AN ABSTRACT OF THE THESIS OF

Danielle Lynn Moruzzi for the degree of Master of Science in Ocean, Earth, and Atmospheric Sciences presented on January 3, 2019.

Title: Developing a Drought Metric with Water Managers

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Though numerous drought metrics have been developed by the research community, adoption of these metrics by water managers has been limited. The reasons for this vary, but some include mismatches in time scales and spatial scales between the metric supplied and the operational decisions (e.g. water managers often work within political boundaries, such as counties). The focus of many drought metrics is on the physical parameters with little regard to actual available water supply or societal demand. A drought in 2015 in the Pacific Northwest was unlike any other before it and caused drought advisors to seek out help with drought prediction.

One of the objectives of this study is to co-develop a metric with water managers in the Pacific Northwest to ensure that the results are useful and applicable for water management and drought declarations. Multiple discussions with the water managers led to developing a metric that is based on a measure of total moisture. Total moisture is derived from snow water equivalent and soil moisture modeled by Variable Infiltration Capacity (VIC) hydrologic model. We have developed an indicator that projects probabilistically how the year may progress based

on historical patterns. This indicator enables water managers to see the probability of recovery from current drought conditions and can aid in drought declaration and water allocation.

The results of the first part of this study prompted the second part, the purpose of which is to understand the atmospheric flow and temperature patterns in spring that distinguish recovery conditions from continued dry conditions using reanalysis data. Recovery years are characterized by low geopotential height anomalies that indicate spring storms and precipitation, whereas continued dry conditions are characterized by high geopotential height anomalies that indicate reduced storm activity in the region. During years when a ridge is present over the Pacific Northwest or Eastern Pacific Ocean, optimism about spring precipitation averting an incipient drought – though historically common – is shown to be unrealistic. Understanding these relationships between geopotential height during years with low total moisture and years when total moisture recovers give insight into the drivers of these conditions.

Developing a Drought Metric with Water Managers

by
Danielle Lynn Moruzzi

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Dean of the College of Earth, Ocean, and Atmospheric Sciences

Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Danielle Lynn Moruzzi, Author

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TABLE OF CONTENTS

Page

TABLE OF CONTENTS (Continued)

Page

LIST OF FIGURES

LIST OF FIGURES (Continued)

LIST OF FIGURES (Continued)

LIST OF APPENDIX FIGURES

1. Introduction

Droughts are natural disasters that affect everyone directly or indirectly and predicting the onset of them can be challenging. Droughts require western governors to make tough decisions that have political and economic consequences. However, the staff who advise them often struggle to evaluate and synthesize disparate sources of data. In 2015, the Pacific Northwest (PNW) experienced a drought unlike any other, revealing how unprepared the region is for a warming climate. The winter (DJF) of 2015 was the warmest on record, leading to record low mountain snowpack across the region due to the precipitation falling as rain instead of snow (Mote et al., 2016). The Climate Impacts Research Consortium (CIRC), which is a National Oceanic and Atmospheric Administration (NOAA) Regional Integration Sciences and Assessments (RISA) team, collaborated with the people who advise the governors of Oregon, Washington, and Idaho. CIRC collaborated with these people in order to create a usable drought prediction method with support from NOAA's National Integrated Drought Information System (NIDIS) program. The NIDIS program was approved by Congress in 2006 with instructions to coordinate and incorporate drought research. This study is in support of NIDIS' work in the PNW region. In this work we determine the probability of recovering from drought and explore the causes of drought recovery in the PNW by examining the atmospheric flow. This process began because of the impacts that drought has on a region. The factors that go into this process are how drought is defined, the causes of drought, how drought plays out in the PNW, and the different ways drought is measured and predicted currently. States implement policies based on all of these factors and declare droughts because of certain impacts on the state or regions.

1.1 Impacts

The impacts of drought can be categorized as both direct and indirect (Wilhite et al., 2007). Direct impacts can be things like reduced crop yield, increased fire hazards, and reduced water availability (Wilhite et al., 2007). Indirect impacts result from these direct impacts, for example reduced income for farmers, increase in the price of food, and unemployment (Wilhite et al., 2007). Often, drought impacts are broken down into economic, social, and environmental, and may also overlap into multiple categories (Wilhite et al., 2007).

Drought is the costliest natural disaster in the United States (US) (Cook et al., 2007; Wilhite, 2000). Between 1980 and 2003, droughts totaled 10 of the 58 weather-related disasters in the US (Ross & Lott, 2003). These 10 events cost an estimate of $144 billion out of the $349 billion of the collection of weather-related disasters (Ross & Lott, 2003). In 2002, drought caused over $10 billion in damages (Ross & Lott, 2003) in a majority of the continental United States. This drought event led to a heightened fire season in much of the Western US and led to an estimated $2 billion in costs (Ross & Lott, 2003). A drought in 1988 covering a majority of the US took a toll of an estimated $40 billion on the US economy (Mishra & Singh, 2010).

In the Northwest too, droughts have been costly. The drought in 2015 in Washington State led to reduced crop size, quality, and yield. The dairy industry in Washington State had increased costs because of purchasing feed, renting grazing land, and reductions in milk production. The total economic losses during 2015 for Washington were estimated to range from $633 million to $773 million (Washington State Department of Agriculture, 2017).

The impacts of another drought in 2018 affected the Klamath Basin in Oregon, where irrigators received $10.3 million for emergency drought relief (Dillemuth, 2018). Washington saw massive losses in hay in 2015, Kittitas County had an estimated $7.6 million loss because hay harvest was 80 to 90 percent of normal for the second cutting of the season (Wheat, 2015).

The effects of a drought in 2012 were felt in Idaho, where some farmers lost all their wheat to the drought, while others took out loans of $2.3 million to take care of the cost of operating their farms, such as electricity to irrigate (Wheat, 2015). These examples show some economic impacts of drought, but there can be other societal costs as well.

Social impacts of drought can include anything from health effects to recreation restrictions, as the 2015 drought illustrated. In Yakima Valley, Washington, residential wells ran extremely low or even completely dried up that summer (Prengaman, 2015a). Shallow wells are filled mainly by rain and snow unlike deeper wells that tap into aquifers, and in the case of 2015, more water was pumped because of high temperatures, less rain, and not as much water for irrigation causing them to dry up earlier (Prengaman, 2015a). Hayden Lake, northern Idaho, had cases of toxic blue-green algal blooms that had negative effects on public health because of warm water temperatures early in the summer, along with low snowpack and early runoff ("Toxic algae bloom found in Hayden Lake," 2015). Priest Lake, also in Northern Idaho, did not have enough water to both sustain recreational use, and also have a healthy amount of flow downstream for fish (Kramer, 2015). The Idaho Department of Water Resources made the decision to halve the outflow in order to keep the lake full; this resulted in the river being low and dry (Kramer, 2015).

Environmental impacts can include loss or damage of wildlife habitat, low streamflow, and loss of biodiversity. On the normally wet Oregon coast in 2015, the Oregon Department of Fish and Wildlife's North Nehalem Hatchery had to release approximately 1,500 rainbow trout early. The trout were about half the size when they were released in June that they would have been if they had been released in September as scheduled. (Miller, 2015). In the summer of 2015, the drought in Oregon caused Detroit Lake water levels to be so low that the docks did not float, and there were no boats at the marina, the lake was essentially empty (KOIN6, 2016). The water levels were so low in Detroit Lake, that in fall of 2015 a wagon that had been buried at the bottom of the lake, since it was filled in 1953, was discovered (KOIN6, 2016). The 2018 drought in Oregon caused conifers, such as red cedar, ponderosa pine, and Douglas-firs, to die from the lack of water (Pokorny, 2018). However, tree mortality is not only from water loss since drought can lead to disease and insect infestation in trees, also causing death (Pokorny, 2018). During the 2015 drought in Washington, people were building rock dams on rivers to pool the water, which inhibited the flow for many species of fish and create problems for spawning fish. These dams also make it more difficult for juvenile fish to survive during the drought (Prengaman, 2015b). Economic, social, and environmental impacts are closely related and are often overlapping. These different impacts are all results from the different types of drought that can occur.

1.2 Drought Definition

There are multiple specific definitions of drought but a general definition is that the water supply through precipitation is not meeting the demands of humans and the environment (Mann & Gleick, 2015; Redmond, 2002). This results in individual definitions typically pertaining to a specific region and they are not transferable to another (Wilhite & Glantz, 1985). Given that drought can impact any region while the severity of the impact due to economic and social situations is different for every drought and every location leads to the definitions of drought being categorized into meteorological, agricultural, hydrologic, and socio-economic (Wilhite & Glantz, 1985). Meteorological drought occurs because of atmospheric conditions that cause a decrease in precipitation for a certain amount of time, depending on the region (Wilhite & Glantz, 1985). Agricultural drought is a result of meteorological drought and has impacts such as insufficient soil moisture and water for crops (Wilhite & Glantz, 1985). Hydrologic drought refers to insufficient water in streams, rivers, and subsurface (Dracup et al., 1980; Wilhite & Glantz, 1985) and often comes about with both meteorological and agricultural drought.

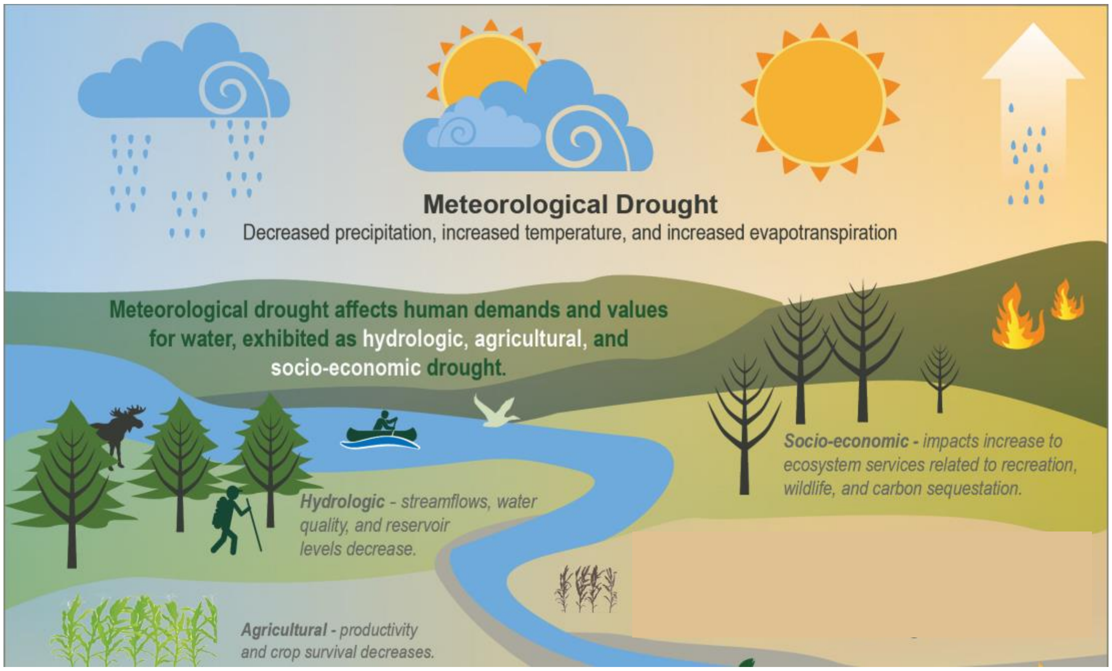

Figure 1: An illustration of the different types of drought that occur. Each category of drought has specific influences associated with it and they are outlined here. These five different types of drought can occur at the same time or separately and have a variety of different impacts (Adapted from US Forest Service, n.d.)

Each of these different types of drought can cause socio-economic drought which deals with supply and demand influencing human life. These categories of drought can occur all together or separately and are illustrated in Figure 1. Defining drought is challenging but originates with the atmospheric conditions.

1.3 Atmospheric Conditions

The atmospheric conditions that lead to drought in California and the Pacific Northwest (PNW) have been well studied. It is understood that meteorological drought comes from a lack of precipitation, but what is the underlying cause of the decrease in precipitation? Atmospheric flow in the Northeast Pacific Ocean (best visualized with 500mb geopotential height anomalies) is the driver behind the droughts seen in the Western US. The positive geopotential height anomaly that is observed over the Northeast Pacific during the drought years of 2012 to 2017 was called the "Ridiculously Resilient Ridge" (Mann & Gleick, 2015; Swain et al., 2014). The anomalously high geopotential height indicate that the Pacific westerlies are weakened, and the westerlies are strengthened over Alaska (Swain et al., 2014; Wang & Schubert, 2014). This configuration interferes with the storm track and forces it Northeast through Canada, over the US, creating a sort of barrier between the storms and the PNW (Nakamura & Wallace, 1989). The ridging over the West reduces the precipitation and causes warm and dry conditions (Namias, 1978; Swain et al., 2014; Wang & Schubert, 2014). While the atmospheric flow is the driver of drought, there are a few different ways that drought can occur in the PNW.

1.4 Drought in the Pacific Northwest

In this study we define the PNW as Oregon, Washington, and Idaho. Western Oregon and Washington typically receive an abundant amount of winter precipitation and experience dry summers (Fig. 2). The rest of the PNW is typically dry for most of the year but still receives the majority of annual precipitation in winter. In different parts of the PNW, the annual precipitation can range from as little as 200 mm/year to exceeding 2500 mm/year (Xiao et al., 2016). The mountain ranges (Cascade Range, Rocky Mountains) orographically enhance precipitation and create natural storage for water in the snowpack (Xiao et al., 2016) which are the drivers of the hydrology for this region. In the Rockies, late spring precipitation is more common than in the rest of the region. Precipitation from October to March and the timing of spring snowmelt determine streamflow in the PNW. Depending on temperature and topography, precipitation will fall as rain or accumulate as snow (Miles et al., 2000). Streamflow on the West side of the Cascades at lower elevations, is dominated by winter rain; however, at intermediate elevations, streamflow is dominated by fall and winter precipitation, and then by spring snowmelt (Miles et al., 2000). East of the Cascade Mountains the rivers are snowmelt dominated. The majority of winter precipitation falls and accumulates as snow at higher elevations that then melts in the spring. This normally leads to low streamflow in the winter, with high peak flows in the spring and summer (Miles et al., 2000). In a normal year spring snowmelt supplies the region with moisture for most of the summer, even though most summers in the PNW are hot and dry,

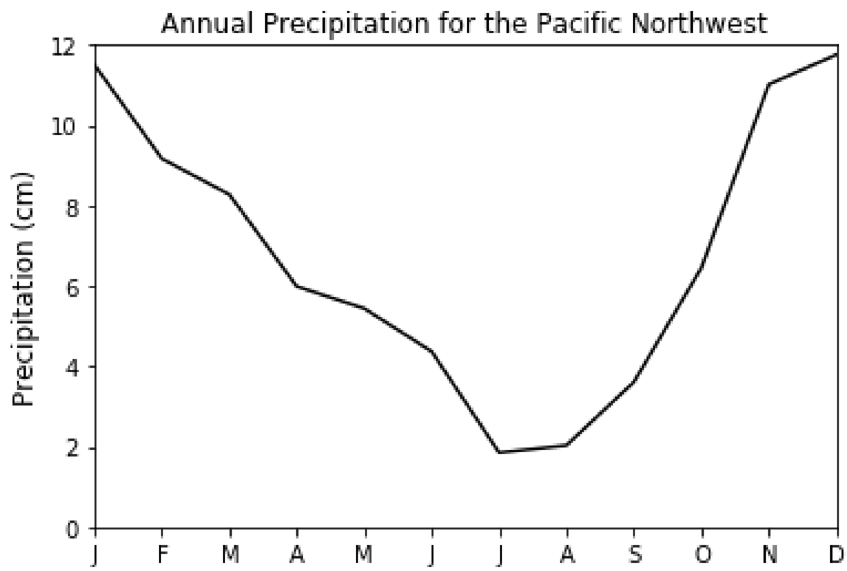

Figure 2: The annual cycle of precipitation for the Northwest using monthly averaged data from 1901-2000 (NOAA National Centers for Environmental information, n.d.)

experiencing drought-like conditions at some point (Bumbaco & Mote, 2010). Since snow is such a large influence on the spring and summer water supply, warming by itself can lead to drought in the PNW by affecting snowpack (Bumbaco & Mote, 2010).

Along with different categories (e.g., meteorological, hydrological, agricultural) of drought, there are different types of drought in the PNW (Bumbaco & Mote, 2010). Droughts can originate from different seasonal climate anomalies in the PNW because of the varying importance across the region of the sources of spring and summer water availability. In some places, it comes from late winter and early spring snowmelt, and low snowpack in those places can lead to a snow drought, which can be further categorized into warm or dry. Warm snow drought occurs when there are high temperatures causing precipitation to fall as rain instead of snow (Bumbaco & Mote, 2010; Harpold et al., 2017; Hatchett & Mcevoy, 2018) resulting in the rain melting some of the snow that already exists on the ground. A dry snow drought occurs when there is low winter precipitation (Bumbaco & Mote, 2010; Harpold et al., 2017; Hatchett & Mcevoy, 2018) leading to low snowpack and soil moisture, which creates drought conditions early in the summer. Summer climate anomalies can also matter, especially west of the Cascades: even if winter snowpack is at or above normal, a warm and dry summer can lead to unusually low streamflow and drought (Bumbaco & Mote, 2010). Drought can arise in the PNW in these ways, and there are many different ways to measure the severity of drought depending on the variable of interest.

1.5 Drought Metrics

There are many different drought metrics, most of which are developed with a specific region or purpose in mind. One of the most widely used drought metrics is the Palmer Drought Severity Index (PDSI), developed in the 1960s (Palmer, 1965). The PDSI was one of the first ways of measuring drought using temperature, precipitation, and water balance data (Alley, 1984). It was created for agricultural regions in the US (Palmer, 1965), and has a timescale of approximately nine months which can lead to months of lag in identifying drought conditions due to simplifications in the calculation of the soil moisture (Alley, 1984). PDSI has been used to show the severity and spatial extent of drought occurrences (Karl & Quayle, 1981) as well as to examine the spatial and temporal characteristics of drought (Jones et al., 1996; Klugman, 1978; Lawson et al., 1971). PDSI has also been used for tracking hydrologic trends, crop forecasts, and determining fire severity (Heddinghaus & Sabol, 1991). While PDSI has been widely utilized, not everyone can use this metric for what they need, for example it does not take into account snowmelt and assumes all precipitation is rain (Alley, 1984) and therefore PDSI has been adapted for different uses. For water supply monitoring, a version called the Palmer hydrologic drought index was created (Karl, 1986) while there is also a real time version of PDSI, known as modified PDSI (Heddinghaus & Sabol, 1991). Although PDSI has many applications, it also has many limitations that have been analyzed in many studies (Alley, 1984; Guttman, 1998; Willeke et al., 1994). One of the major limitations is that PDSI can have a slow response to evolving and declining droughts (Hayes et al., 1999). The use of PDSI is common, but there are other metrics to measure the severity of drought.

The Standardized Precipitation Index (SPI) was developed in 1992 (Mckee et al., 1993) and was recommended by the World Meteorological Organization in 2009 to be used as a standard index globally to measure meteorological droughts (Hayes et al., 2011). This index only uses precipitation to determine drought conditions and was developed to examine the relationships between drought and frequency, duration, and timescales (Mckee et al., 1993). To calculate SPI, the long term precipitation record for the period in question is fitted to a probability distribution, which is then transformed to a normal distribution, such that the mean SPI is zero (Mckee et al., 1993). The main advantage of using SPI is that it can be calculated for multiple time scales (Mishra & Singh, 2010). There are two main limitations to using SPI, the record length of precipitation and the probability distributions. When the SPI is computed during different time records, but all of those records have similar distributions, then the SPI values tend to be consistent. When the distributions are not similar then the SPI value have discrepancies (Mishra & Singh, 2010). The distributions are a limitation in climates where precipitation is seasonal and there are large amounts of zero values during the dry season. These zero values cause the distributions to be highly skewed the precipitation distributions which leads to the SPI values not being normally distributed (Mishra & Singh, 2010).

The US Drought Monitor (USDM) was designed to illustrate the magnitude and extent of drought throughout the country (Svoboda et al., 2002). The USDM classifies drought based on the intensity of the drought, from D0 to D4 where D0 is “abnormally dry” and D4 is “exceptionally dry” (Svoboda et al., 2002). The USDM combines multiple variables to illustrate both the short- and long-term drought on one map. To determine which category a location is in the Drought Monitor uses multiple indices and indicators such as PDSI, SPI, CPC Soil Moisture Model Percentiles (Huang et al., 1996), US Geological Survey Daily Streamflow Percentiles, Percent of Normal Precipitation (Willeke et al.,1994), and Satellite Vegetation Health Index (Kogan, 1995). Newer indices and indicators such as the Evaporative Stress Index (Anderson et al., 2013, 2011, 2007), Evaporative Demand Drought Index (Hobbins et al., 2016), and Vegetation Drought Response Index (Brown et al., 2008), and other data sources enable the authors of the USDM to produce maps at finer resolutions (Fuchs, 2019). The data is incorporated in the maps using Geographic Information System (GIS) technology. The use of GIS and higher resolution data sources has increased the accuracy of the USDM by enabling the authors to draw the drought intensity contours along the data contours (Fuchs, 2019). Also incorporated in the USDM is the feedback of experts in the field that report on the validity of the map based on local conditions, adding to the accuracy of the USDM (Anderson et al., 2013). There are many other indices that are not included in this thesis. However, a common theme among all of these indices mentioned here is that they all can give a measure of past or current drought conditions. There is not yet an index that enables us to see the likelihood of recovering from or remaining in drought conditions. While each of these indices has its own use, none of them have a predictable nature to them.

