td>
<td>198</td>
<td>198</td>
</tr>
<tr>
<td>1998</td>
<td>226</td>
<td>237</td>
<td>309</td>
<td>274</td>
<td>274</td>
</tr>
<tr>
<td>1999</td>
<td>156</td>
<td>163</td>
<td>211</td>
<td>184</td>
<td>183</td>
</tr>
<tr>
<td>2001</td>
<td>206</td>
<td>221</td>
<td>279</td>
<td>247</td>
<td>250</td>
</tr>
<tr>
<td>2007</td>
<td>193</td>
<td>219</td>
<td>264</td>
<td>230</td>
<td>233</td>
</tr>
<tr>
<td>2008</td>
<td>110</td>
<td>185</td>
<td>209</td>
<td>189</td>
<td>190</td>
</tr>
<tr>
<td>2010</td>
<td>217</td>
<td>233</td>
<td>239</td>
<td>209</td>
<td>212</td>
</tr>
</tbody>
</table>
Table 3.5  Coefficient of variation of regional monthly total precipitation for model domain 3 from the GHCN station data, UW gridded data, and the three WRF simulations.  Positive PDO ensemble years are shown.

<table>
<thead>
<tr>
<th>Year</th>
<th>Observations</th>
<th>GHCN</th>
<th>UW</th>
<th>WRF Lin</th>
<th>WRF Thompson</th>
<th>WRF Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>1981</td>
<td></td>
<td>0.59</td>
<td>0.75</td>
<td>0.79</td>
<td>0.69</td>
<td>0.67</td>
</tr>
<tr>
<td>1982</td>
<td></td>
<td>0.71</td>
<td>0.83</td>
<td>0.81</td>
<td>0.72</td>
<td>0.70</td>
</tr>
<tr>
<td>1983</td>
<td></td>
<td>0.62</td>
<td>0.66</td>
<td>0.68</td>
<td>0.61</td>
<td>0.59</td>
</tr>
<tr>
<td>1984</td>
<td></td>
<td>0.88</td>
<td>0.97</td>
<td>0.82</td>
<td>0.77</td>
<td>0.73</td>
</tr>
<tr>
<td>1985</td>
<td></td>
<td>0.72</td>
<td>0.74</td>
<td>0.71</td>
<td>0.66</td>
<td>0.64</td>
</tr>
<tr>
<td>1986</td>
<td></td>
<td>0.91</td>
<td>0.96</td>
<td>0.78</td>
<td>0.75</td>
<td>0.72</td>
</tr>
<tr>
<td>1987</td>
<td></td>
<td>0.60</td>
<td>0.81</td>
<td>0.79</td>
<td>0.68</td>
<td>0.66</td>
</tr>
<tr>
<td>1993</td>
<td></td>
<td>0.79</td>
<td>0.91</td>
<td>0.81</td>
<td>0.78</td>
<td>0.76</td>
</tr>
<tr>
<td>1997</td>
<td></td>
<td>0.95</td>
<td>1.03</td>
<td>0.90</td>
<td>0.88</td>
<td>0.84</td>
</tr>
<tr>
<td>2003</td>
<td></td>
<td>0.67</td>
<td>0.81</td>
<td>0.74</td>
<td>0.67</td>
<td>0.65</td>
</tr>
</tbody>
</table>
Table 3.6. Coefficient of variation of regional monthly total precipitation for model domain 3 from the GHCN station data, UW gridded data, and the three WRF simulations. Negative PDO ensemble years are shown.

<table>
<thead>
<tr>
<th>Year</th>
<th>GHCN</th>
<th>UW</th>
<th>WRF Lin</th>
<th>WRF Thompson</th>
<th>WRF Morrison</th>
</tr>
</thead>
<tbody>
<tr>
<td>1988</td>
<td>0.86</td>
<td>0.96</td>
<td>0.75</td>
<td>0.70</td>
<td>0.68</td>
</tr>
<tr>
<td>1989</td>
<td>1.05</td>
<td>1.15</td>
<td>1.00</td>
<td>0.98</td>
<td>0.94</td>
</tr>
<tr>
<td>1990</td>
<td>0.95</td>
<td>1.06</td>
<td>0.92</td>
<td>0.88</td>
<td>0.85</td>
</tr>
<tr>
<td>1994</td>
<td>0.91</td>
<td>1.05</td>
<td>0.89</td>
<td>0.86</td>
<td>0.82</td>
</tr>
<tr>
<td>1998</td>
<td>0.90</td>
<td>1.06</td>
<td>0.90</td>
<td>0.86</td>
<td>0.82</td>
</tr>
<tr>
<td>1999</td>
<td>1.00</td>
<td>1.21</td>
<td>0.94</td>
<td>0.93</td>
<td>0.89</td>
</tr>
<tr>
<td>2001</td>
<td>0.77</td>
<td>0.88</td>
<td>0.74</td>
<td>0.67</td>
<td>0.64</td>
</tr>
<tr>
<td>2007</td>
<td>0.81</td>
<td>1.00</td>
<td>0.88</td>
<td>0.81</td>
<td>0.78</td>
</tr>
<tr>
<td>2008</td>
<td>0.77</td>
<td>0.88</td>
<td>0.78</td>
<td>0.69</td>
<td>0.68</td>
</tr>
<tr>
<td>2010</td>
<td>0.66</td>
<td>0.72</td>
<td>0.80</td>
<td>0.70</td>
<td>0.69</td>
</tr>
</tbody>
</table>
Figure 3.1. PDFs of daily precipitation totals (mm) for the University of Washington (UW) dataset and the WRF Thompson simulation for both PDO ensembles. Figures in the bottom row are an enlarged portion of figures in the top row.
Figure 3.2. Differences in total monthly precipitation (mm) for the month of December between the WRF run beginning on 00Z December 1, 1982 and 00Z November 31, 1982.
### Table 3.7.
Regional means and coefficient of variation in monthly total precipitation for model domain 3 from the UW gridded data, GHCN station data, and the three WRF simulations. Results for the positive PDO ensemble are shown.

<table>
<thead>
<tr>
<th>Positive PDO</th>
<th>Observations</th>
<th>WRF Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UW</td>
<td>GHCN</td>
</tr>
<tr>
<td>Mean (mm)</td>
<td>169</td>
<td>153</td>
</tr>
<tr>
<td>Coefficient of Variation</td>
<td>0.94</td>
<td>0.84</td>
</tr>
</tbody>
</table>

### Table 3.8.
Regional means and coefficient of variation in monthly total precipitation for model domain 3 from the UW gridded data, GHCN station data, and the three WRF simulations. Results for the positive PDO ensemble are shown.

<table>
<thead>
<tr>
<th>Negative PDO</th>
<th>Observations</th>
<th>WRF Model</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UW</td>
<td>GHCN</td>
</tr>
<tr>
<td>Mean (mm)</td>
<td>174</td>
<td>147</td>
</tr>
<tr>
<td>Coefficient of Variation</td>
<td>1.05</td>
<td>0.97</td>
</tr>
</tbody>
</table>
Figure 3.3. Difference in ensemble average total precipitation (mm) between the positive and negative PDO ensembles for each of the three WRF ensembles.
Figure 3.4. Difference in ensemble average total precipitation (mm) between the positive and negative PDO ensembles for the UW gridded data.
Figure 3.5. Percent precipitation change between the positive and negative PDO ensemble averages for the three WRF ensembles.
Figure 3.6. Locations of the north and south boxes.
Table 3.9. Mean monthly total precipitation (mm) at high and low elevations in the North and South boxes for both PDO ensembles. The University of Washington (UW) dataset and the three WRF MP ensembles are shown.