1.6 Drought Prediction

Being able to predict a drought and its duration and recovery time is crucial for planning and preparedness (Luo & Wood, 2007). There have been many approaches to drought prediction. Luo and Wood (2007) developed a drought monitoring and prediction system. This prediction method utilizes both dynamic climate model forecasts and observed climatology and combines them using a Bayesian merging procedure (Luo & Wood, 2007; Luo et al., 2007). They compare these current conditions with historical data that is similar in both spatial and temporal precipitation anomaly patterns and use this to find the 10 most similar years (Luo & Wood, 2007). They showed in (Luo & Wood, 2008) that this method better predicts the streamflow and soil moisture. However, there are also uncertainties associated with predicting soil moisture and snow extent, and issues can arise when there is early snowmelt (Luo & Wood, 2008).

The Global Integrated Drought Monitoring and Prediction System (GIDMaPS) is another drought prediction tool that uses multiple drought indicators to make these forecasts (Hao et al., 2014). GIDMaPS utilizes probabilistic forecasts to provide information about early warning, preventative planning, and ways to mitigate drought. This tool utilizes both precipitation and soil moisture data from simulations and observations, these datasets are described in Hao et al. (2014). GIDMaPS also utilizes three drought indicators when making predictions, these are SPI, Standardized Soil Moisture Index (SSI) (Hao & AghaKouchak, 2013), and Multivariate Standardized Drought Index (MSDI) (Hao & AghaKouchak, 2014). The main purpose of SPI is to capture meteorological drought, whereas SSI captures agricultural drought (Hao et al., 2014). MSDI is based on both precipitation and soil moisture and is an indicator of both meteorological and agricultural drought (Hao et al., 2014). The drought prediction component of GIDMaPS gives the probability of drought occurrence, using the same scale as the USDM, from D0-D4. This tool allows for one to six month drought forecasts based on available data and can be found at http://drought.eng.uci.edu/ (Hao et al., 2014).

The USDM, along with reporting current drought conditions, also provides seasonal and monthly drought outlooks (Pugh & Fan, 2018). The monthly prediction comes out at the end of the month, and is valid for the whole next month, and the seasonal outlook comes out in the middle of the month and is valid for three months past the date it is released. Both of these outlooks are based on probabilities that are derived from large-scale trends (Pugh & Fan, 2018) and are shown as maps. These maps provide information about how drought conditions may change in the coming months.

The development of drought monitoring and prediction systems face several challenges in addition to the multitude of possible drought metrics. Access to global or regional real time hydroclimate data at fine resolutions poses a challenge to develop drought monitoring and prediction systems (Hao et al., 2017). The limitations of data and a universal drought metric make it difficult for tools like the drought monitoring and prediction system and GIDMaPS to work for all countries or regions. A specific limitation of the drought monitoring and prediction system is that it does not work properly if there is early snowmelt, which is important for mountainous regions. The USDM drought outlook tool provides a vague description of how this metric is calculated and leaves a lot open to interpretation. The three methods of drought prediction discussed in this section are not ideal for predicting drought in the PNW. There is a clear need for a tool specifically created for the PNW and prediction of drought recovery, and this is one of the many goals of NIDIS (Sheffield, 2017).

An important project of NIDIS is the network of regional Drought Early Warning Systems (DEWS) ("What is NIDIS?," n.d.). DEWS is in place to make climate and drought science accessible, understandable, and useable for decision makers. Another objective of this system is to allow stakeholders to be able to monitor, forecast, plan for, and cope with drought and its impacts. The goal of NIDIS is to enable the nation to manage drought-related risks and impacts by making information and tools accessible thus allowing for the nation to be prepared for and mitigate drought effects ("What is NIDIS?," n.d.). Since drought is different across the US, NIDIS has implemented regional DEWS in order to build a foundation for the national DEWS. The regional DEWS have researchers, academics, resource managers, policymakers, along with stakeholders who collaborate and inform communities to enable them to handle drought ("What is NIDIS?," n.d.). In order for the regional DEWS to be able to improve the prediction skill, it is important that each region's specific needs are understood to ensure that the region's specific characteristics of drought lines up with the method that is being used to predict drought. The onset of drought is difficult to predict, and policies need to be in place for when these events do come about.

1.7 Pacific Northwest Drought Declaration Policies

1.7.1 Oregon

Drought is typically declared at the county scale for Oregon. Under the Oregon Revised Statute (ORS) 536.740 the Governor has the authority to declare that drought exists across the entire state of Oregon, or in any and all of the drainage basins (Oregon Office of Emergency Management & Oregon Water Resources Department, 2016). The Governor can then direct state agencies to put in place water conservation plans. Typically, the first step for drought declaration happens at the county government level. This process begins when the local emergency officials assess the situation with water providers and the Water Resource Department (WRD). This assessment can lead to the county government declaring drought within its governing boundaries or coming to another resolution to move forward. If drought conditions continue, the county government can then request assistance from state agencies or access to temporary water rights tools. The cities and districts that are requesting these assistance tools must appeal to the county that they lie within, and then that county can request the state declare a drought. This request is then evaluated by the Water Supply Availability Committee (WSAC), and then it is up to the Drought Readiness Council to inform the Governor and make a suggestion (Oregon Office of Emergency Management & Oregon Water Resources Department, 2016).

1.7.2 Washington

For Washington State, the drought threshold is defined as a prediction that the water supply will fall below 75 percent of normal (Members of the Drought Contingency Planning Task Force, 2018). The Washington WSAC is a group of water experts from both state and federal agencies that are knowledgeable in water availability forecasting, drought monitoring, and climate who are responsible for the water supply measurement and prediction (Members of the Drought Contingency Planning Task Force, 2018). The WSAC meets throughout the year as needed, typically more often in the winter and spring than in the summer and fall. During these meetings they take a variety of variables into consideration and then if the water supply forecast is less than 75 percent of normal the WSAC needs to determine whether this is likely to remain the case. Then it is the responsibility of the WSAC to recommend that the Executive Water Emergency Committee (EWEC) meet to determine the impacts of the water shortage (Members of the Drought Contingency Planning Task Force, 2018). The EWEC makes the final suggestion for either a drought advisory or an emergency declaration to the governor. The governor will then submit a formal request to The Department of Ecology to issue an “Order and Determination of Drought” (Members of the Drought Contingency Planning Task Force, 2018). It is also the responsibility of the state to inform the tribes in the drought areas and notify them of the drought response actions that will take place in these areas (Members of the Drought Contingency Planning Task Force, 2018).

1.7.3 Idaho

Local emergency disasters are declared by either the local governing body or an approved official (Idaho Department of Water Resources, 1995). These will normally be issued when there is an existing or threatening disaster, such as drought, within the political boundaries of a city, county, or city and county. Idaho lets county and local governments approach the situation how they see fit, unless there is an extreme water shortage. If a local emergency is declared then this provides the local government the legal authority to request that the governor announce a state of emergency, obtain supplies and equipment, and conduct emergency operations, among many other things (Idaho Department of Water Resources, 1995). By declaring an emergency, the local government is formally notifying the Federal Government, the Congressional Delegation, State Legislature, State of Idaho, and the public that there is a severe crisis (Idaho Department of Water Resources, 1995). It also formally organizes all of the agencies within the jurisdiction that are capable of aiding with the emergency response effort. Finally, this declaration also paves the way for future federal support and assistance (Idaho Department of Water Resources, 1995).

This study has two goals; the first is to create a statistical method of predicting drought and the second is to understand the atmospheric conditions that occur when drought conditions are present or have improved. The current methods of predicting drought do not provide enough detail to water managers in Oregon, Washington, and Idaho to prove effective with decision making. These water managers need a tool that will aid them with decision making on the county level for when they inform the governor of what current conditions are. The first aspect of this study aims to help with the decision-making process by providing a new way of representing possible future outcomes of drought using a new variable over a geographic aggregation that was specified by the stakeholders. The second aspect of this study is to understand the atmospheric conditions and the surface conditions that are behind drought recovery and persistent dry conditions.

The overarching questions guiding this research are:

(1) Can we come up with a way to determine the likelihood of drought recovery?

(2) What are the drivers of drought and drought recovery?

2. Data and Methods

2.1 Datasets

2.1.1 Hydrologic Model

This study utilized daily soil moisture and snow water equivalent (SWE) data from the Variable Infiltration Capacity (VIC) hydrologic model (Liang et al., 1994), implemented at 1/16° spatial resolution across the Western United States (Xiao et al., 2016). The data used in this study is the same as that produced by the "UCLA Drought Monitoring System for the West US" (Xiao et al., 2016), for which the data from 1920 through 2015 were readily available. For the creation of this dataset the VIC model is driven by observations of daily precipitation, maximum temperature, and minimum temperature from various NOAA Cooperative Observer sites across the domain and gridded to the VIC resolution (Wood & Lettenmaier, 2006). The drought monitoring system is updated (http://www.hydro.ucla.edu/SurfaceWaterGroup/forecast/monitor_west/index.shtml) daily and provides percentiles for soil moisture, SWE, and total moisture percentiles, along with SWE values. The VIC model contains three soil layers (Xiao et al., 2016), and balances water and energy fluxes at the land surface (Liang et al., 1994). The model also has the capability of simulating movement of soil moisture through infiltration and baseflow processes (Liang et al., 1994). VIC has also been shown to successfully simulate hydrologic conditions in large basins and regions, such as Western North America (Mote et al., 2005; Nijssen et al., 2001). Using the VIC model, Mote et al. (2016) found that the 2015 drought was the most severe warm snow drought documented in Oregon and Washington. Xiao et al. (2016) used VIC and the severity-area-duration method to evaluate historic total moisture droughts in the PNW. VIC model data has been used in a variety of studies including those about water supply, snowpack decline, and drought (Mote et al., 2018, 2016; Xiao et al., 2016).

For this analysis, the daily soil moisture and SWE data were each averaged for each month of the 1920 to 2015 period of record and aggregated by county. Using these two variables, total moisture (TM) was created, which Xiao et al. (2016) states that TM is the sum of soil

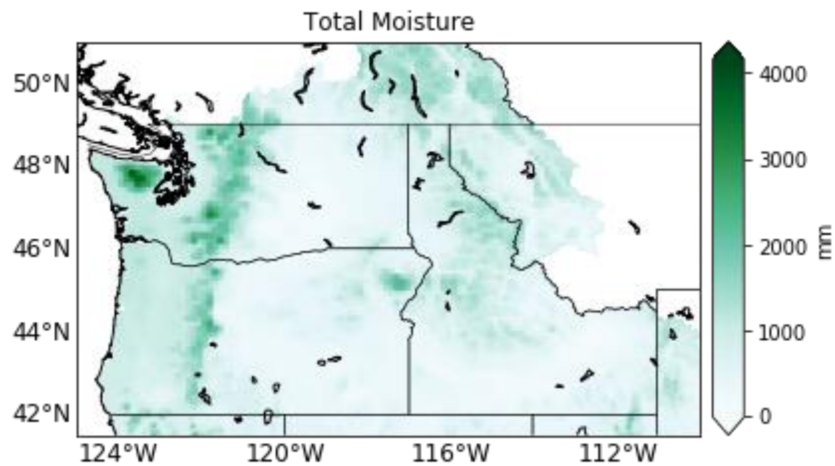

Figure 3: Total Moisture for a random month, March, displayed over the study domain.

moisture and SWE. An example of total moisture is illustrated in Figure 3, displaying a sample month of March.

Soil moisture is an important measure of water availability and responds to both precipitation and snowmelt. Soil moisture observational data are available through the International Soil Moisture Network (ISMN; Dorigo et al., 2011, 2013) and the North American Soil Moisture Database (NASMD; Quiring et al., 2016). However, the ISMN is made up of networks that have a variety of different stations that have various years on record, number of instruments, soil moisture depths measured, and measurement intervals (Dorigo et al., 2011, 2013). As with ISMN, the NASMD also is made up of networks that have a variety of different stations in which they have varying years of record and soil moisture levels (Quiring et al., 2016). Soil moisture observations are inconsistent and sparse, making VIC model data crucial for this analysis. Utilizing VIC allows for consistent years of record with data that are spatially uniform and have three levels of soil moisture. Access to uniform soil moisture data is a key part of this analysis.

In order to perform this study, each county was spatially averaged and annual percentiles, 0-100, were created for each month of data in order to allow comparisons in time and space. The 119 counties in the PNW have a wide range of average TM values, so we convert the data for each calendar month to percentiles. While TM values can vary drastically throughout the year, using percentiles allows the comparison of TM between months that have extreme high values and months that have extreme low values.

2.1.2 Atmospheric Data

Monthly mean geopotential height (GPH) data were obtained using the National Center for Environmental Protection (NCEP)/National Center for Atmospheric Research (NCAR) "20th Century Reanalysis" data and with 2.0° spatial resolution (Compo et al., 2011). Retrospective analysis (reanalysis) data is gridded estimates of historical weather and climate data over regular time intervals (Parker, 2016). Reanalysis datasets are created by using a numerical weather prediction model and data assimilation method as well as historical data records (Parker, 2016). The "20th Century Reanalysis" data were chosen for this study because the period of record extends back to 1851 and overlaps with the VIC data. Other reanalysis data available only covers the second half of the 20th century (Kalnay et al., 1996). The data were trimmed to start in 1921 and extend through 2015 to align with the spring of each water year in the VIC data. There are 24 different pressure levels in the dataset, ranging from 10 to 1000mb. We have selected the 500mb pressure level which shows conditions in the middle troposphere, ranging approximately from 5,000 to 6,000 meters above sea level. This height field displays troughs and ridges in the upper atmosphere, which correspond to cyclonic and anticyclonic systems on the surface, respectively. The 500mb GPH allows the examination of large-scale atmospheric features over the entire Eastern Pacific Ocean. The 500mb GPH anomalies used in this study were derived from the reanalysis data by removing the 94-year monthly means from each month's value.

2.1.3 Surface Temperature Data

Monthly minimum and maximum surface temperature data were obtained from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group at Oregon State University (PRISM Climate Group). PRISM generates estimates of climate values based on point data, a digital elevation model, other spatial datasets, and an encoded spatial climate knowledge base, which are then interpolated to a grid for use (Daly et al., 2008). PRISM was developed to interpolate and extrapolate data in complex terrain, such as mountainous regions and areas near a coast, creating an ideal dataset for studying the PNW (Daly et al., 2008). The "Historical Past" and "Recent Years" data were combined and trimmed to extend from 1921 through 2015 to align with the spring of each water year in the VIC data. The maximum and minimum temperatures were used to derive the average surface temperature. The PRISM data has ~4km resolution. The temperature anomalies used in this study were derived from the PRISM data by removing the 94-year monthly means from each month's value.

2.2 Study Region

This study was performed because of a need expressed by water managers for a drought prediction tool in the PNW. The VIC data were aggregated into counties to support drought monitoring and decisions about drought declarations, as explained in *section 1.7*. This study was performed on each individual county. Each county in the PNW can be seen in Figure 4. Only the

TM data inside the thick black lines in Figure 4 were used in this analysis. Washington State also uses hydrologic unit code (HUC) 8 to determine drought conditions. Future studies could also be performed on the HUC8 level and other boundaries.

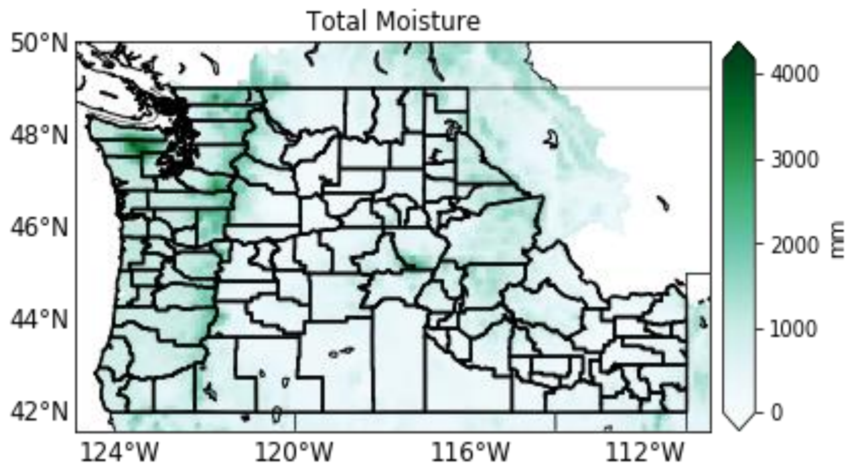

Figure 4: The study domain divided into counties.

2.3 Stakeholder Engagement

We worked with stakeholders to create a drought metric and tool that will help with decision making and informing the public of the availability of water. Coproduction of knowledge is the development of usable and useful science through partnerships between scientists and those who are using science for policy decisions (Meadow et al., 2015). It has been shown that when science is produced this way it is more likely to be used and trusted by decision makers (Meadow et al., 2015). With stakeholder participation in the production of science, the outcome is more likely to be on the spatial and temporal scales useful to them (Dilling & Lemos, 2011), the creation of the product is better understood (Cash et al., 2006), and there is a sense of ownership over the final product due to the stakeholder contributions (Robinson & Tansey, 2006). Coproduction is vital for the creation of science that is useful to decision makers. By working with stakeholders, we are ensuring the understanding and utility of the drought metric created.

In order to ensure that the final product from this work was usable and useful we worked with stakeholders from each state in the PNW. Our stakeholders consisted of a key person in the following state water management agencies: the Washington Department of Ecology, Oregon Water Resources Department, and the Idaho Department of Water Resources. In Washington, we worked with the state drought coordinator who is also a member of the Washington WSAC. The main role of this committee is to assess the water supply conditions in the state of Washington and if necessary, recommend a drought advisory or declaration to the governor. In Oregon, we worked with the surface water hydrology manager and the chair of the Oregon WSAC. In Idaho,

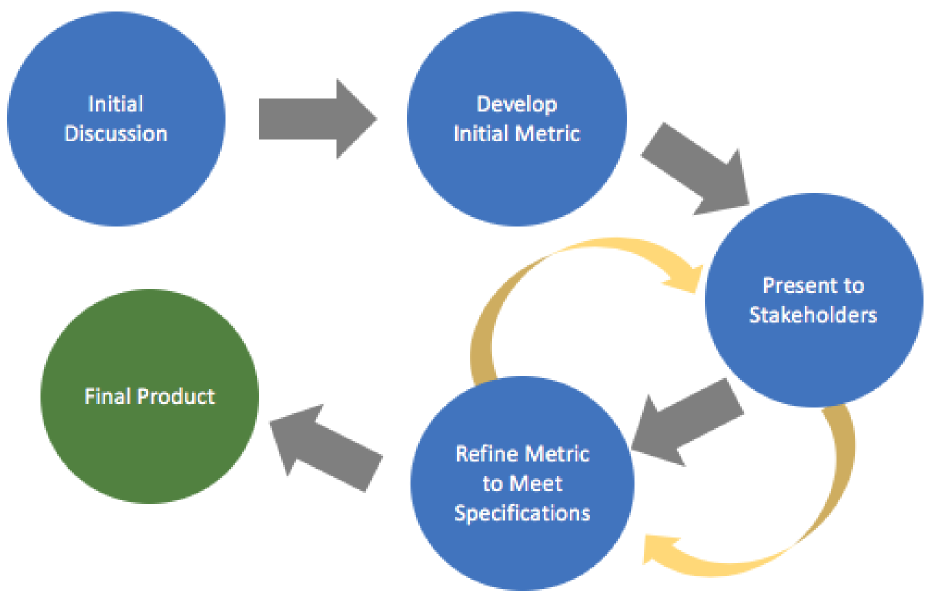

Figure 5: Process with stakeholders to produce drought tool

we worked with a hydrologist who is the coordinator for drought designation suggestions from Idaho's Water Supply Committee to the USDM.

To gather the stakeholders' input on the drought metric, we held a series of webinars with them. The process that we went through with the stakeholders is shown in Figure 5. An initial meeting with them indicated that they would like this tool to incorporate soil moisture and to use county averages. In following stakeholder meetings, we received feedback about the plots displaying ideas for the drought metric. Their advice for making our end product useful included: make the start and end months of the tool adjustable; have the drought tool available for different boundaries, such as Hydrologic Unit Code (HUC) 8; and have illustrations that are easy to communicate to the public for when our stakeholders make decisions. When the tool is created and made available, the features that our stakeholders have suggested will be incorporated. For this analysis we used examples of many of the ideas they suggested, like county political boundaries, and having our start and end months being February and July.