<table>
<thead>
<tr>
<th></th>
<th>North Box</th>
<th>South Box</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UW</td>
<td>WRF Lin</td>
</tr>
<tr>
<td>Elevations &gt; 1300 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive PDO</td>
<td>190</td>
<td>247</td>
</tr>
<tr>
<td>Negative PDO</td>
<td>274</td>
<td>326</td>
</tr>
<tr>
<td>Elevations &lt; 500 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive PDO</td>
<td>154</td>
<td>169</td>
</tr>
<tr>
<td>Negative PDO</td>
<td>195</td>
<td>220</td>
</tr>
<tr>
<td>Elevations &gt; 1300 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive PDO</td>
<td>132</td>
<td>282</td>
</tr>
<tr>
<td>Negative PDO</td>
<td>102</td>
<td>225</td>
</tr>
<tr>
<td>Elevations &lt; 500 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive PDO</td>
<td>248</td>
<td>249</td>
</tr>
<tr>
<td>Negative PDO</td>
<td>193</td>
<td>216</td>
</tr>
</tbody>
</table>
Table 3.10  Monthly coefficient of variation at high and low elevations in the North and South boxes for both PDO ensembles. The University of Washington (UW) dataset and the three WRF MP ensembles are shown.

<table>
<thead>
<tr>
<th></th>
<th>North Box</th>
<th>South Box</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>UW</td>
<td>WRF Lin</td>
</tr>
<tr>
<td>Elevations &gt; 1300 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive PDO</td>
<td>0.61</td>
<td>0.72</td>
</tr>
<tr>
<td>Negative PDO</td>
<td>0.60</td>
<td>0.71</td>
</tr>
<tr>
<td>Elevations &lt; 500 m</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Positive PDO</td>
<td>0.56</td>
<td>0.54</td>
</tr>
<tr>
<td>Negative PDO</td>
<td>0.51</td>
<td>0.61</td>
</tr>
</tbody>
</table>
Figure 3.7. 700 hPa wind roses for the North and South boxes for both PDO ensembles. Wind speeds are shown in m/s, with the average wind speed for each direction indicated at the end of each line.
Figure 3.8. 700 hPa average winds (kts, shown as wind barbs), heights (m, shown as blue contour lines), and temperatures (C, shown as color contours) for the positive PDO (left) and negative PDO (right). WRF Thompson ensemble averages are shown for model domain 1.
Figure 3.9. 300 hPa wind roses for the North and South boxes for both PDO ensembles. Wind speeds are shown in m/s, with the average wind speed for each direction indicated at the end of each line.
Figure 3.10. 700 hPa average winds (kts, shown as wind barbs), heights (m, shown as blue contour lines), and temperatures (C, shown as color contours) for the positive PDO (left) and negative PDO (right). WRF Thompson ensemble averages are shown for model domain 1.
Chapter 4

DISCUSSION

4.1 WRF Physics Options

4.1.1 PBL Schemes

Changing the PBL scheme from YSU to MYJ made very little difference in the WRF simulation of total precipitation, regardless of the MP schemes used. Awan et al (2011) found that WRF simulations over the Alpine region were less sensitive to physics parameter choices in winter, and hypothesize that this could be due to the dominance of large-scale forcing over small-scale processes during the cold season. Because large-scale weather systems and moisture flux play primary roles in creating regional precipitation patterns (Salathe et al 2010), the smaller-scale processes represented by the PBL scheme are likely less influential when simulating winter precipitation in the Pacific Northwest.

4.1.2 Microphysics Schemes

Comparison of the different WRF MP ensembles indicates that the two double-moment (DM) schemes, Thompson and Morrison, simulate monthly total precipitation and standard deviation more accurately than the single-moment (SM) scheme, Lin. While all three schemes over-predict monthly total precipitation, the DM schemes over-predict to a lesser extent. The Lin and Thompson schemes produce a coefficient of variation that is within the range of observations more frequently than the Morrison scheme.
Thompson et al (2004) found that precipitation scenarios with weak lift, including orographic forcing, tend to be more sensitive to changes in MP options. This could partially explain the sensitivity to changing MP options in these simulations. The large differences between SM MP options and DM MP options are likely due in large part to the differences in representation of particle size distributions for the various hydrometeors. The size distributions are defined by three parameters, the intercept, slope, and shape, and describe how many particles of a given diameter can be found per volume of air. In the DM schemes, for any predicted number concentration variables, the intercept parameter of the particle size distribution is allowed to vary throughout the simulation, while in the SM scheme, it is held constant. Because this intercept parameter, and therefore the size distribution, can change throughout a storm (for example, during a transition from convective to stratiform precipitation), allowing it to vary in the simulation can create more realistic results. Morrison et al (2009) found that when comparing a SM and DM scheme, no single value of the constant intercept parameter in the SM scheme was able to reproduce the results of the DM scheme.

Because the Thompson and Morrison schemes produce the most accurate total mean precipitation, and the Lin and Thompson schemes produce the most accurate precipitation variability as measured by the coefficient of variation, the Thompson scheme appears to be the most accurate overall. It appears that the additional complexity offered by the Morrison scheme (in the form of simulating additional number concentration variables) does not increase the accuracy of the simulation of monthly total precipitation for this region. Morrison et al (2009) found that when comparing a single- and double-moment version of the same MP scheme, the
prediction of number concentration for snow and graupel had much less impact on the simulation than the prediction of number concentration for rain. Because both the Thompson and Morrison schemes predict number concentration for rain, the additional number concentration variables predicted by Morrison may have minimal impact on the simulation.

4.2 Effects of the PDO

The PDO exhibits effects on Pacific Northwest precipitation based on both latitude and elevation. These signals are robust, appearing in both observational data and model output. Together, the shift from a low elevation signal under the positive PDO to a high elevation signal under the negative PDO, combined with the 700 hPa and 300 hPa wind analysis, indicate that different factors control precipitation response under each phase of the PDO. Under the positive PDO, wind direction and moisture transport are most important. When positive PDO conditions are present, Washington and Oregon receive more frequent southwesterly flows compared to the negative PDO. Combined with stronger warm air advection (WAA) off the California and Oregon coasts under the positive PDO, the southern part of our study area receives more total December precipitation than the north at low elevations. Leung et al (2003) found that in the Western U.S., southwesterly flows are associated with higher moisture flux into the region. The Olympic Mountains and areas east of the Cascade Mountain Range receive their heaviest precipitation under a southwesterly flow pattern, because orographic forcing from westerly winds is less critical for these regions.

In contrast, under the negative PDO, westerly winds and orographic precipitation enhancement are the most important driver of precipitation at high
elevations. Luce et al (2013) demonstrated that 700 hPa westerly winds were strongly correlated with high-elevation winter precipitation in the Pacific Northwest, but weakly correlated with low-elevation winter precipitation. Under the negative PDO, there is a larger difference between the average westerly wind speed in the northern and southern boxes when compared to the positive PDO. Stronger westerly winds occur in the north under the negative PDO, while stronger westerly winds occur in the south under the positive PDO. This difference in westerly wind speeds can also be interpreted as a difference in orographic forcing, which will lead to differences in total precipitation in the high elevations of the Cascade Mountain Range. Because northwesterly flows and CAA are common throughout the domain, this change in orographic forcing and its impact on high elevation precipitation is the dominant signal under the negative PDO.

The WRF model is an excellent tool to assess the regional impacts of the PDO. The high spatial and temporal resolution allowed by the WRF model allow for examination of small-scale, regional trends that might not be resolved by a global climate model or by observational networks. WRF’s terrain resolution also allows for a more realistic representation of topography, which is critical in an area of complex terrain and allows PDO response by elevation to be more thoroughly examined. We can also view the dynamically downscaled output at a high vertical resolution, allowing for the assessment of winds, temperature, and moisture at various pressure levels.
4.3 Relative Effects of PDO Regime, MP Scheme, Model Noise, and Observational Data Uncertainty

The effects of MP scheme and the PDO discussed in Sections 4.1 and 4.2 must be considered within the context of WRF internal variability and observational data uncertainty. WRF internal variability is quantified through the differences shown in Figure 3.2. The differences between the two simulations, initialized one day apart, are large in some cases (up to 100 mm over the 31-day period of analysis). However, the lack of a spatial pattern to the differences suggests that model noise is not a strong factor in the latitudinal or elevation responses to PDO, or in the large differences between MP schemes around areas of complex terrain.