2.4 Drought Analysis

Here we define drought recovery as a county that was at or below the 25th percentile in February, and then rose above the median percentile in July of the same year. During one of the initial meetings discussed in *section 2.3,* the stakeholders advised us to use February as a start month for this analysis. When years have low snowpack in the PNW, our stakeholders begin to worry about the spring and summer water supply. Focusing attention on conditions in February, and how the next few months may alter the likelihood of drought, allows us to provide quantitative insights on a common expectation that spring precipitation may prevent drought. We show that already by February in most of the PNW, drought can only be averted by an exceptionally wet spring. Another decision during the initial meeting was to use the 25th percentile to represent a dry year, a value that is equivalent to D0 drought in the USDM and is also a high enough value that we had a large enough sample to work with. The end month for evaluating drought recovery was chosen as July. The summers are hot and dry (Fig. 2) in this region and if the PNW has not recovered from drought by this point, the normally dry summers almost guarantee no improvement after July. The 50th percentile was chosen as the recovery threshold because this value is high enough that if a county has reached this point by the summer it will likely be fine, but low enough that we had a large enough sample size to work with.

In addition to years that recover from drought as just described, there are other paths that the TM can take in each county. It can remain below the 50th percentile in July, defined here as persisting dry conditions (which may or may not be severe enough to qualify as drought). Third, TM can be above the 25th percentile in February and also be above the 50th percentile in July. Finally, TM could be above the 25th percentile in February but then below the 50th percentile in July. For the second part of the analysis (discussed further in *section 2.5 and 2.6*), recovery is defined as a climate division being at or below the 40th percentile in February, and then rose above the median percentile in July of the same year. Also, for the second part of the analysis dry conditions are defined as remaining below the 50th percentile in July (which may or may not be severe enough to qualify as drought). In addition to examining cases in which the February TM value is below the 25th or 40th percentile, we are also interested in the broader pattern of change from an arbitrary n^{th} percentile. Using the historical data, we are able to determine the probability of drought recovery for each county from each February percentile.

$$Recovery\ Probability = \frac{\Sigma TM_n \geq 50}{\Sigma TM_n}$$

where *n* is the percentile below which the county's total moisture lies in February. The denominator is the total number of years that are at or below the n^{th} percentile as of February. The numerator is the number of years that were below the n^{th} percentile in February that then recovered. This probability was calculated for all integer values of n. Although this calculation could be repeated for other months and thresholds, and even used to build a more flexible tool for our stakeholders, for our purposes we use February and July as example months for all analyses.

2.5 Geopotential Height Analysis

The purpose of this part of the analysis is to understand the conditions that lead to continuing dry conditions and those that lead to recovering from dry conditions. Analyzing the 500mb GPH can explain the large-scale atmospheric features that lead to dry conditions or recovery. Linear regression may identify important relationships between the variables. The regression analysis can tell us where these relationships are strongest and thus influence the recovery and dry conditions. By compositing the GPH values for the recovery years and dry years separately, we aim to see what is causing these conditions.

The 500mb geopotential height anomalies were averaged over the months of March, April, May, and June (MAMJ) and were used to diagnose the drivers of drought and drought recovery. These months were chosen for this study because this is the critical time for drought to arise or recover in the PNW. The MAMJ GPH anomalies were linearly regressed with the change in percentile between February and July (QF-J) for each climate division, for years in which the total moisture percentile is below the 40th percentile in February. The 40th percentile was used for this part of the analysis to have more years to work with. The 40th percentile will still capture the extremely dry years but will ensure that there are more years that have increased to the 50th percentile in July. For this part of the analysis, climate division boundaries are used. Climate divisions are used because the counties did not have enough recovery years to show significant characteristics of atmospheric flow. Climate divisions are boundaries that were created with the consideration of climate conditions, county lines, drainage basins, and crop districts (Guttman & Quayle, 1996). There are nine climate divisions in Oregon, and 10 in both

Washington and Idaho. Climate divisions were included in the analysis if there were at least eight recovery years that also had a strong coefficient of correlation between QF-J and the MAMJ GPH anomalies.

The height anomaly at each grid cell in the geopotential height data was regressed to the QF-J for every year below the 40^{th} percentile in February for each climate division. From the linear regression analysis, the slopes were calculated. The maps of the slopes from the regression analysis show the relationships between QF-J and the MAMJ GPH anomalies. The correlation coefficients from regression analysis have been used to study teleconnections to identify spatial patterns (Wallace & Gutzler, 1981). The correlation coefficient is a reflection of the scatter and the slope is a reflection of the sensitivity between the two variables. Here we use the slope because we are interested in how sensitive the relationship between GPH and QF-J is. Casola et al. (2009) used the slopes of regression analysis to determine the sensitivity between April 1 SWE and temperature in the Cascades.

The 500mb MAMJ geopotential height fields were composited for both recovery years and dry years to determine what the pressure fields looked like during those years. Here, the probability of recovery was calculated using the 40^{th} percentile in February in order to separate recovery years from dry years. These composite plots, along with the regression maps, can illustrate the high- and low-pressure anomalies and large-scale features. Typically, when troughs are present in the middle troposphere this indicates stormy and usually cool weather at the surface, whereas ridges in the middle troposphere indicate warm and dry weather at the surface. The location of these troughs and ridges over the Eastern Pacific Ocean and the PNW influence weather patterns and can indicate how the atmospheric flow is changing the TM percentile. This will be discussed further in the results section. To further examine the conditions in each climate division we turn to temperature.

2.6 Temperature Analysis

The surface temperature anomalies that were averaged over the months of MAMJ were also used to determine the drivers of drought and drought recovery. The surface temperature was composited for both recovery years and dry years. Here, the probability of recovery was calculated using the 40^{th} percentile in February in order to separate recovery years from dry years. These composite plots complement the geopotential height composite plots in order to tell a more complete story. Small changes in temperature can determine whether precipitation falls as rain or snow, depending on the location and elevation within the region (Elsner et al., 2010). As mentioned in *section 2.5*, troughs and ridges at the 500mb pressure level can indicate what the surface temperature will be. If there was a trough over the PNW, cool surface temperatures would be expected during the spring season. If the trough is located in the Eastern Pacific Ocean, west of the PNW it pumps warm air into the region from Southwest in the Pacific. However, if ridging occurs over the PNW, warm surface temperatures are expected to occur. If the ridge is located in the Eastern Pacific, west of the PNW, it can bring cool air down from the Northeast over Canada. Cool temperatures could indicate that the snowpack did not melt early allowing for natural storage to occur. This leads to runoff in the spring and early summer, along with maximum streamflow and soil moisture (Elsner et al., 2010). Warm temperatures can lead to early snowmelt, or even precipitation falling as rain instead of snow, leading to even more snowmelt during early spring. When there is early snowmelt and runoff, peak streamflow occurs earlier in the season coinciding with a peak in soil moisture (Elsner et al., 2010). Early snowmelt depletes the natural storage of the region, leaving dry conditions with not much available water for the rest of the year.

3. Results

3.1 Drought Recovery Forecast

In this section, the states are examined separately because they are each made up of distinct geographic regions. Oregon can be divided into two different areas, Western and Eastern Oregon. Washington can be divided into three different areas, the Western Washington, Puget Sound, and Eastern Washington. Idaho can be divided into three different areas, the Rocky Mountains, the Columbia Plateau, and the Basin and Range Region. One county was selected from two different geographic areas from each state as representative counties. A representative county from each of the other geographic areas can be seen in the appendices.

3.1.1 Oregon Counties

The two geographic regions chosen to examine are the Western and Eastern Oregon. Within those regions, the two counties selected are Tillamook (Western) and Harney (Eastern). Tillamook is located on the northern part of the coast, whereas Harney County is located in the southeastern part of the state (Fig. 8). For each county, every year plays out differently depending on the atmospheric conditions, time, and location. Each year in the VIC record can be seen in Figures 6 and 7 for these two counties. These figures show the seasonal evolution of TM, and the individual traces provide context that will be useful in future years as droughts develop. The driest (red) and wettest (blue) years as of February are displayed to visualize how these years can change during the spring season. Figure 6 shows that the path can change dramatically in Tillamook County over the course of the spring, whereas in Figure 7 what happens in Harney County is predetermined by what occurs in the beginning of the water year. For Harney County,

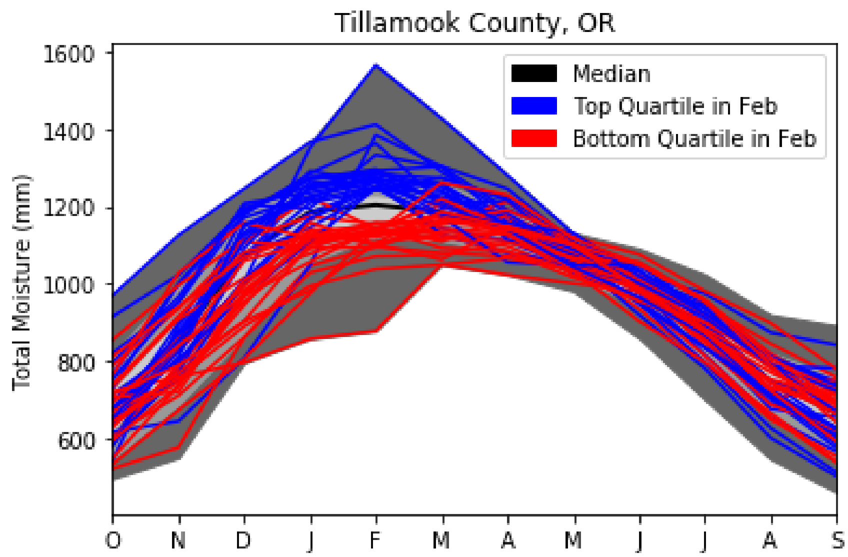

Figure 6: The distribution of monthly mean total moisture from VIC, for Tillamook County, Oregon from 95 years of data. The upper and lower 10th percentiles are shown with dark shading, 10th-30th and 70th-90th percentiles in medium grey shading, and the 30th-70th percentiles with light grey shading. The median is the heavy black curve. Traces for years that were in the bottom quartile in February are shown in red, and years that were in the top quartile are shown in blue.

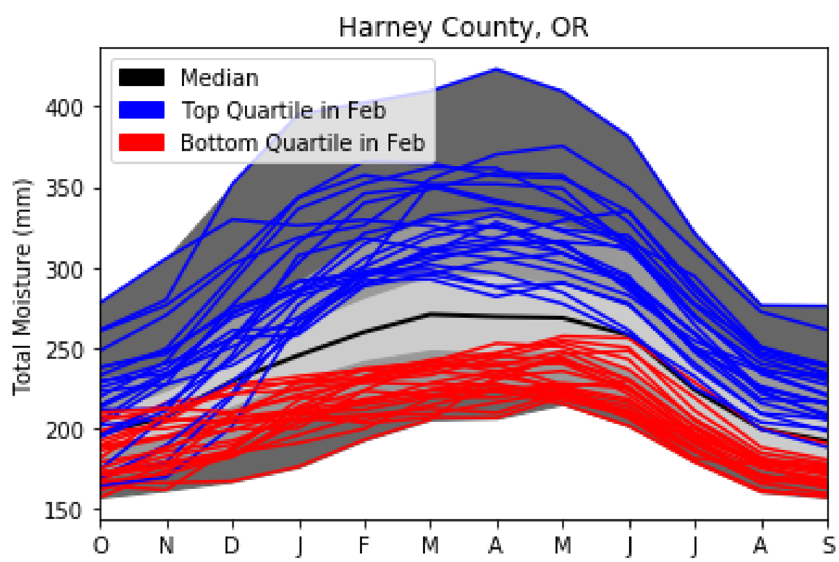

Figure 7: The distribution of monthly mean total moisture from VIC, for Harney County, Oregon from 95 years of data. The upper and lower 10th percentiles are shown with dark shading, 10th-30th and 70th-90th percentiles in medium grey shading, and the 30th-70th percentiles with light grey shading. The median is the heavy black curve. Traces for years that were in the bottom quartile in February are shown in red, and years that were in the top quartile are shown in blue.

the quartiles do not change much once winter is over; if the TM is low it remains low and if it is high, it typically remains above the median value. A distinct difference between Figures 6 and 7 is the amount of TM each receives. Tillamook is a coastal county, and the lowest values associated with the driest years in this county are higher than the wettest years in Harney County. Harney County is considered to be a high desert and receives little precipitation, whereas Tillamook is a coastal county that receives an abundant amount of precipitation.

The probabilities of recovery were calculated for all counties in Oregon and can be seen in Figure 8. The shaded value shown in Figure 8 is proportional to the number of red lines, in

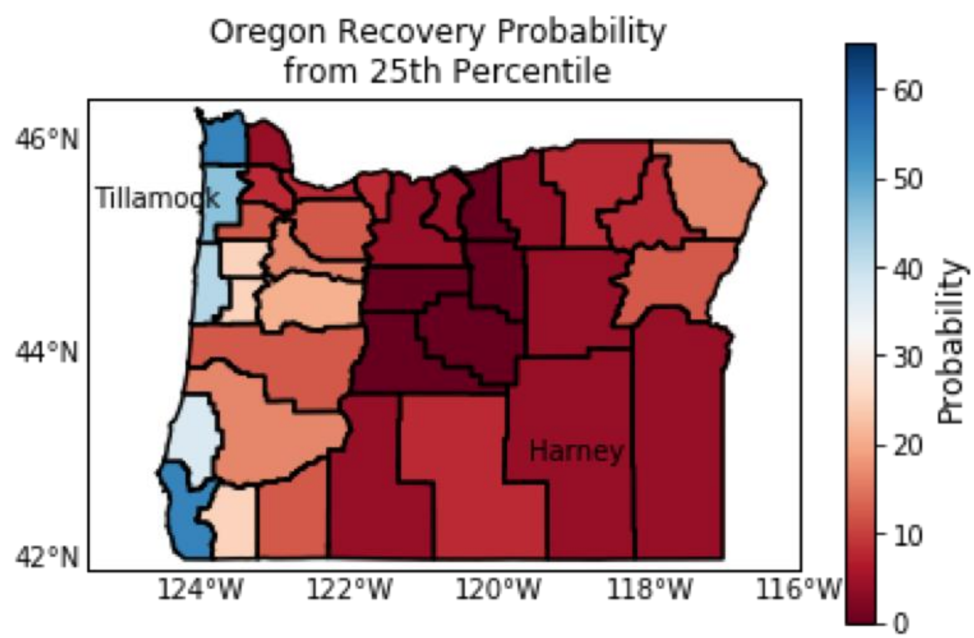

Figure 8: The probability of each county recovering from being at or below the 25th percentile in February and recovering to the median percentile in July for Oregon.

Figures 6 and 7, that exceed the median in July for those specified counties. Blue indicates a higher chance of recovery and red indicates low chances of recovery. The spatial patterns of recovery are also apparent in Figure 8, where most coastal counties have a higher chance of

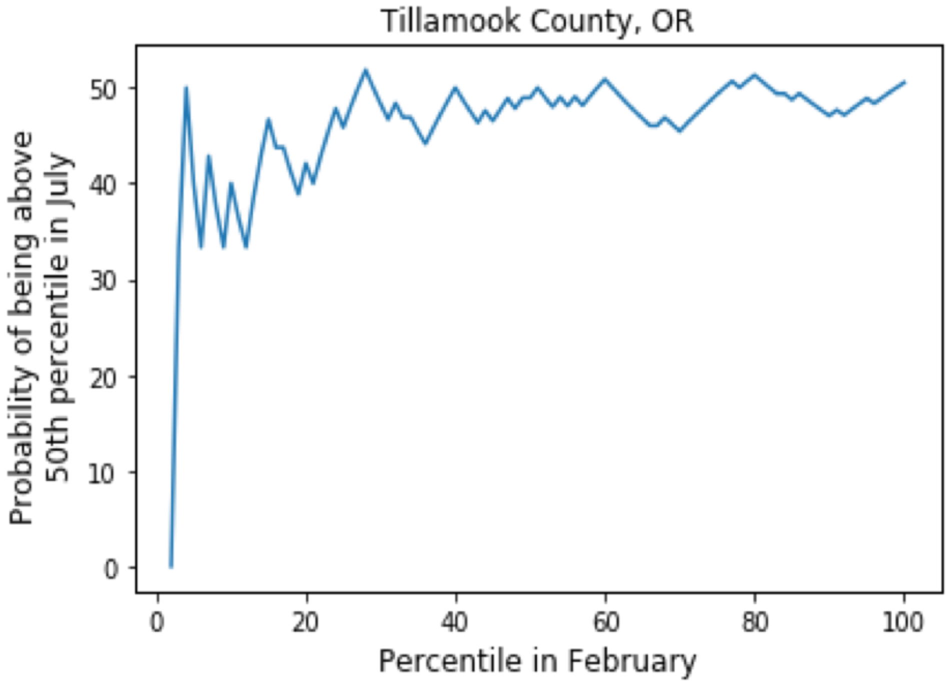

Figure 9: The probability of being above the median in July for Tillamook County, Oregon for all percentiles as of February.

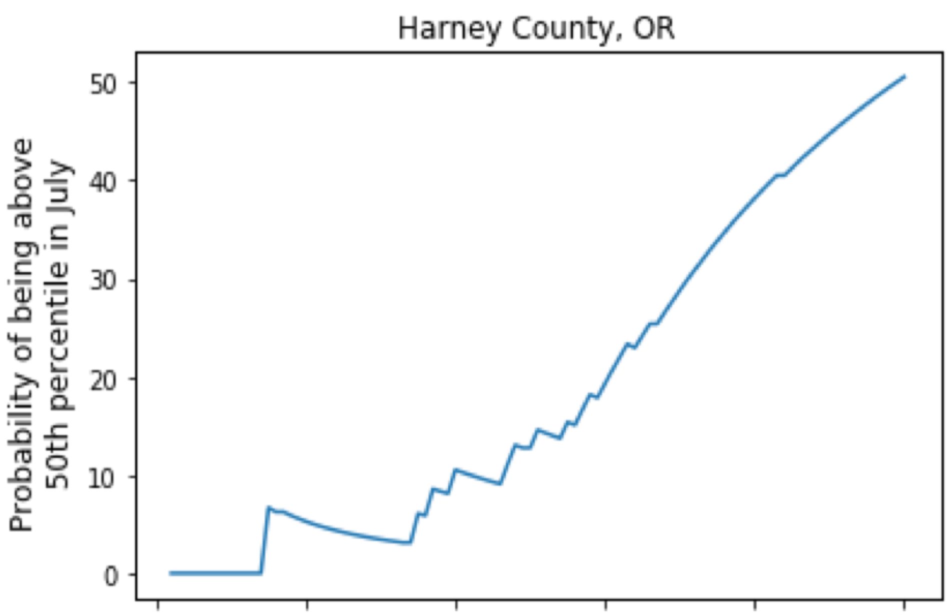

Figure 10: The probability of being above the median in July for Harney County, Oregon for all percentiles as of February.

recovering from spring conditions and counties in and east of the Cascades have the lowest chances of recovery. Lane and Douglas County are two coastal counties that are red because they have some coastal land but most of the county area is inland. Figure 8 shows the spatial patterns of the state for the probability of recovering in the driest ~25% of years but to understand the complete story of each county we turn to Figures 9 and 10.

Looking again at Tillamook and Harney Counties, we can see the chance of being above the 50th percentile in July for any percentile as of February in Figures 9 and 10. At about the 30th percentile, Tillamook has the same probability as Harney County does near the 100th percentile. This shows that Tillamook, a coastal county with plenty of spring precipitation, has a higher chance recovering from lower percentiles. The reason the line on the plots fluctuate between increasing and decreasing is because at every percentile about one year is added to the calculation and depending on whether that year reached the 50th percentile, the cumulative probability will change accordingly. Thus, no matter what the conditions are in February, the probability of being above the median by July can be determined.

3.1.2 Washington Counties

The two geographic regions chosen to examine are Western and Eastern Washington. Within those regions, the two counties selected are Pacific (Western) and Stevens (Eastern). Pacific County is located on the coast in the Southwest. Stevens County is located in Northeastern Washington where some of the Rocky Mountains pass through (Fig. 13). Each year in the VIC record can be seen in Figures 11 and 12 for Pacific and Stevens County. The driest and the wettest quartiles as of February are displayed to visualize how these years can change through the course of the spring season. As in Oregon, the coastal county (Pacific County, in Figure 11) has a larger total moisture than the inland county (Stevens County, in Figure 12). Figures 11 and 12 show the seasonal evolution of TM, and the individual traces provide context

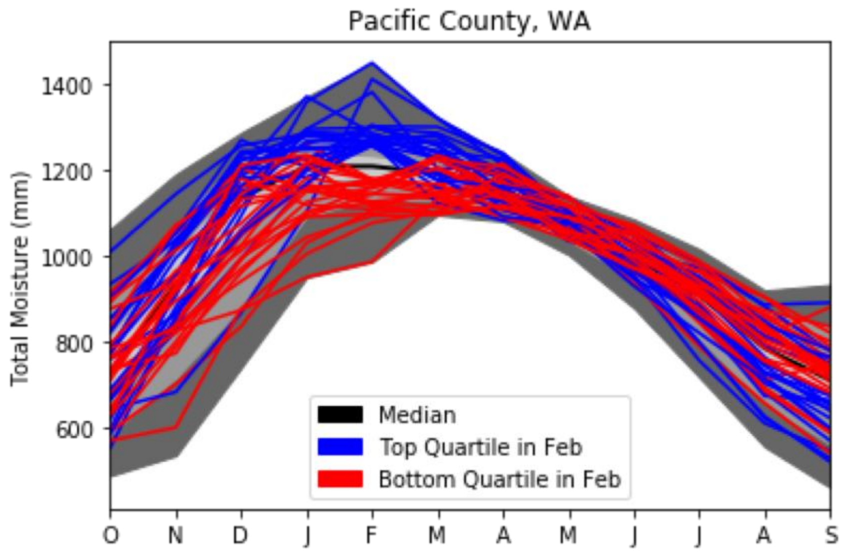

Figure 11: The distribution of monthly mean total moisture from VIC, for Pacific County, Washington from 95 years of data. The upper and lower 10th percentiles are shown with dark shading, 10th-30th and 70th-90th percentiles in medium grey shading, and the 30th-70th percentiles with light grey shading. The median is the heavy black curve. Traces for years that were in the bottom quartile in February are shown in red, and years that were in the top quartile are shown in blue.

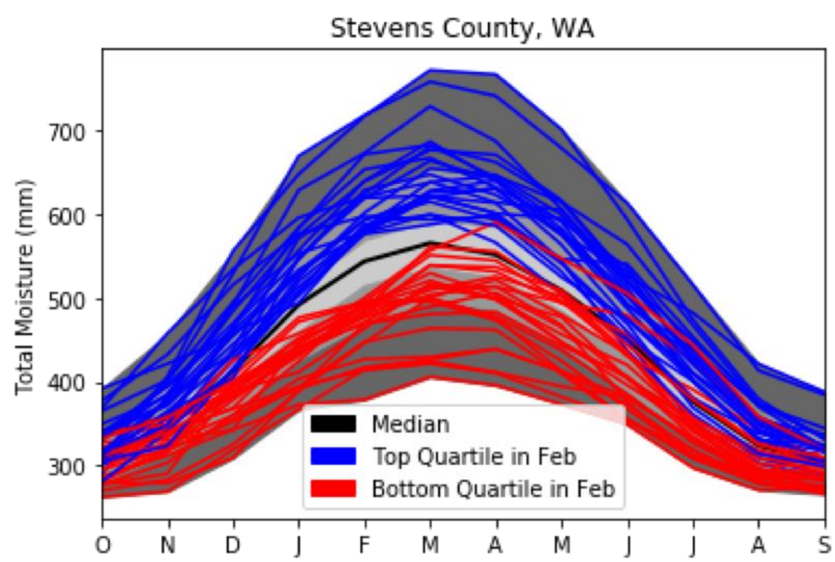

Figure 12: The distribution of monthly mean total moisture from VIC, for Stevens County, Washington from 95 years of data. The upper and lower 10th percentiles are shown with dark shading, 10th-30th and 70th-90th percentiles in medium grey shading, and the 30th-70th percentiles with light grey shading. The median is the heavy black curve. Traces for years that were in the bottom quartile in February are shown in red, and years that were in the top quartile are shown in blue.

that will be useful in future years as droughts develop. Figure 13 shows the spatial pattern of recovery from the 25th percentile across the state of Washington.

The probabilities of recovery were calculated for all counties in Washington and are mapped in Figure 13. In Washington, three of the coastal counties have a higher chance of recovery than the rest of the state, which resembles the Oregon Coast. However, Jefferson County is the only coastal county in red, perhaps because only a small section of the county is on

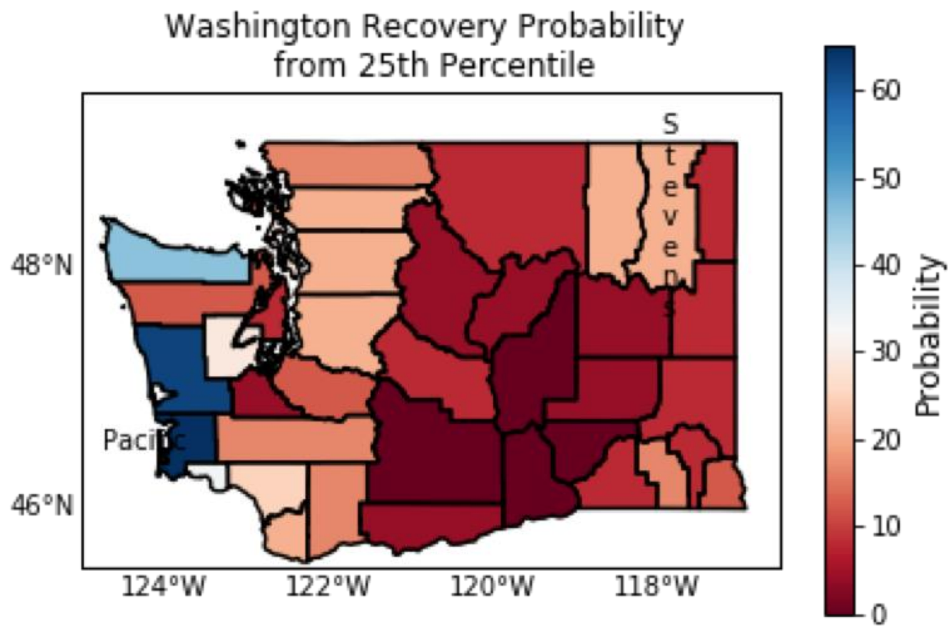

Figure 13: The probability of each county recovering from being at or below the 25th percentile in February and recovering to the median percentile in July for Washington.

the coast and much of it is inland. The Puget Sound lowlands are between the coastal counties and the Cascade Counties and all have approximately a 20% chance of recovery. As we look east of the Cascades at the rest of the state the probabilities are smaller, some in the darkest of red indicating a near zero chance of recovery. In the Northeastern part of the state, Stevens is one of the two counties, the other being Ferry directly west of Stevens, that does have a higher chance of recovery than its neighboring counties. To understand these patterns better for each

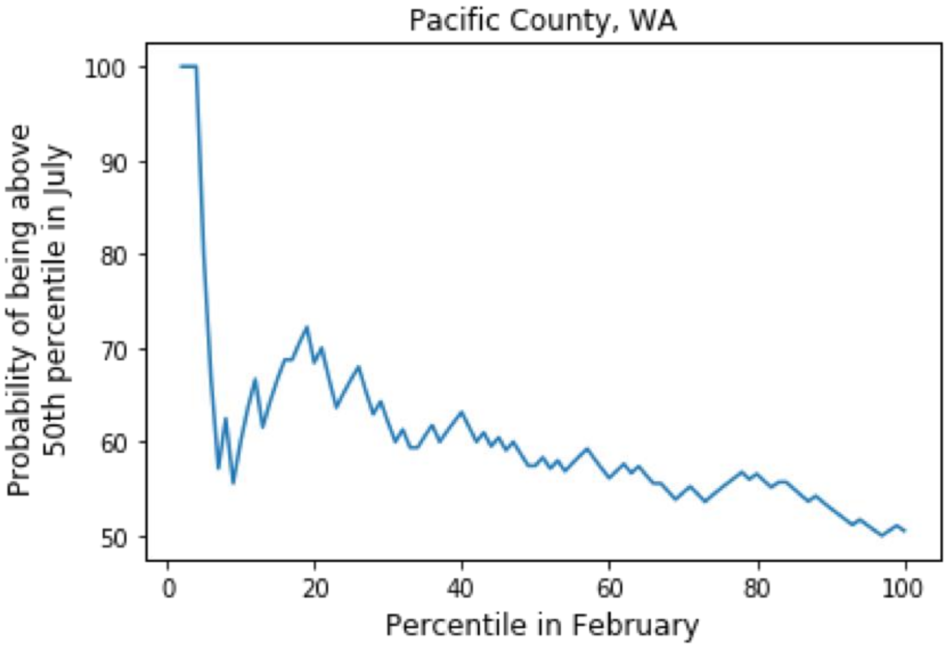

Figure 14: The probability of being above the median in July for Pacific County, Washington for all percentiles as of February.

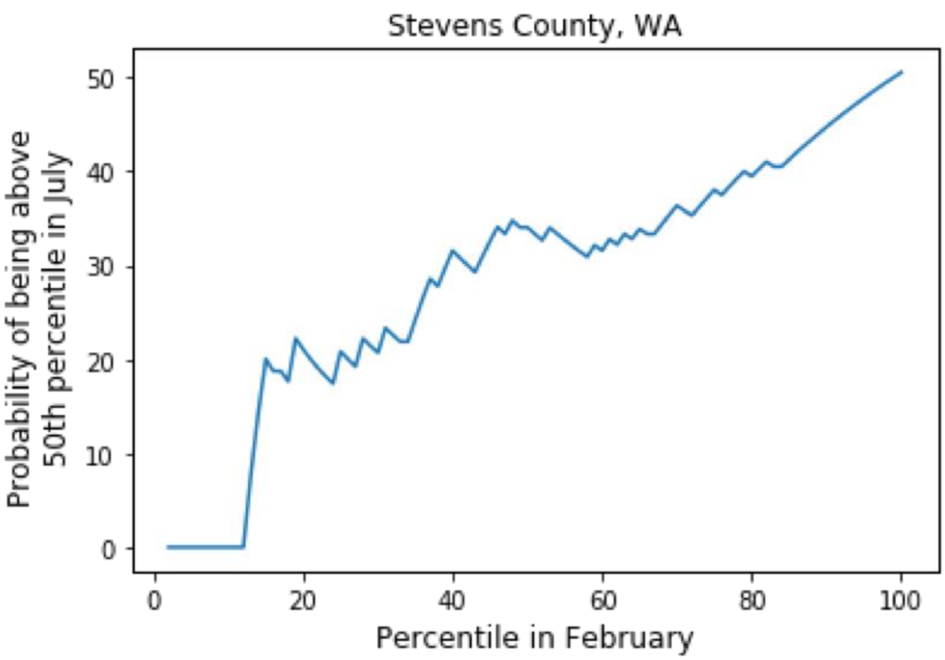

Figure 15: The probability of being above the median in July for Stevens County, Washington for all percentiles as of February.

county we can look at how the cumulative probability of recovery changes with starting percentile.

In Figures 14 and 15, we concentrate on Pacific and Stevens County respectively. For Pacific County, the driest few years all reached the 50th percentile (hence the probability of recovery is, unusually, 100%) and then there is a sharp decline before a more gradual decrease to about a 50% chance of recovery. This is an interesting contrast to Tillamook county, where the driest year stayed dry. Stevens County has a zero probability of recovery for about the first 15 percentiles, then a jump in probability when the first recovery year is added, followed by a gradual increase in probability. The increase in probability seen in Stevens County could be because once the Rocky Mountains have enough snowpack, the chance of recovering increases. Both the amount of TM and the probability of recovery are dependent on the locations, the conditions during each year, timing of events, and other factors. Whatever the conditions are in February, we can determine the likelihood of being above the 50th percentile in July.

3.1.3 Idaho Counties

The two geographic regions chosen to examine are the Columbia Plateau and the Rocky Mountains. Within those regions, the two counties selected are Owyhee (Columbia Plateau) and Lemhi (Rocky Mountains). Owyhee County is located in the Southwestern corner of Idaho and is geographically dominated by highland desert. Part of Lemhi County is in the Rocky Mountains and the other part consists of valleys. Each year in the VIC record can be seen in Figures 16 and 17 for Owyhee and Lemhi County. Figures 16 and 17 show the seasonal evolution of TM, and the individual traces provide context that will be useful in future years as droughts develop. The driest and the wettest quartiles as of February are displayed to visualize how these years can

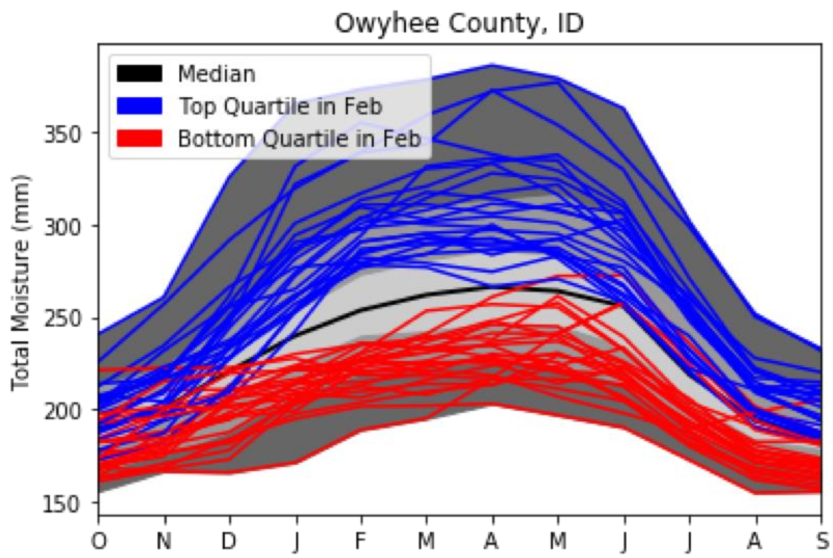

Figure 16: The distribution of monthly mean total moisture from VIC, for Owyhee County, Idaho from 95 years of data. The upper and lower 10th percentiles are shown with dark shading, 10th-30th and 70th-90th percentiles in medium grey shading, and the 30th-70th percentiles with light grey shading. The median is the heavy black curve. Traces for years that were in the bottom quartile in February are shown in red, and years that were in the top quartile are shown in blue.

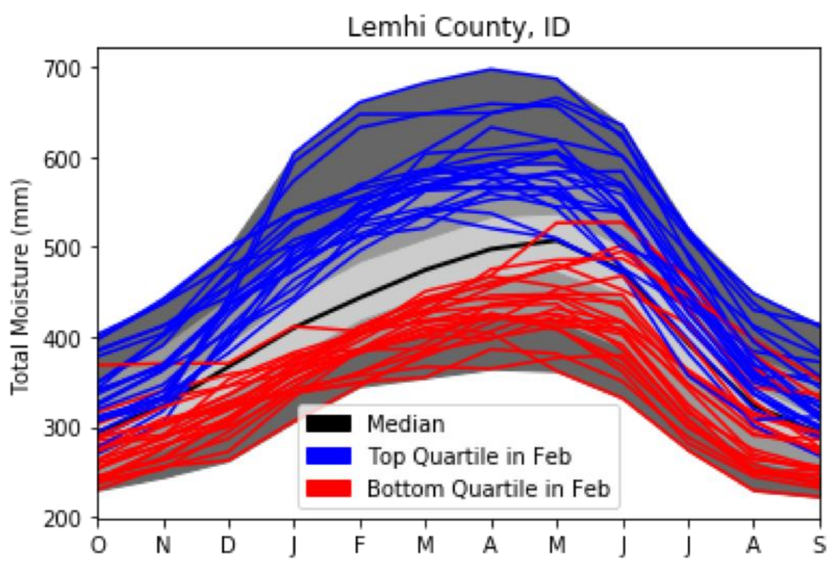

Figure 17: The distribution of monthly mean total moisture from VIC, for Lemhi County, Idaho from 95 years of data. The upper and lower 10th percentiles are shown with dark shading, 10th-30th and 70th-90th percentiles in medium grey shading, and the 30th-70th percentiles with light grey shading. The median is the heavy black curve. Traces for years that were in the bottom quartile in February are shown in red, and years that were in the top quartile are shown in blue.

change throughout the course of the spring season. The TM values for Owyhee County are very low, similar to Harney County in Oregon; both are dry highland areas. Lemhi County has a larger mean value of total moisture, which could be due to the mountain range running through it and providing storage in snowpack. Idaho has a very different spatial pattern than both Oregon and Washington, as seen in Figure 18.

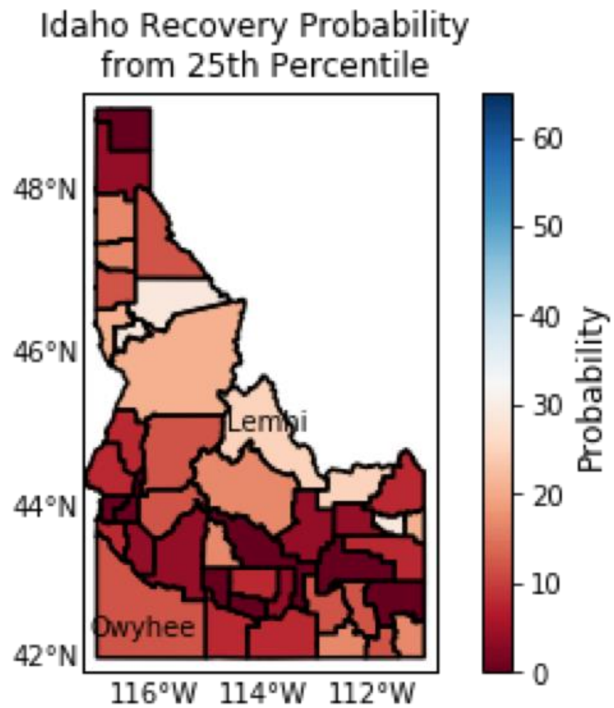

Figure 18: The probability of each county recovering from being at or below the 25th percentile in February and recovering to the median percentile in July for Idaho.

While Oregon and Washington have the highest chance of recovery along the coast, in Idaho the greatest chance of recovery from below the 25th percentile in February is where the Rocky Mountains run through the state. The largest chance of recovery in Idaho is about half that of the largest chance of recovery for both Oregon and Washington. Lemhi County has one of the highest chances of recovery and is seen in a beige, indicating a probability of about 25%. Owyhee County, in the Southwestern corner, has approximately a 12% chance of recovery and is a medium shade of red in Figure 18. When starting below the 25th percentile in February, neither of these counties has a very high chance of recovery by July. Figure 19 and 20 provide a better understanding of how the cumulative probability of recovery changes with starting percentile.

Both Owyhee and Lemhi County have never seen recovery in the driest ~15% of years. Around the 15th percentile, the likelihood of recovery for Owyhee County begins to increase until reaching about a 50% likelihood of being above the 50th percentile. Lemhi County, at approximately the 15th percentile, has a more drastic increase to about a 25% chance of recovery, and then very gradually increases until reaching a 50% chance of recovery.

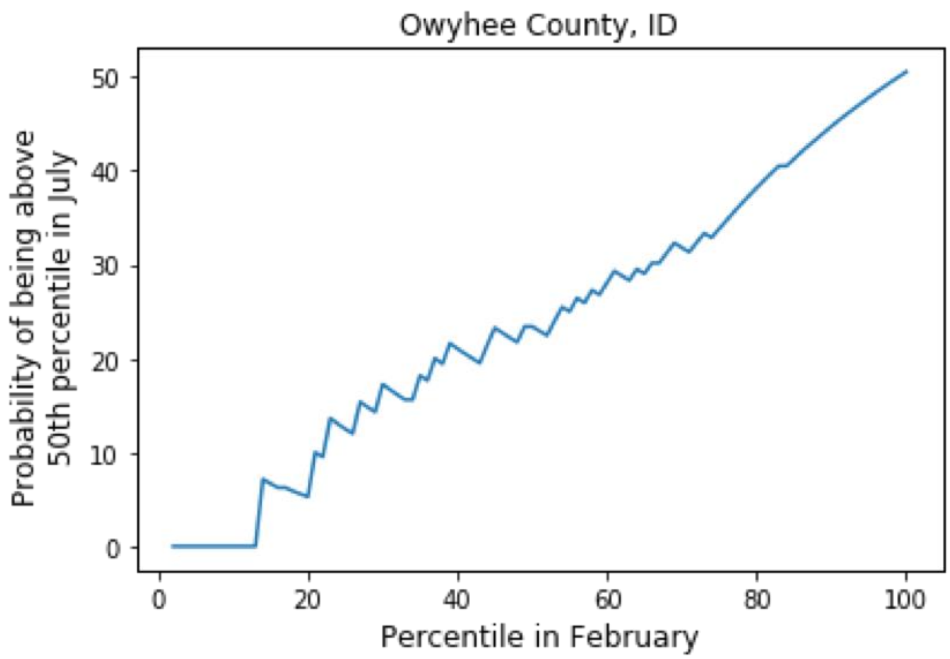

Figure 19: The probability of being above the median in July for Owyhee County, Idaho for all percentiles as of February.

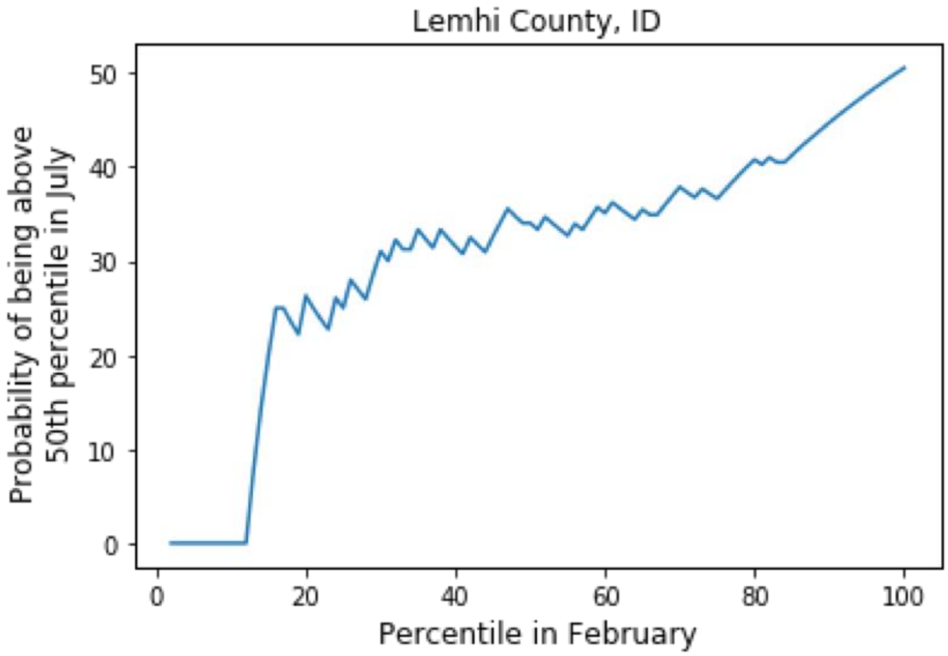

Figure 20: The probability of being above the median in July for Lemhi County, Idaho for all percentiles as of February.