The magnitude of observational data uncertainty is in the range of 20-30 mm of total monthly precipitation based on the number in Tables 3.3 and 3.4. This is similar to the magnitude of the differences between MP schemes (Tables 3.3, 3.4, 3.7, and 3.8).

The magnitude of changes based on PDO regime (Figure 3.1) are larger than the changes based on MP scheme or observational uncertainty, and exhibit more of a spatial pattern and more areas of large changes (>100 mm) than WRF internal variability. This is also true for the low-elevation positive PDO signal and high-elevation negative PDO signal shown in Tables 3.9 and 3.10. These differences also exhibit strong spatial patterns based on latitude and elevation.

The relative magnitudes of these differences show that changes based on PDO regime are the most robust. Changes based on MP scheme are less robust, and are of a similar magnitude to observational data uncertainty and model noise. However, the differences between MP schemes are still compelling due to the added realism of
number concentration simulation in the DM schemes, which produce results more similar to the observational data.

4.4 Other Considerations

4.4.1 High Precipitation Bias

All simulations in this study had a high precipitation bias. This could be attributable to at least two causes. First, NARR data have a high precipitation bias during the winter months in the Pacific Northwest (Gurguis and Avissar 2008b). Second, RCMs, including WRF, tend to over-predict winter precipitation in the western U.S. Caldwell (2010) examined this effect and found some evidence that the over-prediction increased with increasing resolution, and could be due to sensitivity to model parameterizations. The fact that over-prediction is reduced in this study by using double-moment MP schemes supports this hypothesis.

4.4.2 ENSO and PDO

Brown and Comrie (2004) describe the modulation of the ENSO signal in the western U.S. by the PDO. During positive PDO years, a strong ENSO signal is seen in the Southwest, while during negative PDO years, a strong ENSO signal is seen in the Northwest. During El Niño years, the Northwest tends to experience drier winters, and wetter winters during La Niña years. This stronger ENSO signal during negative PDO winters could lead to the higher standard deviation in the negative PDO ensemble.

Two limitations to this study arise from data availability issues. First, because NARR data were only available from 1979 onward, positive PDO Decembers that fell within a larger positive regime were limited to 1979 through the late 1990s, and
negative PDO years within a negative regime were limited to the late 1990s through the present. Having more years with suitable model input data available would make it easier to select only positive (negative) Decembers that fell within a positive (negative) regime, and could allow comparisons across more than one long-term PDO regime.

Additional input data could also allow for more exploration of ENSO effects. Because of the limited availability of NARR data, it was not possible to obtain a balance of positive, negative, and neutral ENSO conditions in each PDO ensemble. Having more years to choose from would allow for more comparison of these ENSO effects within the PDO ensembles.
Chapter 5

SUMMARY

Mountain snowpack provides a crucial source of water during the dry summers in the U.S. Pacific Northwest. Because of this dependence on snowpack, understanding factors that influence winter precipitation in the Pacific Northwest is critical to understanding the region’s water resources. In this study, two primary research questions were addressed: 1) Which of WRF’s planetary boundary layer (PBL) and cloud microphysics (MP) parameterizations produce the most accurate simulation of monthly precipitation in the Pacific Northwest? and 2) What effect does the Pacific Decadal Oscillation have on winter precipitation in the Pacific Northwest and Cascade Mountain Range?

5.1 WRF Simulation of Winter Precipitation

WRF simulations using different configurations of physics parameterizations were compared to three sources of observational precipitation data – GPCP satellite data, UW gridded data, and GHCN station data.

Two PBL schemes, YSU and MYJ, were used during the test runs for this study. Because the test runs results indicated that changing the PBL scheme had little effect for this application, only one scheme, MYJ, was used in the final runs, primarily because it was favored in a similar study of mid-latitude cyclones (Otkin and Greenwald 2008). Three MP schemes were also used in the final runs: Purdue Lin, Thompson, and Morrison. While all three MP schemes over-predicted total monthly
precipitation, the double-moment Thompson and Morrison schemes over-predicted to a lesser extent. The Lin and Thompson schemes predicted the coefficient of variation in the range of observational data more frequently than Morrison scheme. Taken together, these results suggest that the Thompson scheme is producing the most accurate precipitation simulation. The additional complexity of the Morrison scheme does not appear to offer an advantage over the Thompson scheme for this application.