3.2 Atmospheric Flow Patterns

In this section, one climate division was examined from each state. Climate divisions can be seen in Figure 21 and are a way of grouping weather stations in climatically similar areas.

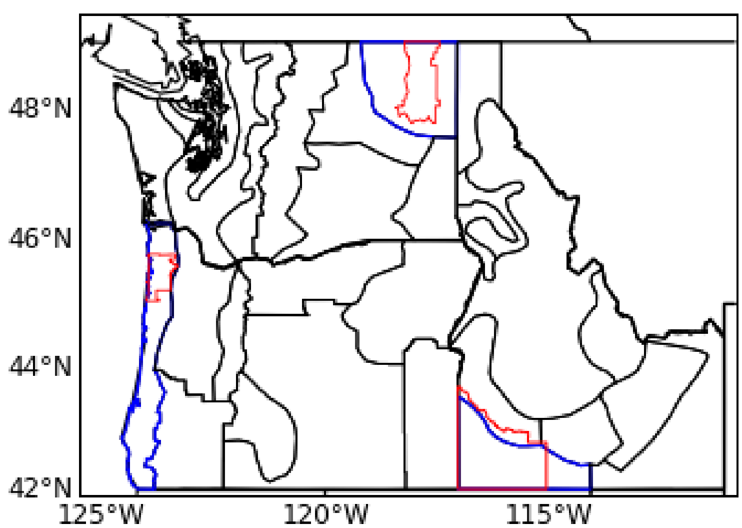

Figure 21: All Climate Divisions in the Pacific Northwest outlined in black. Outlined in blue are the three climate divisions examined. Outlined in red are the counties that are within the climate division.

Only one climate division was selected in each state because the large-scale atmospheric flow patterns were similar across climate divisions within each state. To be included, each of these climate divisions had to have at least eight years that were below the 40th percentile in February that also were above the 50th percentile in July. Out of the climate divisions that have at least 8 years of recovery the one from each state was selected if it contains one of the counties discussed in *Section 3.1*. In Oregon, the Coastal Area climate division was chosen, and it encompasses all of the coastal counties, including Tillamook County. For Washington, the Northeastern climate division (which includes Stevens County) was chosen. For Idaho the Southwestern Highlands climate division (which includes Owyhee County) was chosen. The Coastal Area has 14 years of recovery, Northeastern has 11, and the Southwestern Highlands has nine.

3.2.1 Regression Analysis

The slopes for the Coastal Area (Fig. 22) in Oregon, the Northeastern climate division (Fig. 23) in Washington, and the Southwestern Highlands (Fig. 24) in Idaho, show similar

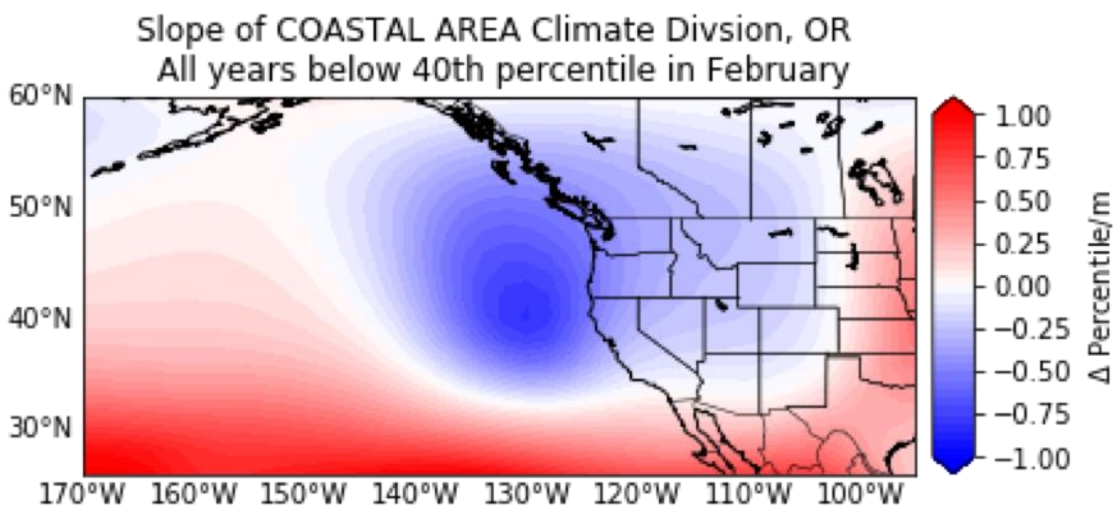

Figure 22: A regression map for the Coastal Area climate division. The slope of the linear regression between the change in percentile (July – February) and the MAMJ height anomalies for all years below the 40th TM percentile.

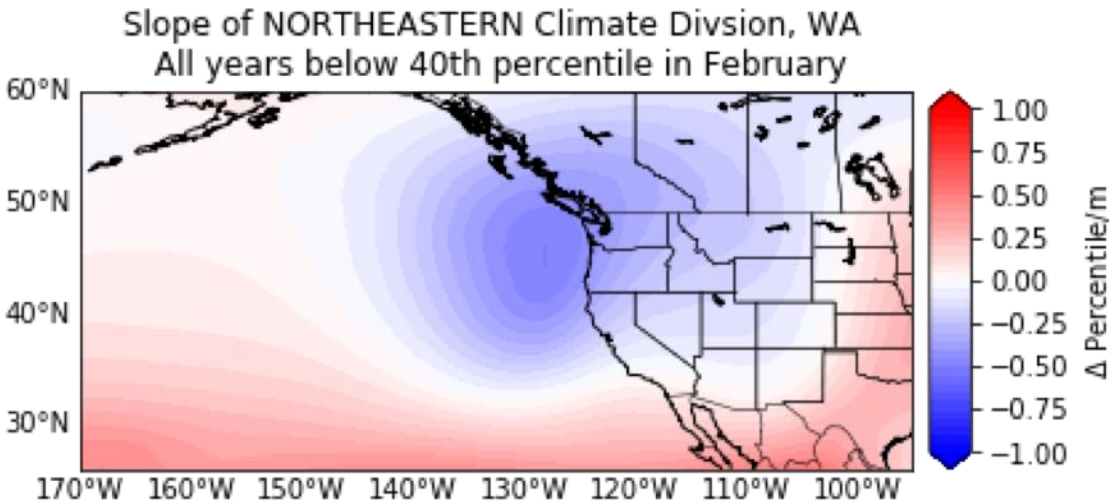

Figure 23: A regression map for the Northeastern climate division. The slope of the linear regression between the change in percentile (July – February) and the MAMJ height anomalies for all years below the 40th TM percentile.

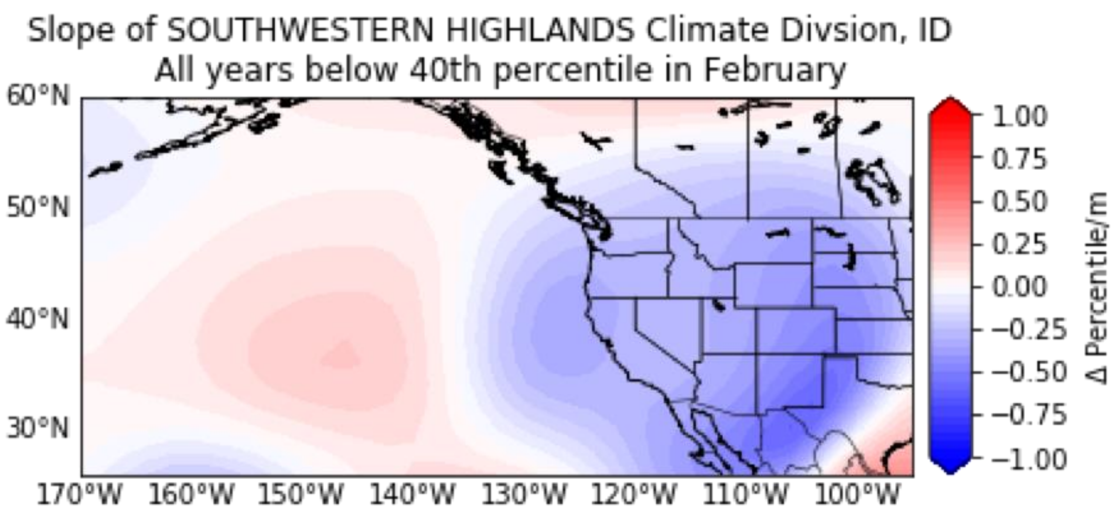

Figure 24: A regression map for the Southwestern Highlands climate division. The slope of the linear regression between the change in percentile (July – February) and the MAMJ height anomalies for all years below the 40th TM percentile.

patterns. Having a negative slope indicates that an increase (decrease) in the change in percentile is related to low (high) geopotential height anomalies (Fig. 25). The Coastal Area climate division in Oregon shows the strongest negative relationship out of the three figures (Fig. 22), with the most negative point being off the Oregon Coast. The Northeastern climate division also has a central point located off the coast near Oregon and Washington; while there is a negative relationship it is not as strong as the one for the coastal climate division. The negative slope for the Southwestern Highlands extends over most of the continental US. In Figure 24, there are two centralized points of the negative slope, one off the Coast of Oregon and California, and another over New Mexico and Texas. The negative slopes indicate that during years when the conditions remain persistently dry throughout the spring and summer, there would be high geopotential

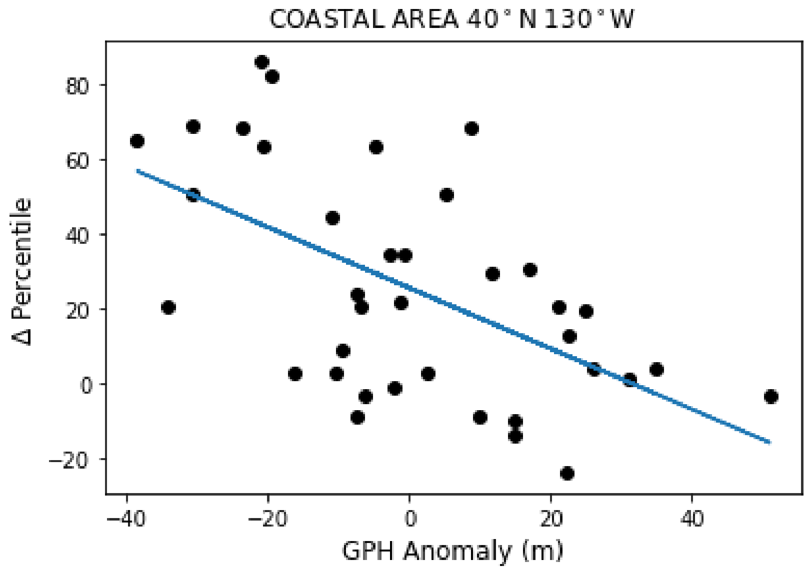

Figure 25: The slope for the relationship between the GPH anomalies at point 40°N 130°W and the change in percentile for the Coastal Area. Each dot represents one year that is below the 40th TM percentile.

height anomalies off the coast whereas during years when dry conditions improve there would be low geopotential height anomalies off the coast. The low anomalies indicate that there are low-pressure systems bringing precipitation and cool temperatures into the PNW, and high anomalies indicate high-pressure systems that would be blocking the storms track and bringing warmer temperatures from reaching the coast. To examine the anomalies further, we will look at the geopotential height composites of the 500mb pressure level and the surface temperature composites.

3.2.2 Composites

We investigate the conditions for years in which a county's TM starts below the 40th percentile in February and are above the median percentile in July (recovery years), and years when the TM is below the 40th percentile in February and remains there (dry years). In the Coastal Area climate division, recovery years are characterized by strong negative average MAMJ geopotential height anomalies in the Northeast Pacific and over the PNW (Fig. 26). The recovery years in the Coastal Area climate division show high temperatures directly along the Oregon Coast, and neutral temperatures directly inland from the coast (Fig. 27). During the dry years in the Coastal Area climate division, there is anomalously high average MAMJ geopotential height over the PNW and into the Eastern Pacific Ocean (Fig. 28). Figure 29 shows that the dry years in the Coastal Area climate division are uniformly high temperatures of about 0.5°C. In the Coastal Area climate division, recovery years are characterized by strong negative average MAMJ geopotential height anomalies in the northeast Pacific and over the PNW (Fig. 26).

These results show that in the Coastal Area, recovery happens when there are spring storms. Figure 26 shows the geostrophic flow around the low-pressure, bringing warm, wet air in from the Southwest to the Coastal Area climate division. The average temperature during recovery years is a patchwork of high, low, and average temperatures in the in the Coastal Area climate division (Fig. 27). Warm temperatures may increase evapotranspiration and snowmelt, but these processes appear to be less important than the fact that spring storms increase the soil moisture enough that drought conditions are not present as of July. The Coastal Area TM relies on precipitation for recovery because there is minimal snowpack in this area. Dry years illustrate a strong ridge centered just west of the PNW in the Eastern Pacific (Fig. 28). This ridge indicates

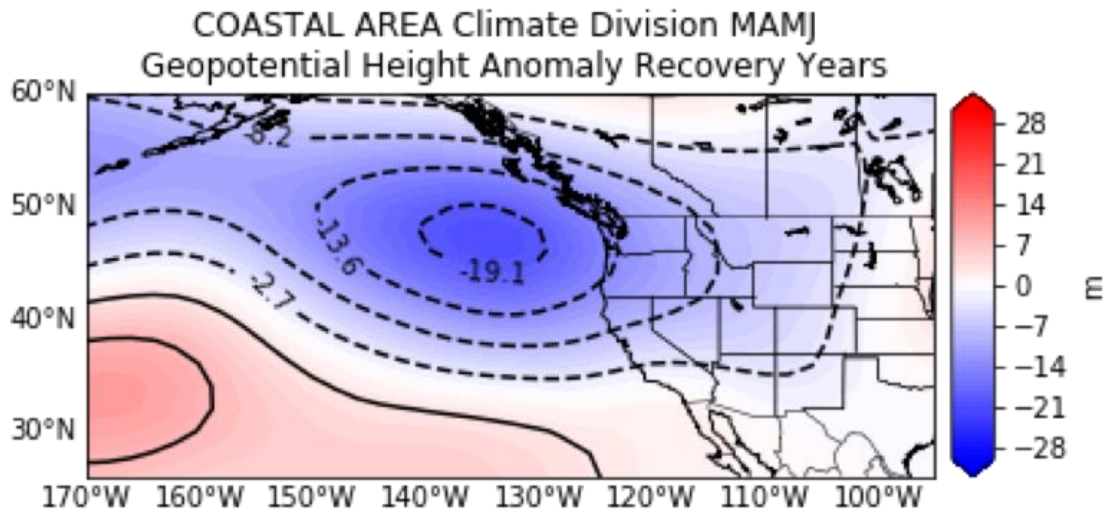

Figure 26: The average MAMJ geopotential height anomaly composite for all years that are below the 40th percentile in February and above the 50th percentile in July for the Coastal Area Climate Division.

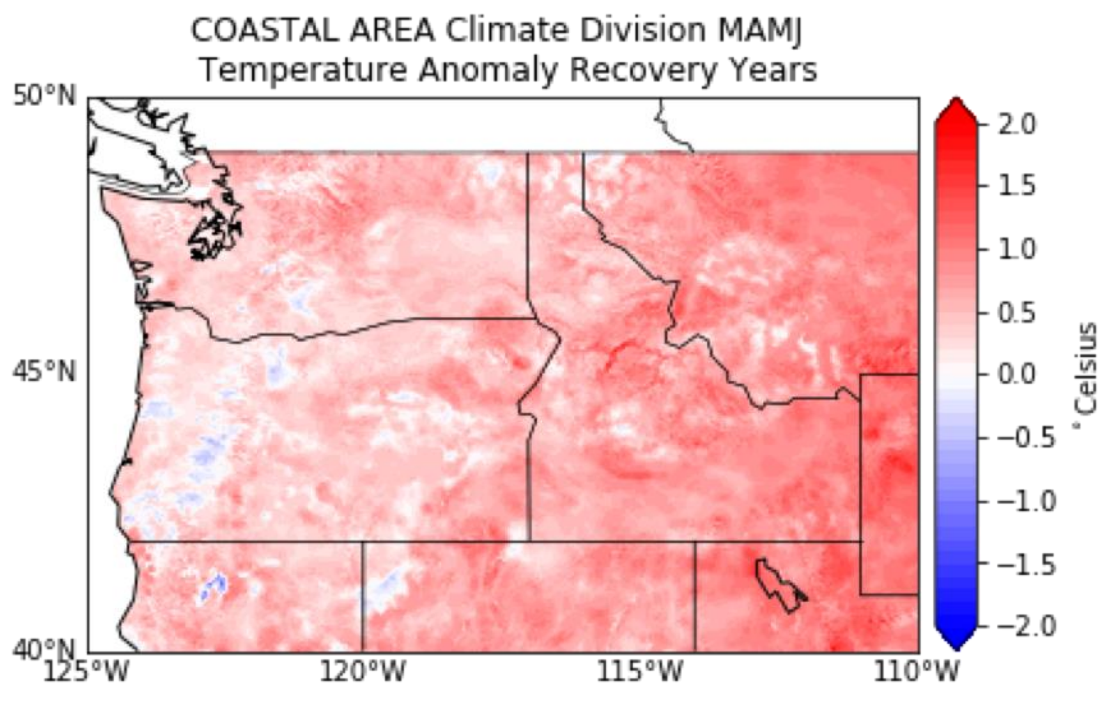

Figure 27: The average MAMJ temperature anomaly composite for all years that are below the 40th percentile in February and above the 50th percentile in July for the Coastal Area Climate Division.

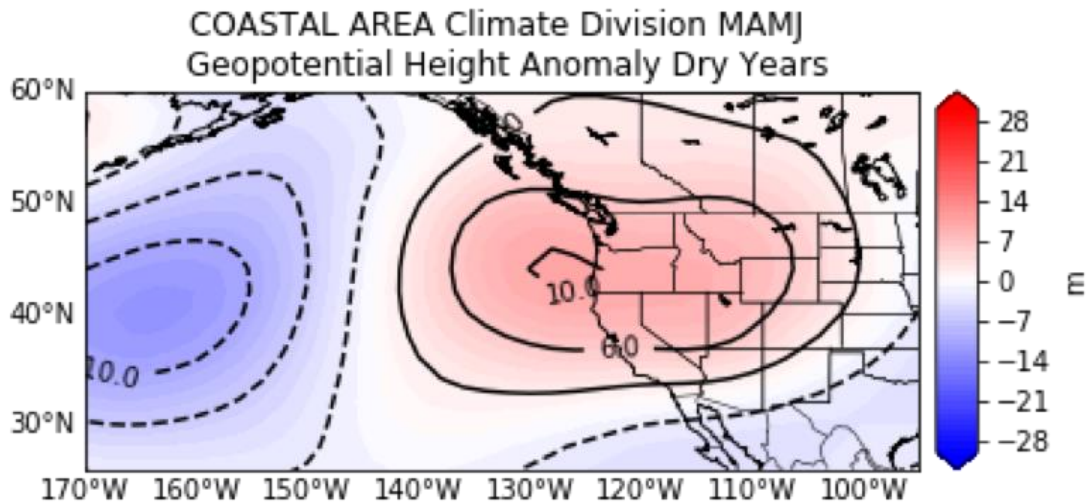

Figure 28: The average MAMJ geopotential height anomaly composite for all years that are below the 40th percentile in February and remains below into July for the Coastal Area Climate Division.

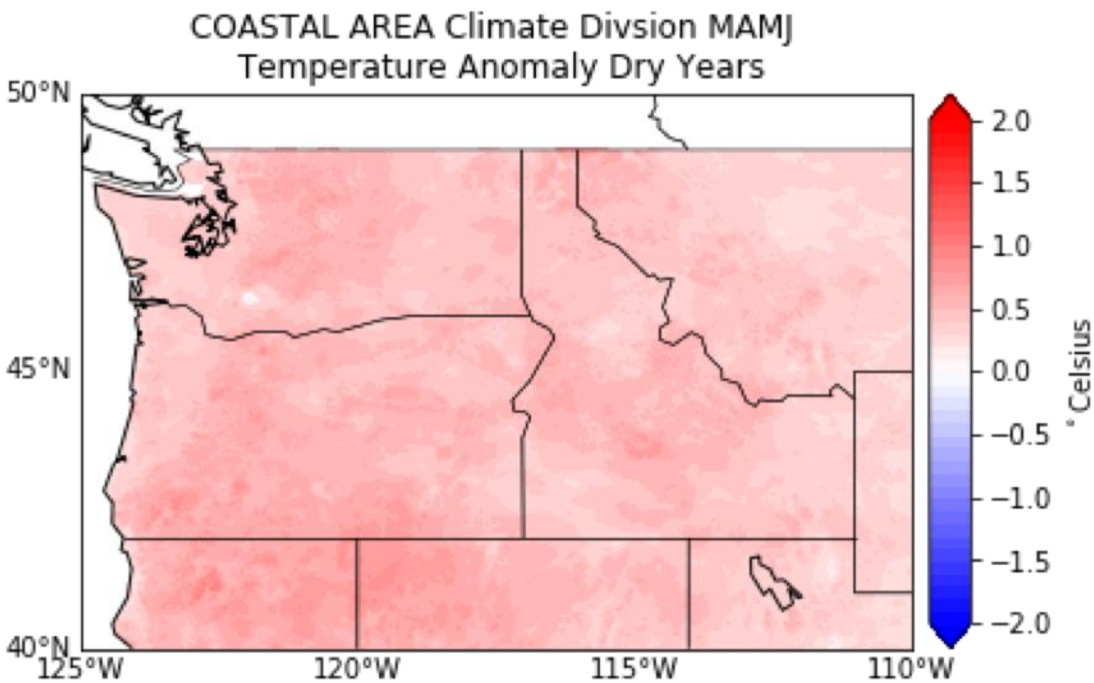

Figure 29: The average MAMJ temperature anomaly composite for all years that are below the 40th percentile in February and remains below into July for the Coastal Area Climate Division.

that during these years there are areas of high pressure that are blocking storms from reaching the PNW. The geostrophic flow surrounding the high-pressure is bringing in warm, dry air from the Southeast. The high temperatures (Fig. 29) increasing evapotranspiration along with the lack of precipitation could be depleting the soil moisture and lowering the TM for the Coastal Area, leading to dry conditions.

The Northeastern climate division in Washington has similar geopotential height patterns to that of the Coastal Area for recovery years. There are strong negative MAMJ GPH anomalies over the PNW and in the Eastern Pacific (Fig. 30). The center of the trough is located southwest of the Northeastern climate division. The average temperature during recovery years is a patchwork of high, low, and average temperatures in the Northeastern climate division (Fig. 31). The dry years in the Northeastern climate division (Fig. 32) have anomalously high MAMJ GPH anomalies over the eastern Pacific and PNW, as well as most of the continental US. The center of the ridge is located southwest of the Northeast climate division. These dry years are associated with slightly positive MAMJ temperature anomalies of less than 0.5°C (Fig. 33).

The GPH for recovery years in the Northeastern climate division show a trough in the Eastern Pacific (Fig. 30). The trough is centered southwest of the climate division and the geostrophic flow brings warm, wet air from the Southwest. These spring storms increase the soil moisture and enable this climate division to recovery from dry conditions. Figure 31 also indicates that during these recovery years, the temperature anomaly is typically between -0.5°C and 0.5°C. The high temperature anomalies can be explained by the geostrophic flow bringing in warm air form the Southwest. The higher temperatures increase evapotranspiration, which reduce soil moisture, but with enough precipitation from spring storms the climate division is still able to recover. The lower temperatures may be preserving snowpack in the climate division. The snowpack increases TM and enables this climate division to recover. During dry years there

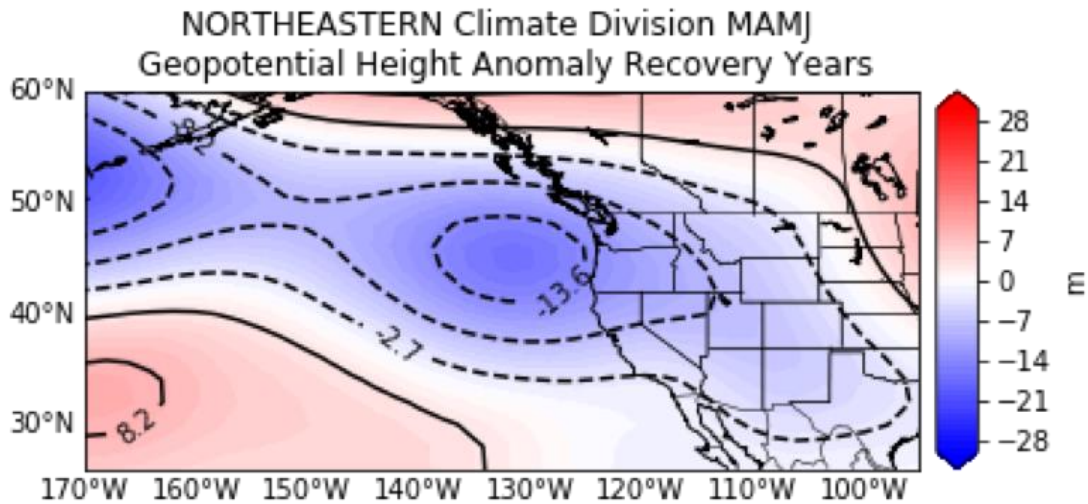

Figure 30: The average MAMJ geopotential height anomaly composite for all years that are below the 40th percentile in February and above the 50th percentile in July for the Northeastern Climate Division.

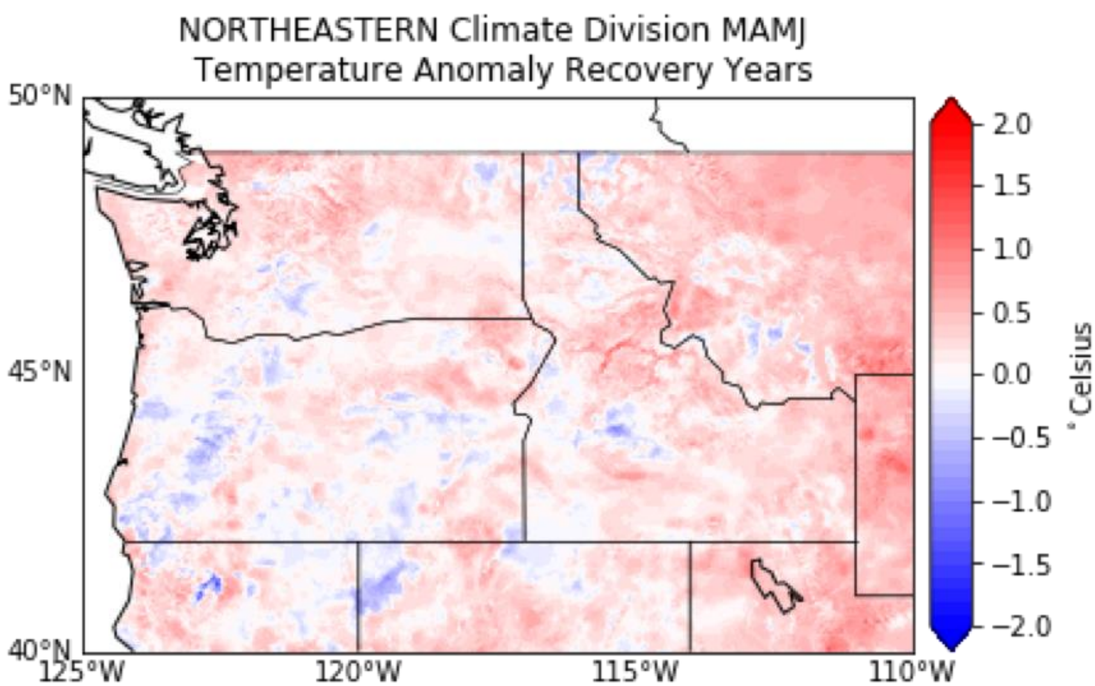

Figure 31: The average MAMJ temperature anomaly composite for all years that are below the 40th percentile in February and above the 50th percentile in July for the Northeastern Climate Division.

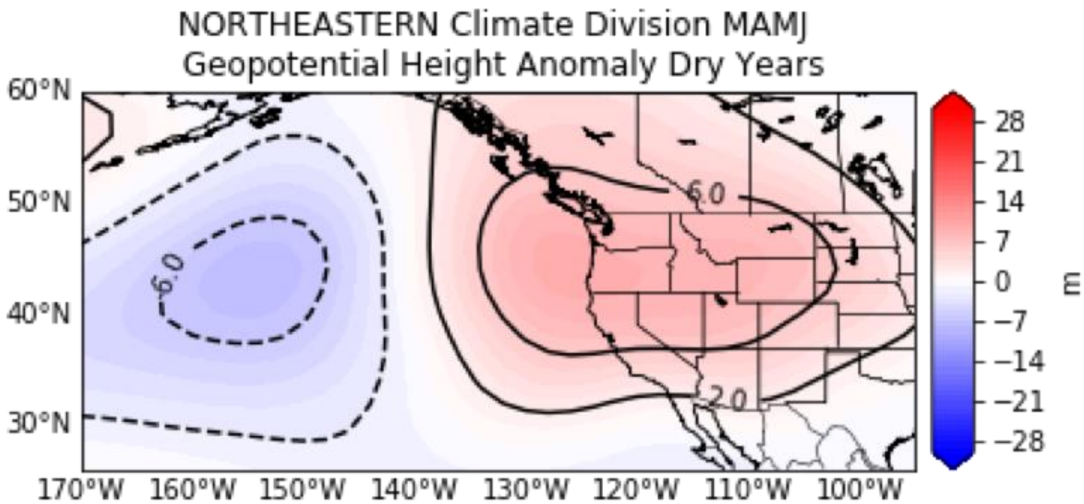

Figure 32: The average MAMJ geopotential height anomaly composite for all years that are below the 40th percentile in February and remains below into July for the Northeastern Climate Division.

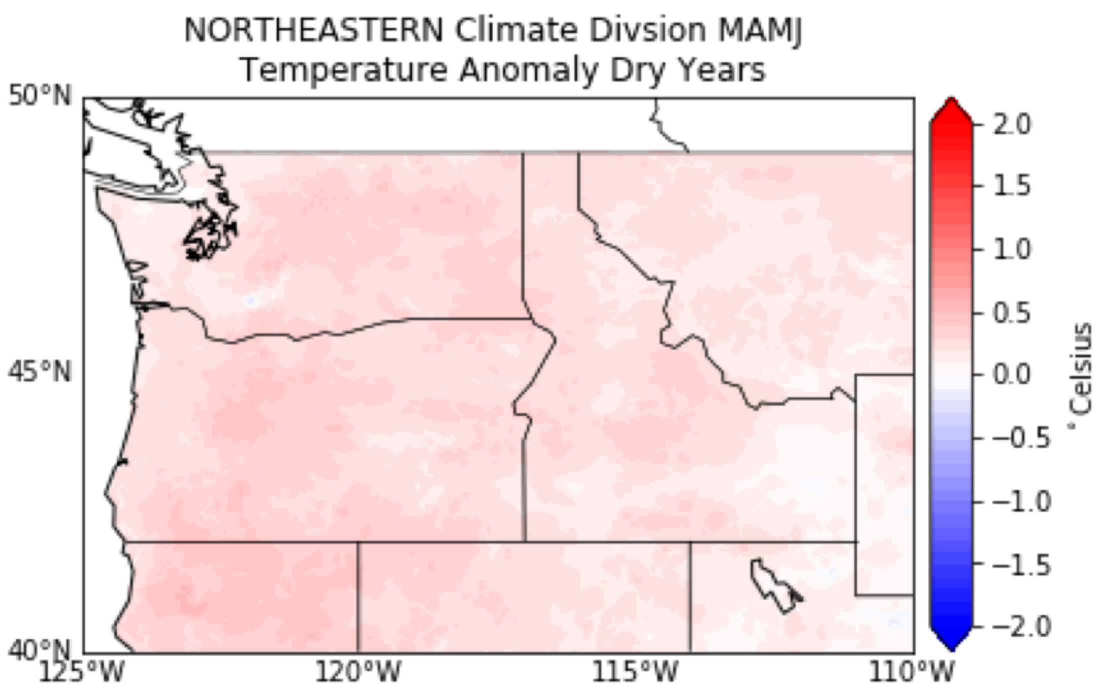

Figure 33: The average MAMJ temperature anomaly composite for all years that are below the 40th percentile in February and remains below into July for the Northeastern Climate Division.

is a ridge centered southwest of the Northeastern climate division (Fig. 33). The geostrophic flow around this ridge brings warm, dry air from the Southeast into this climate division. This ridge also redirects storms north of the PNW. The high temperatures (Fig. 33) are caused by the air from the Southeast. The high temperatures in addition to the lack of spring storms is depleting the snowpack and resulting in dry conditions.

In the Southwestern Highlands of Idaho, recovery years show a significant trough (Fig. 34) centered just south of Idaho and covering the PNW, most of the Continental US, and stretching out into the Pacific Ocean. This trough indicates that there is a low-pressure system over the climate division and the geostrophic flow brings cool, dry air down from the northeast. These years also show negative MAMJ temperature anomalies of -1°C (Fig. 35) over the climate division, which are associated with the low-pressure system. These lower temperatures associated with low-pressure systems could be an indication that this climate division's recovery may rely on both precipitation and snow storage in order for the TM to increase in the spring. The cold temperatures in this Southwestern Highlands climate division can preserve the snowpack and keep TM levels high, resulting in recovery. The dry years for the Southwestern Highlands climate division have high anomalous MAMJ geopotential heights centered over Southern Idaho and also covering most of the Continental US shown, and the Eastern Pacific (Fig. 36). The dry years (Fig. 36) are associated with a ridge that is pushing the storms north of the US, making it so storms are not reaching the PNW. These dry years shown in Figure 37 also display slightly positive MAMJ temperature anomalies over the Southwestern Highlands climate division, and as the distance gets further away from this area the temperature anomalies decrease.

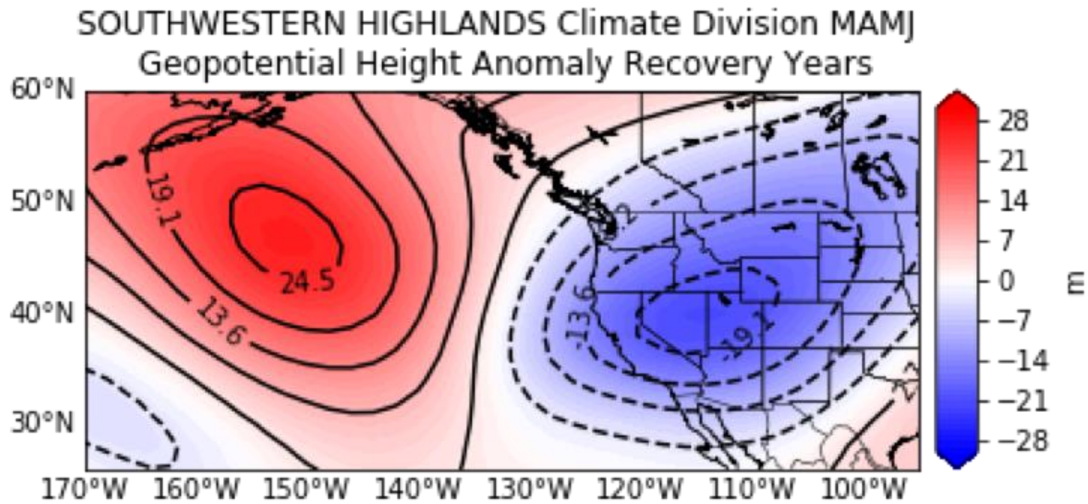

Figure 34: The average MAMJ geopotential height anomaly composite for all years that are below the 40th percentile in February and above the 50th percentile in July for the Southwestern Highlands Climate Division.

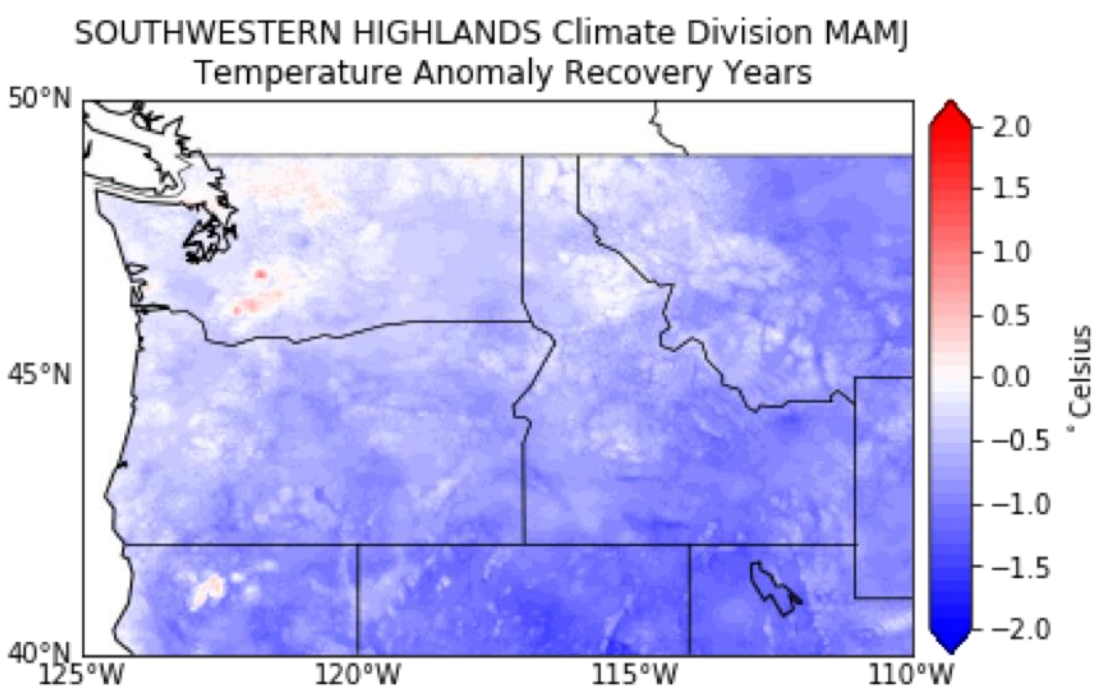

Figure 35: The average MAMJ temperature anomaly composite for all years that are below the 40th percentile in February and above the 50th percentile in July for the Southwestern Highlands Climate Division

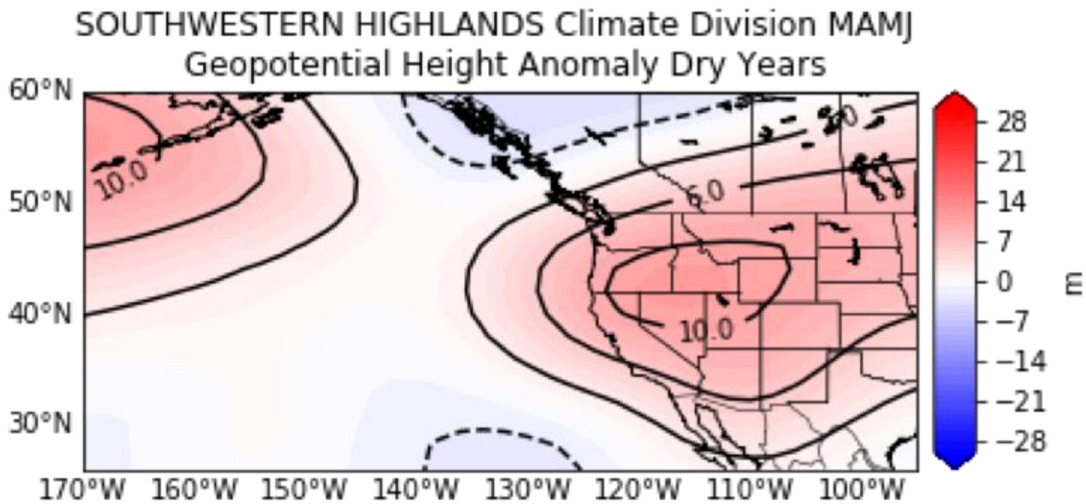

Figure 36: The average MAMJ geopotential height anomaly composite for all years that are below the 40th percentile in February and remains below into July for the Southwestern Highlands Climate Division.

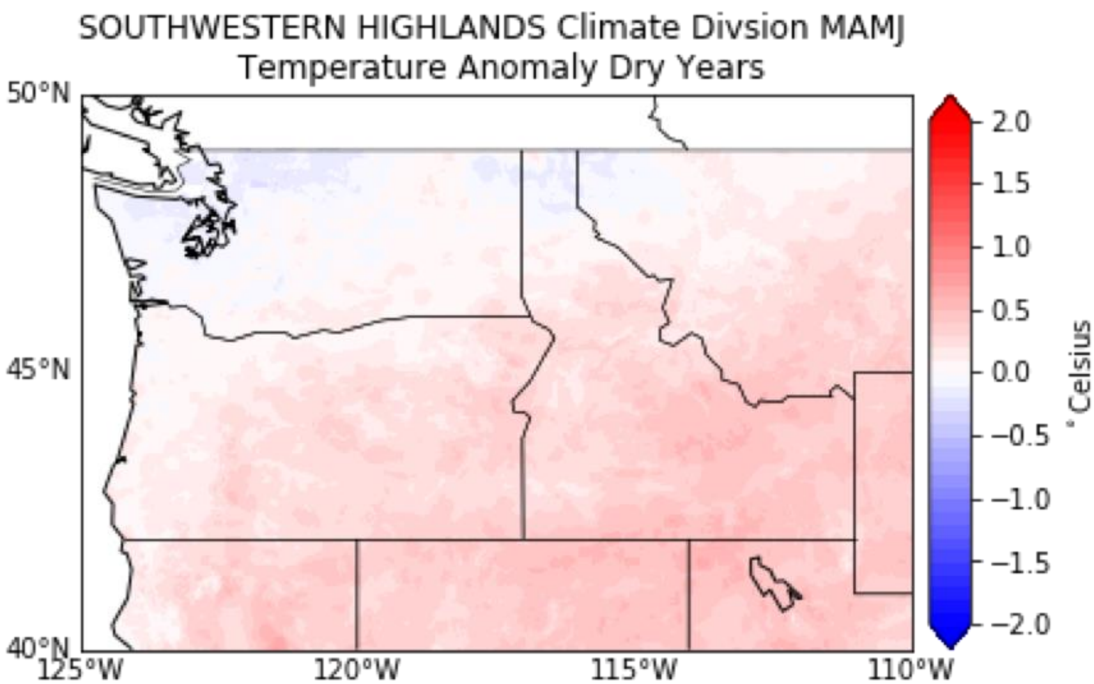

Figure 37: The average MAMJ temperature anomaly composite for all years that are below the 40th percentile in February and remains below into July for the Southwestern Highlands Climate Division.