5.2 Effects of the PDO on Winter Precipitation in the Pacific Northwest

To investigate the effects of the PDO on winter precipitation, two ensembles of WRF simulations were performed. One ensemble consisted of ten Decembers with a positive PDO index, while the other consisted of ten Decembers with a negative PDO index. The southern portion of the model domain tends to get more precipitation during the positive PDO, while the northern part of the domain gets more precipitation during the negative PDO. The entire model domain experiences a higher coefficient of variation of precipitation during the negative PDO, which could be due to a stronger ENSO signal. Brown and Comrie (2004) found that the “canonical” ENSO signal occurs in the Pacific northwest during the negative PDO, with the strong ENSO signal absent during the positive PDO.

In addition to the latitudinal trend in precipitation, there are also trends by elevation. Under the positive PDO, a strong PDO signal is seen at elevations lower than 500 m. This is because southwesterly winds and WAA are bringing more moisture into the southern portion of the domain, increasing precipitation at low elevations. Under the negative PDO, a strong PDO signal is seen at elevations higher than 1000 m. This is because westerly winds are stronger in the northern part of the domain, enhancing orographic precipitation forcing.
Both the latitudinal and elevation-based trends are robust, appearing in both observational data and model simulations. The magnitude of changes based on PDO phase are also larger than changes in MP scheme, model internal variability, or observational data uncertainty.

5.3 Future Considerations

Several results from this study could shed light on the effects of climate change in the Pacific Northwest. Salathe et al (2010) performed two regional climate projections for the state of Washington, and found that differences in circulation lead to a decrease in the strength of the rain shadow, resulting in lower precipitation in the Cascade Mountain Range and higher precipitation amounts in eastern Washington. Luce et al (2013) found that decreases in winter westerlies have led to reduced orographic forcing in the Pacific Northwest, leading to reduced high-elevation precipitation. Finally, Held and Soden (2006) find that an increase in poleward moisture transport is a robust result found in most climate change projections. Together, these results suggest that the Pacific Northwest may experience a future with weaker orographic forcing, increased moisture flux, and more frequent occurrence of circulation patterns that lead to low-elevation precipitation. This could enhance the low-elevation signal in the region during the positive PDO by increasing moisture flux and circulation anomalies, while potentially weakening the high-elevation signal seen during the negative PDO as orographic forcing decreases.

The projections for a decrease in the strength of the rain shadow, weaker orographic forcing, and increased moisture flux have implications for water resources in the Pacific Northwest. A decreased rain shadow and weaker orographic forcing will lead to less high-elevation precipitation, and therefore less mountain snowpack.
However, increased moisture flux will lead to more low-elevation precipitation in the region, especially in the southern part of the domain during the positive PDO, when conditions are already favorable. This suggests that in addition to warming-induced early melting of mountain snowpack, the region will also have to deal with a shift from high-elevation precipitation to low-elevation precipitation. This will present a challenge for water resource planners, as the “natural reservoir” of mountain snowpack will need to be replaced with reservoirs that can accommodate low-elevation precipitation.
REFERENCES


Climate of Washington. Western Regional Climate Center. http://www.wrcc.dri.edu/narratives/WASHINGTON.htm
Comparisons. PRISM Climate Group, Oregon State University.
http://www.prism.oregonstate.edu/comparisons/


http://www.hydro.washington.edu/Lettenmaier/Data/gridded/index_maurer.html


The North American Regional Reanalysis (NARR) Archive at NCAR. National Center for Atmospheric Research, Boulder, CO. http://rda.ucar.edu/datasets/ds608.0/


PRISM Gridded Climate Data. PRISM Climate Group. Oregon State University, Corvallis, OR. http://prism.oregonstate.edu


Shafran, P., Woollen, J., Ebisuzaki, W., Shi, W., Fan, Y., Grumbine, R., and Fennessy, M. Observational Data Used for Assimilation in the NCEP North American Regional


ORNL/CDIAC-53, NDP-041. Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, Oak Ridge, Tennessee.