The positive temperature anomalies could be depleting the soil moisture and snow storage; thus, lowering the TM and amplifying the dry conditions during these years.

4. Discussions and Conclusions

4.1 Drought Recovery

A lack of snowpack can be a precursor for hydrological, agricultural, and socioeconomic drought. Indices such as SPI and PDSI that only consider precipitation and have no measure for snowpack would not capture the depth of an emerging drought in the PNW. We have included SWE in this study to give a reliable estimate of snowpack in order to illustrate the effects on drought. For many basins in the PNW, available water in spring and early summer comes mainly from snowmelt and if there is a winter season with low snowpack the region's summer water supply suffers. Studies have shown that there has been a decline in snowpack within the past century (Hamlet et al., 2005; Mote et al., 2005, 2018) and other studies have shown that winter precipitation is falling as rain instead of snow (Hamlet et al., 2005; Knowles et al., 2005). In snowmelt dominated areas like the Cascade or Rocky Mountains, peak streamflow occurs during peak runoff in the spring (Elsner et al., 2010). These regions also tend to see maximums in soil moisture during peak streamflow periods, and minimums in summer due to low precipitation and increased temperature (Elsner et al., 2010). However, if an area is rain dominated, peak streamflow occurs during the time of maximum precipitation, typically late fall or winter (Elsner et al., 2010). When snow dominated region have years with low snowpack, they tend to see peak streamflow earlier in the year (Canyan et al., 2001; Dettinger & Cayan, 1994; Regonda et al., 2005; Stewart et al., 2005), which leads to low soil moisture levels in the spring and summer, and maximums occurring in winter. The streams and rivers that flow from the winter snowpack deliver soil moisture and water to the rest of the region, and with declining snowpack and increasing rain during winter months the region experiences peaks in soil moisture and SWE earlier in the year. Using TM for the PNW, we aimed to capture the key sources of moisture for the whole region.

Counties west of the Cascades have much higher average TM values than the counties east of the Cascades. Coastal counties have higher variability in spring precipitation relative to February TM, leading to higher chances of recovery. Counties east of the Cascades have lower average TM and depend on mostly snowpack for TM, hence lower variability in spring precipitation relative to February TM and lower chance of recovery. Oregon and Washington coastal counties have the highest chance of recovery out of all three states. Even the driest years as of February in coastal counties have a good chance of recovery. The variability in spring precipitation is greater than the variability in TM in February and can easily erase February TM anomalies. Snow storage on the coast plays a very small role in the TM leaving soil moisture as the main component. The high variability of precipitation on the coast leads to these counties having high probabilities of recovery at lower percentiles in February. The fact that the coastal counties have a high chance of recovery for the driest years could indicate that TM is not the strongest indicator for these regions. A variable such as precipitation may be better suited to predict recovery for the coastal counties. There are many different paths the TM can take after February, it is variable. The precipitation has a higher variability than the TM and knowing what is to come with precipitation could give a better understanding of what is enabling the coastal counties to recover.

The counties east of the Cascades in Oregon, Washington, and Southern Idaho are dry and rely mostly on spring snowmelt for moisture. The counties in Oregon and Washington between the Coast and the Cascades have high TM values and rely on both spring precipitation and snowmelt. The counties east of the Cascades all need to be approximately in the 80^{th}

percentile of TM in February to have about a 40% chance of being above the median in July. The ratio of the probability to the percentile illustrates that all of these counties east of the Cascades rely on high snowpack in order to be above the median percentile by July; in other words, if February TM is low, there is only a small chance of recovery. The Idaho Rockies have similar climatology and hydrology but there is a wide range of probabilities of recovery that each county in this area can have. For all but the coastal counties, the TM does not vary much after February. The conditions as of February give a good idea of what is to come in the next few months. This indicator is able to capture spring snowmelt with the use of TM and is well suited for areas east of the Cascades.

Water managers in the PNW expressed a need for a predictive drought tool for the region. Every county in the PNW has a different range of TM values, and utilizing percentiles allowed us to compare each county using the same scale. An indicator of drought was created by comparing the TM percentiles to historical years to see how many did or did not recover from low conditions. In order to get a sample of years, the 25^{th} percentile was chosen for the drought recovery forecast. The 25^{th} percentile is roughly equivalent to D0 drought in the USDM. The 25^{th} percentile encompasses all years that range from slightly dry to the severest of droughts. Using the 25^{th} percentile enabled us to place all counties at the same starting point and examine the spatial differences across the state. After examining the spatial differences based on the 25^{th} percentile, all *n* percentiles were examined for the representative counties. Many coastal counties have high chances of recovery for lower percentiles. This is true for both Tillamook and Pacific County, but other counties that stretch further inland have lower chances of recovery. Eastern Counties such as Harney and Lemhi, have either zero or a small chance of recovery for most TM percentiles below the 15^{th} in February. These counties are all representative of different geographic regions for Oregon, Washington, and Idaho, but all the inland counties showed similar patterns. This indicator is an improvement from current drought prediction methods and will inform water managers with the probability of being above the median for the coming season. This can help them with decision making, such as water allocation and drought declaration.

A limitation of this study is that this approach does not take into account the changing climate. Warmer temperatures influence the water cycle including evapotranspiration, timing of snowmelt, and even how much water vapor is in the atmosphere. The changing climate is also influencing extremes in variables such as evapotranspiration and precipitation. All of these factors have an influence on TM in the PNW and the probability of recovery.

The work that was done here lays the groundwork for a drought recovery tool that could be updated monthly. The results from *section 3.1* will be used to create an easy to use tool that shows the probability of being above the median percentile depending on the current conditions of the county. This will require updated data from the "UCLA Drought Monitoring System for the West US", and that the tool is updated at the end of each month. Knowing the probability of recovery from current conditions can inform water managers and support them in decision making. They will be able to make informed decisions based on this information.

4.2 Coproduction

By working with stakeholders, we were able to develop an indicator that quantitatively predicts the likelihood of drought recovery for each county. At their request, the indicator is on the county scale, aligning with the drought declaration policies of both Oregon and Idaho. This indicator is an improvement on current drought indicators available to the PNW. This drought indicator will give the stakeholders an idea of what to expect over the next coming months based on the February percentile of TM for each county. Through a series of webinars we were able to incorporate their input into this indicator. The stakeholders' input in this indicator enabled the creation of a useful and usable product and they know the work that went into it. They understand how the indicator works and how it was created. With the use of the USDM and the TM drought indicator created here, our stakeholders will have a more complete picture. The USDM provides current drought conditions and our TM indicator gives a quantitative prediction of what to expect over the spring season for each county.

Meadow et al. (2015) define several approaches to coproduction depending on the level of engagement and the desired outcomes. These different approaches include action research, transdisciplinary, rapid assessment process, participatory integrated assessment, and boundary organization. Each of these depends on a mode of engagement which can be contractual, consultative, collaborative, collegial, or a combination of these four (Biggs, 1989). Each of these different modes has a specific objective, research question, relationship between stakeholders and researchers, stakeholder involvement, and stakeholder representation. The work done for this thesis best fits into the mode of consultative stakeholder engagement. The goal of consultative stakeholder engagement is to use research to solve real world problems during which the researchers work with the stakeholders at specific points of the work to discuss (Meadow et al., 2015). The main difference between what was done here and the consultative mode definition is that our stakeholders represented themselves during our meetings; they were not represented through a third party. The approaches of coproduction that use the consultative mode of engagement are rapid assessment process, participatory integrated assessment, and boundary organization (Meadow et al., 2015). This work was embedded in a boundary organization, the Climate Impacts Research Consortium - the NOAA RISA for the Northwest. It benefited from time previously spent in the stakeholder community, and we were able to communicate effectively via webinar because there was a preexisting relationship with the stakeholders. Being able to develop a trusting relationship with stakeholders is a key piece of coproduction. Through trust and understanding the science produced will be usable and informative for everyone involved. The type of question in this work aligns best with the transdisciplinary approach, but the role of the research team aligns with the participatory integrated assessment. Working with stakeholders in this capacity has guided this work to create a drought indicator suitable for their needs. Producing science through coproduction has the ability to create a larger impact on the communities involved.

Ferguson et al. (2014) discuss 10 heuristics to guide collaborations between scientists and stakeholders. Out of these 10 heuristics four of these proved to be helpful in this work. The first one, “preconditioning activities often set the stage for collaboration” (Ferguson et al., 2014, p. 7) was the foundation to this work. The relationship between members of CIRC and the stakeholders helped this process get started. The initial discussion and questions about a drought indicator began in 2016 at a meeting, however almost a year later this work was started. Often, a researcher may give a presentation and then is contacted weeks to years later with questions and a collaboration is constructed (Ferguson et al., 2014). The second one, “building capacity to work across the science-practice boundary is critical” (Ferguson et al., 2014, p. 9) means that the researchers had to be able to articulate the questions and the findings and the stakeholders had to be able to understand and apply the findings. When creating this drought indicator, one of the most important outcomes was that the stakeholders would use it. In order for this to happen there needed to be a clear and open dialogue about what the stakeholders expected from this work and what was being done at each step of the work. The third one, “catalyzing events provide prime opportunities for collaboration" (Ferguson et al., 2014, p. 10) discusses how specific events lead to collaboration. For this work the catalyzing event was a drought in 2015 that occurred in the PNW. This event led our three stakeholders to ask for a drought indicator. The fourth and final one, "revisiting processes and outcomes nurtures long-term collaborations" (Ferguson et al., 2014, p. 16) discusses the importance of maintaining relationships after the initial project. This is important in the short term to make sure that what was produced is fitting the needs of the stakeholders. In the long term this is important because future opportunities for collaborations may arise. In this case, communication will be had to ensure that the drought indicator is what they were looking for and is fitting their needs. Communication will be continued with our stakeholders after this project because there are plans to continue this work beyond the scope of this thesis. This will include using other data sources and using machine learning techniques to give the likelihood of drought.

Without working with stakeholders, this indicator would not have been the same. There are many different approaches to coproduction. We used an iterative process with our stakeholders to ensure the use of this indicator. During each webinar the stakeholders were updated on the progress of the indicator. They then gave feedback on what they would like to see incorporated in the indicator. We took each of their ideas into account but there were some instances where the stakeholders' suggestions did not align being that they represent three different states that have different policies. This can be a challenge with coproduction, but compromises can be reached. There are many benefits with coproduction. Science is being done with a purpose to improve society, those involved understand the work, and there is a trust built between the scientists and stakeholders making it more likely that the end product is usable.

4.3 Atmospheric Influences

In all of the climate divisions low-pressure systems bringing spring storms and precipitation cause years with low TM at the end of winter to recover in the spring. The location of the center of the low-pressure system determines the temperatures that occur during recovery years. Some climate divisions, such as the Coastal Area and Northeastern, displayed higher temperatures during recovery years that can increase evapotranspiration which lowers the TM. When recovery years have above average precipitation, even with high temperatures the climate divisions can recover. Other climate divisions, such as the Southwestern Highlands, have colder temperatures during recovery years. Low-pressure systems along with colder temperatures can be an indication that this climate division recovers when there are colder conditions preserving snowpack. The snowpack holds moisture until it melts, and lower temperatures will allow the snowpack to remain and increase the TM in the spring. For all the climate divisions that met the recovery year criteria, dry years are influenced by areas of high-pressure blocking spring storms from reaching the PNW and leading to low TM values. The temperatures may have an influence on these conditions as well. Higher temperatures associated with ridging indicate that the soil moisture and snowpack are reduced, thus further depleting the TM.

Low-pressure systems occurring during recovery years in the Coastal Area climate division indicate that the counties along the coast, such as Lincoln, recover because of spring precipitation. The counties within Northeastern climate division, such as Ferry, also recover when there is spring precipitation. The recovery in these counties may be because the Rocky Mountains receive more than average spring precipitation increasing the TM percentile between February and July. The counties within the Southwestern Highlands climate division, such as Owyhee, recover when there is geostrophic flow around the low-pressure system bringing cold dry air to the area from the Northeast. This cold dry air preserves the snowpack thus keeping the TM at a higher value and allows counties like Owyhee to recover.

Dry years in all of the climate divisions are caused by high-pressure areas. In some of the climate divisions, the center of the high-pressure area is located directly above them, such as the Coastal Area and Southwestern Highlands. For all climate divisions, the entire high-pressure area is located over the PNW and extends into the Eastern Pacific Ocean. Most of the climate divisions have high temperature anomalies during dry years. This indicates that high-pressure areas over the PNW lead to a lack of storms and to high temperatures. High temperatures can amplify dry conditions by increasing the evapotranspiration and melting snow that may exist in the mountains, decreasing the TM. All counties in the PNW experience dry years because of high-pressure areas blocking storms and high temperatures. The counties to the east of the Cascades are influenced more heavily by the temperatures melting snow that may exist in the mountains, since they rely on snowpack for TM. All of the counties TM percentiles are low from increased evapotranspiration and a lack of spring precipitation.

Examining the atmospheric flow gave insight into what happens between February and July to distinguish continuing dry conditions from recovery. For this part of the study, we used the 40th percentile in February and the 50th percentile in July to examine the differences in dry years and recovery years. This percentile choice was made in order to have a large enough sample size to work with, but also to capture the driest years. Climate divisions that encompassed a county discussed in *section 3.1* were used to study the atmospheric flow that causes recovery and dry conditions in these areas. For all cases, years that recover from low TM conditions have prominent troughs in the eastern Pacific and over the PNW, which can be an indication of spring storms bringing precipitation into the region. Depending on the location of the troughs, the air brought into the region may be warm or cool. This leads to the temperatures varying during recovery years. For recovery years with higher temperatures, like in the Coastal Area and Northeastern climate divisions, the evapotranspiration increases which would lower the TM. With spring storms providing enough precipitation the higher temperatures do not impede the recovery of these climate divisions. The Southwestern Highlands climate division recovery years have lower temperatures which is an indication that snowpack is remaining and keeping the TM into the spring. For all climate divisions, there is a ridge present during dry years which blocks spring storms from the PNW. The ridges are associated with warm temperatures, which can further dry out soil and amplify dry conditions. This part of the analysis would benefit from examining the precipitation anomalies and the geostrophic wind anomalies during these years.

Bibliography

Alley, W. M. (1984). The Palmer Drought Severity Index: Limitations and Assumptions. *Journal of Climate and Applied Meteorology*. https://doi.org/10.1175/1520-0450(1984)023<1100:TPDSIL>2.0.CO;2

Anderson, M. C., Hain, C., Otkin, J., Zhan, X., Mo, K., Svoboda, M., … Pimstein, A. (2013). An Intercomparison of Drought Indicators Based on Thermal Remote Sensing and NLDAS-2 Simulations with U.S. Drought Monitor Classifications. *Journal of Hydrometeorology*, *14*(4), 1035–1056. https://doi.org/10.1175/JHM-D-12-0140.1

Anderson, M. C., Hain, C., Wardlow, B., Pimstein, A., Mecikalski, J. R., & Kustas, W. P. (2011). Evaluation of Drought Indices Based on Thermal Remote Sensing of Evapotranspiration over the Continental United States. *Journal of Climate*, *24*(8), 2025–2044. https://doi.org/10.1175/2010JCLI3812.1

Anderson, M. C., Norman, J. M., Mecikalski, J. R., Otkin, J. A., & Kustas, W. P. (2007). A climatological study of evapotranspiration and moisture stress across the continental United States based on thermal remote sensing : 2 . Surface moisture climatology, *112*, 1–13. https://doi.org/10.1029/2006JD007507

Biggs, S. D. (1989). Resource-poor farmer participation in research: A synthesis of experiences from nine national agricultural research systems (No. F/630.711 O3/3).

Brown, J. F., Wardlow, B. D., Tadesse, T., Hayes, M. J., & Reed, B. C. (2008). The Vegetation Drought Response Index (VegDRI): A New Integrated Approach for Monitoring Drought Stress in Vegetation. *GIScience & Remote Sensing*, *45*(1), 16–46. https://doi.org/10.2747/1548-1603.45.1.16

Bumbaco, K. A., & Mote, P. W. (2010). Three recent flavors of drought in the Pacific Northwest. *Journal of Applied Meteorology and Climatology*, *49*(9), 2058–2068. https://doi.org/10.1175/2010JAMC2423.1

Canyan, D. R., Kammerdiener, S. A., Dettinger, M. D., Caprio, J. M., & Peterson, D. H. (2001). Changes in the Onset of Spring in the Western United States. *Bulletin of the American Meteorological Society*, *82*, 399–416. https://doi.org/10.1175/1520-0477(2001)082<2265:CAACOC>2.3.CO;2

Cash, D. W., Borck, J. C., & Patt, A. G. (2006). Countering the loading-dock approach to comparative analysis of El Niño / Southern Oscillation (ENSO) forecasting systems. *Science, Technology, and Human Values*, *31*(4), 465–494.

Casola, J. H., Cuo, L., Livneh, B., Lettenmaier, D. P., Stoelinga, M. T., Mote, P. W., & Wallace, J. M. (2009). Assessing the impacts of global warming on snowpack in the Washington Cascades. *Journal of Climate*, *22*(10), 2758-2772.

Compo, G. P., Whitaker, J. S., Sardeshmukh, P. D., Matsui, N., Allan, R. J., Yin, X., … Worley, S. J. (2011). The Twentieth Century Reanalysis Project. *Quarterly Journal of the Royal Meteorological Society*, *137*(654), 1–28. https://doi.org/10.1002/qj.776

Cook, E. R., Seager, R., Cane, M. A., & Stahle, D. W. (2007). North American drought: Reconstructions, causes, and consequences. *Earth-Science Reviews*, *81*(1–2), 93–134. https://doi.org/10.1016/j.earscirev.2006.12.002

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., … Pasteris, P. P. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States Christopher. *International Journal of Climatology*, *28*, 2031–2064. https://doi.org/10.1002/joc

Dettinger, M., & Cayan, D. (1994). Large-Scale Atmopheric Forcing of recent Trends. *Journal of Climate*.

Dillemuth, H. (2018). $10.3 million in drought relief OK'd. Herald and News.

Dilling, L., & Lemos, M. C. (2011). Creating usable science: Opportunities and constraints for climate knowledge use and their implications for science policy. *Global Environmental Change*, *21*(2), 680–689. https://doi.org/10.1016/j.gloenvcha.2010.11.006

Dorigo, W. A., Wagner, W., Hohensinn, R., Hahn, S., Paulik, C., Xaver, A., … Jackson, T. (2011). The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements. *Hydrology and Earth System Sciences*, *15*, 1675–1698. https://doi.org/https://doi.org/10.5194/hess-15-1675-2011

Dorigo, W. A., Xaver, A., Vreugdenhil, M., Gruber, A., Hegyiová, A., Sanchis-Dufau, A. D., … Drusch, M. (2013). Global Automated Quality Control of In Situ Soil Moisture Data from the International Soil Moisture Network. *Vadose Zone Journal*, *12*(3), 0. https://doi.org/10.2136/vzj2012.0097

Dracup, J. A., Seong Lee, K., & Paulson Jr., E. G. (1980). On the Definition of Droughts. *Water Resources Research*, *16*(2), 297–302. https://doi.org/10.1007/s13752-017-0263-9

Elsner, M. M., Cuo, L., Voisin, N., Deems, J. S., Hamlet, A. F., Vano, J. A., … Lettenmaier, D. P. (2010). Implications of 21st century climate change for the hydrology of Washington State. *Climatic Change*, *102*(1–2), 225–260. https://doi.org/10.1007/s10584-010-9855-0

Ferguson, D. B., Rice, J. L., & Woodhouse, C. A. (2014). *Linking Environmental Research and Practice: Lessons from the Integration of Climate Science and Water Management in the Western United States*.

Fuchs, B., Svoboda, M., Bathke, D., & Riganti, C. (2019, January). *The Always Evolving United States Drought Monitor: Adapting Over Time.* Paper presented at the meeting of the American Meteorological Society, Phoenix, Arizona

Guttman, N. B. (1998). Comparing the palmer drought index and the standardized precipitation index. *Journal of the American Water Resources Association*, *34*(1), 113–121. https://doi.org/10.1111/j.1752-1688.1998.tb05964.x

Guttman, N. B., & Quayle, R. G. (1996). A historical perspective of U.S. climate divisions. *Bulletin of the American Meteorological Society*, *77*(2), 293–303. https://doi.org/10.1175/1520-0477(1996)077<0293:AHPOUC>2.0.CO;2

Hamlet, A. F., Mote, P. W., Clark, M. P., & Lettenmaier, D. P. (2005). Effects of temperature and precipitation variability on snowpack trends in the Western United States. *Journal of Climate*, *18*(21), 4545–4561. https://doi.org/10.1175/JCLI3538.1

Hao, Z., & AghaKouchak, A. (2013). Multivariate Standardized Drought Index: A parametric multi-index model. *Advances in Water Resources*, *57*, 12–18. https://doi.org/10.1016/j.advwatres.2013.03.009

Hao, Z., & AghaKouchak, A. (2014). A Nonparametric Multivariate Multi-Index Drought Monitoring Framework. *Journal of Hydrometeorology*, *15*(1), 89–101. https://doi.org/10.1175/JHM-D-12-0160.1

Hao, Z., AghaKouchak, A., Nakhjiri, N., & Farahmand, A. (2014). Global integrated drought monitoring and prediction system. *Scientific Data*, *1*, 140001. https://doi.org/10.1038/sdata.2014.1

Hao, Z., Yuan, X., Xia, Y., Hao, F., & Singh, V. P. (2017). An overview of drought monitoring and prediction systems at regional and global scales. *Bulletin of the American Meteorological Society*, (September), BAMS-D-15-00149.1. https://doi.org/10.1175/BAMS-D-15-00149.1

Harpold, A. A., Dettinger, M., & Rajagopal, S. (2017). Defining Snow Drought and Why It Matters. *Eos, Trans. Amer. Geophys. Union*.

Hatchett, B. J., & Mcevoy, D. J. (2018). Exploring the Origins of Snow Drought in the Northern Sierra Nevada, California, *22*(2). https://doi.org/10.1175/EI-D-17-0027.1

Hayes, M. J., Svoboda, M. D., Wilhite, D. A., & Vanyarkho, O. V. (1999). Monitoring the 1996 Drought Using the Standardized Precipitation Index. *Bulletin of the American Meteorological Society*, *80*(3), 429–438. https://doi.org/http://dx.doi.org/10.1108/17506200710779521

Hayes, M., Svoboda, M., Wall, N., & Widhalm, M. (2011). The lincoln declaration on drought indices: Universal meteorological drought index recommended. *Bulletin of the American Meteorological Society*, *92*(4), 485–488. https://doi.org/10.1175/2010BAMS3103.1

Heddinghaus, T. R., & Sabol, P. (1991). A Review of the Palmer Drought Severity Index and Where Do We Go from Here? In *7th Conference on Applied Meteorology* (pp. 242–246). https://doi.org/10.1002/bdrb.20338

Hobbins, M. T., Wood, A., McEvoy, D. J., Huntington, J. L., Morton, C., Anderson, M., & Hain, C. (2016). The

Evaporative Demand Drought Index . Part I: Linking Drought Evolution to Variations in Evaporative Demand. *Journal of Hydrometeorology*, *17*(6), 1745–1761. https://doi.org/10.1175/JHM-D-15-0121.1

Huang, J., Van Den Dool, H. M., & Georgakakos, K. P. (1996). Analysis of model-calculated soil moisture over the United States (1931-1993) and applications to long-range temperature forecasts. *Journal of Climate*. https://doi.org/10.1175/1520-0442(1996)009<1350:AOMCSM>2.0.CO;2

Idaho Department of Water Resources. (1995). *Idaho Drought Plan and Federal Water-Related Drought Response Programs*.

Jones, P. D., Hulme, M., Briffa, K. R., Jones, C. G., Mitchell, J. F. B., & Murphy, J. M. (1996). Summer moisture availability over Europe in the hadley centre general circulation model based on the palmer drought severity index. *International Journal of Climatology*, *16*(2), 155–172. https://doi.org/10.1002/(SICI)1097-0088(199602)16:2<155::AID-JOC35>3.0.CO;2-K

Kalnay, E., Kanamitsu, M., Kistler, R., Collins, W., Deaven, D., Gandin, L., … Joseph, D. (1996). The NCEP/NCAR reanalysis project. *Bull. Amer. Meteor. Soc.*, *77*, 437–471. https://doi.org/10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2

Karl, T. R. (1986). The Sensitivity of the Palmer Drought Severity Index and Palmer's Z-Index to their Calibration Coefficients Including Potential Evapotranspiration. *Journal of Climate and Applied Meteorology*. https://doi.org/10.1175/1520-0450(1986)025<0077:TSOTPD>2.0.CO;2

Karl, T. R., & Quayle, R. G. (1981). The 1980 Summer Heat Wave and Drought in Historical Perspective. *Monthly Weather Review*. https://doi.org/10.1175/1520-0493(1981)109<2055:TSHWAD>2.0.CO;2

Klugman, M. (1978). Drought in the Upper Midwest, 1931-1969. *Journal of Applied Meteorology*, *17*(10), 1425–1431.

Knowles, N., Dettinger, M. D., & Canyan, D. R. (2005). Trends in Snowfall versus Rainfall in the Western United States. *Journal of Climate*, *19*(18), 4545–4559. https://doi.org/10.1109/ICDAR.2017.5

Kogan, F. N. (1995). Droughts of the Late 1980s in the United States as Derived from NOAA Polar-Orbiting Satellite Data. *Bulletin of the American Meteorological Society*, *76*(5), 655–668. https://doi.org/10.1175/1520-0477(1995)076<0655:DOTLIT>2.0.CO;2

KOIN6. (2016). Dry Detroit Lake reveals bits of Oregon history.

Kramer, B. (2015). Flow cut out of Priest Lake sparks worry about river's health. *The Spokesman-Review*.

Lawson, M. P., Reiss, A., Phillips, R., & Livingston, K. (1971). Nebraska Droughts a Study of Their Past Chronological and Spatial Extent With Implications for the Future.

Liang, X., Lettenmaier, D. P., Wood, E. F., & Burges, S. J. (1994). A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research*, *99*(D7), 14415. https://doi.org/10.1029/94JD00483

Luo, L., & Wood, E. F. (2007). Monitoring and predicting the 2007 U.S. drought. *Geophysical Research Letters*, *34*(22), 1–6. https://doi.org/10.1029/2007GL031673

Luo, L., & Wood, E. F. (2008). Use of Bayesian Merging Techniques in a Multimodel Seasonal Hydrologic Ensemble Prediction System for the Eastern United States. *Journal of Hydrometeorology*, *9*(5), 866–884. https://doi.org/10.1175/2008JHM980.1

Luo, L., Wood, E. F., & Pan, M. (2007). Bayesian merging of multiple climate model forecasts for seasonal hydrological predictions. *Journal of Geophysical Research Atmospheres*, *112*(10), 1–13. https://doi.org/10.1029/2006JD007655

Mann, M. E., & Gleick, P. H. (2015). Climate change and California drought in the 21st century. *Proceedings of the National Academy of Sciences*, *112*(13), 3858–3859. https://doi.org/10.1073/pnas.1503667112

Mckee, T. B., Doesken, N. J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *AMS 8th Conference on Applied Climatology*, (January), 179–184. https://doi.org/citeulike-article-id:10490403

Meadow, A. M., Ferguson, D. B., Guido, Z., Horangic, A., Owen, G., & Wall, T. (2015). Moving toward the Deliberate Coproduction of Climate Science Knowledge. *Weather, Climate, and Society*, *7*(2), 179–191. https://doi.org/10.1175/WCAS-D-14-00050.1

Members of the Drought Contingency Planning Task Force. (2018). *Washington State Drought Contingency Plan*.

Miles, E. L., Snover, A. K., Hamlet, A. F., Callahan, B., & Fluharty, D. (2000). PACIFIC NORTHWEST REGIONAL ASSESSMIENT : THE IMPACTS OF CLIMATE VARIABILITY AND CLIMATE CHANGE ON THE WATER RESOURCES OF THE COLUMBIA RIVER BASIN. *Journal Of The American Water Resources Association*, *36*(2), 399–420.

Miller, H. (2015). Hatcheries releasing fish early because of drought. *Statesman Journal*.

Mishra, A. K., & Singh, V. P. (2010). A review of drought concepts. *Journal of Hydrology*, *391*(1–2), 202–216. https://doi.org/10.1016/j.jhydrol.2010.07.012

Mote, P. W., Hamlet, A. F., Clark, M. P., & Lettenmaier, D. P. (2005). Declining Mountain Snowpack in Western North America. *Bulletin of the American Meteorological Society*, *86*(1), 39–50. https://doi.org/10.2509/pnwf.2006.001.011

Mote, P. W., Li, S., Lettenmaier, D. P., Xiao, M., & Engel, R. (2018). Dramatic declines in snowpack in the western US. *Nature Partner Journals: Climate and Atmospheric Science*, *1*(1), 2. https://doi.org/10.1038/s41612-018-0012-1

Mote, P. W., Rupp, D. E., Li, S., Sharp, D. J., Otto, F., Uhe, P. F., … Allen, M. R. (2016). Perspectives on the causes of exceptionally low 2015 snowpack in the western United States. *Geophysical Research Letters*, 10980–10988. https://doi.org/10.1002/2016GL069965.Received

Nakamura, H., & Wallace, J. M. (1989). Observed Changes in Baroclinic Wave Activity during the Life Cycles of Low-Frequency Ciculation Anomalies. *Journal of Atmospheric Sciences*, *47*(9), 1100–1116.

Namias, J. (1978). Recent Drought in California and Western Europe, *16*(3).

Nijssen, B., Schnur, R., & Lettenmaier, D. P. (2001). Global Retrospective Estimation of Soil Moisture Using the Variable Infiltration Capacity Land Surface Model, 1980-93. *Journal of Climate*, *14*(8), 1790–1808.

NOAA National Centers for Environmental information. (n.d.). Climate at a Glance: Regional Time Series. Retrieved from https://www.ncdc.noaa.gov/cag/

Oregon Office of Emergency Management, & Oregon Water Resources Department. (2016). Drought Annex State of Oregon Emergency Operations Plan.

Palmer, W. C. (1965). Meteorological Drought. *U.S. Weather Bureau, Res. Pap. No. 45*. Retrieved from https://www.ncdc.noaa.gov/temp-and-precip/drought/docs/palmer.pdf

Parker, W. S. (2016). Reanalyses and Observations: What's the Difference? *Bulletin of the American Meteorological Society*, *97*(9), 1565–1572. https://doi.org/10.1175/BAMS-D-14-00226.1

Pokorny, K. (2018). Oregon conifers hit hard by years of drought; here's how to keep trees healthy. *The Oregonian*.

Prengaman, K. (2015a). Drought drying up some private wells in Yakima Basin. *Yakima Herald*.

Prengaman, K. (2015b). Rock dams causing problems for fish on low-flowing rivers. *Yakima Herald*.

PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu, created 4 Feb 2004

Pugh, B., & Fan, Y. (2018). US Drought Monitor Current Conditions and Outlooks.

Quiring, S. M., Ford, T. W., Wang, J. K., Khong, A., Harris, E., Lindgren, T., … Li, Z. (2016). The north American soil moisture database development and applications. *Bulletin of the American Meteorological Society*, *97*(8), 1441–1460. https://doi.org/10.1175/BAMS-D-13-00263.1

Redmond, K. T. (2002). The depiction of drought, (August), 1143–1147.

Regonda, S. K., Rajagopalan, B., Clark, M., & Pitlick, J. (2005). Seasonal cycle shifts in hydroclimatology over the western United States. *Journal of Climate*, *18*(2), 372–384. https://doi.org/10.1175/JCLI-3272.1

Robinson, J., & Tansey, J. (2006). Co-production, emergent properties and strong interactive social research: the Georgia Basin Futures Project. *Science and Public Policy*, *33*(2), 151–160.

Ross, T., & Lott, N. (2003). A Climatology of 1980-2003 Extreme Weather and Climate Events, (December).

Sheffield, A. (2017, July). *THE NATIONAL INTEGRATED DROUGHT INFORMATION SYSTEM (NIDIS)*. Presented at the NASA Applied Sciences Water Resources Team Meeting, Pasadena, CA

Stewart, I. T., Canyan, D. R., & Dettinger, M. D. (2005). Changes toward Earlier Streamflow Timing across Western North America. *Journal of Climate*, *18*, 1136–1155. https://doi.org/10.1007/978-3-642-10248-6_1

Svoboda, M., LeComte, D., Hayes, M., Heim, R., Gleason, K., Angel, J., … Stephens, S. (2002). The Drought Monitor. *Bull. Am. Meteor. Soc*, (August), 1181–1190.

Swain, D. L., Tsiang, M., Haugen, M., Singh, D., Charland, A., Rajaratnam, B., & Diffenbaugh, N. S. (2014). The Extraordinary California Drought of 2013 / 2014 : Character , Context , and the Role of Climate Change. *Bull. Amer. Meteor. Soc.*, *95*(September), S3–S7.

Toxic algae bloom found in Hayden Lake. (2015). *The Spokesman-Review*.

US Forest Service. (n.d.). Drought. Retrieved from https://www.fs.fed.us/managing-land/sc/drought

Wallace, J. M., & Gutzler, D. S. (1981). Teleconnections in the Geopotential Height Field during the Northern Hemisphere Winter. *Monthly Weather Review*, *109*(4), 784–812.

Wang, H., & Schubert, S. (2014). CAUSES OF THE EXTREME DRY CONDITIONS OVER CALIFORNIA DURING EARLY 2013. *Bull. Amer. Meteor. Soc.*, *95*, S7–S11.

Washington State Department of Agriculture. (2017). 2015 Drought and Agriculture.

What is NIDIS? (n.d.). Retrieved from https://www.drought.gov/drought/

Wheat, D. (2015). Kittitas hay losses in millions from drought. *Capital Press*.

Wilhite, D. A. (2000). Drought as a natural hazard: Concepts and definitions. *Drought: A Global Assessment*, 3–18. https://doi.org/10.1177/0956247807076912

Wilhite, D. A., & Glantz, M. H. (1985). Understanding the Drought Phenomenon : The Role of Definitions Understanding the Drought Phenomenon : The Role of Definitions.

Wilhite, D. A., Svoboda, M. D., & Hayes, M. J. (2007). Understanding the complex impacts of drought: A key to enhancing drought mitigation and preparedness*. *Water Resources Management*, *21*(5), 763–774. https://doi.org/10.1007/s11269-006-9076-5

Willeke, G., United States., Water Resources Support Center (U.S.), & U.S. Army Engineer Institute for Water Resources. (1994). *The national drought atlas*. Fort Belvoir, VA: U.S. Army Corps of Engineers, Water Resources Support Center, Institute for Water Resources.

Wood, A. W., & Lettenmaier, D. P. (2006). A TEST BED FOR NEW SEASONAL HYDROLOGIC FORECASTING APPROACHES IN THE WESTERN UNITED STATES. *Bull. Amer. Meteor. Soc.*, *87*(12), 1699–1712. https://doi.org/10.1175/BAMS-87-I2-I699

Xiao, M., Nijssen, B., & Lettenmaier, D. P. (2016). Drought in the Pacific Northwest, 1920–2013. *Journal of Hydrometeorology*, *17*(9), 2391–2404. https://doi.org/10.1175/JHM-D-15-0142.1

Appendix

Representative counties from the geographic areas in Washington and Idaho that were not included in the Results and Discussion. King County, Washington is representative of Puget Sound. Bear Lake County, Idaho is representative of the Basin and Range Region.

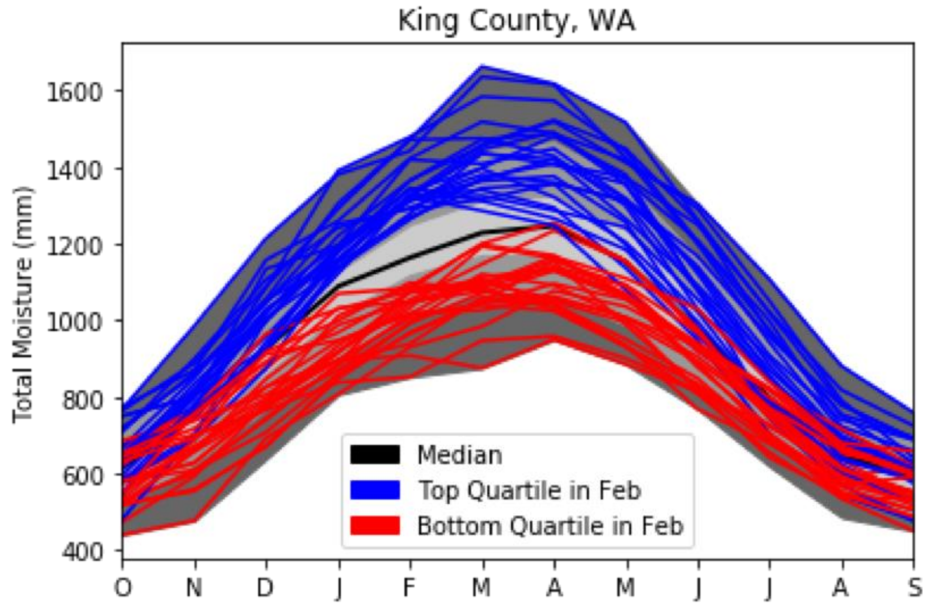

Figure 38: The distribution of monthly mean total moisture from VIC, for King County, Washington from 95 years of data. The upper and lower 10th percentiles are shown with dark shading, 10th-30th and 70th-90th percentiles in medium grey shading, and the 30th-70th percentiles with light grey shading. The median is the heavy black curve. Traces for years that were in the bottom quartile in February are shown in red, and years that were in the top quartile are shown in blue.

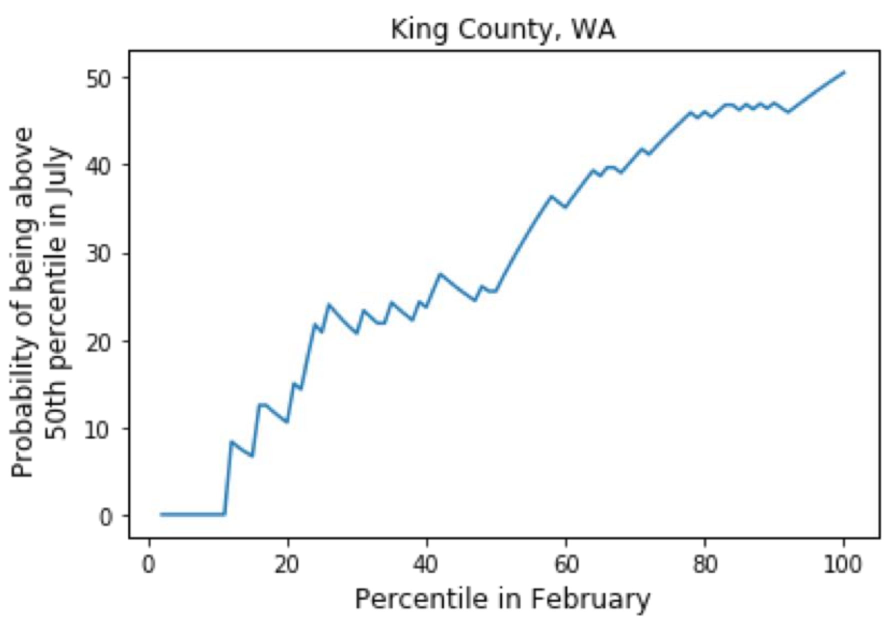

Figure 39: The probability of being above the median in July for King County, Washington for all percentiles as of February.

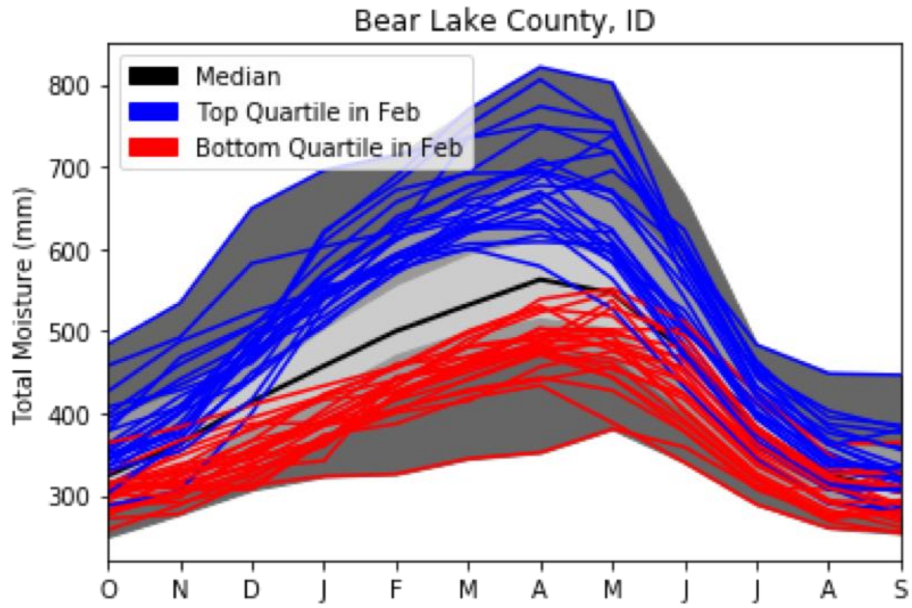

Figure 40: The distribution of monthly mean total moisture from VIC, for Bear Lake County, Idaho from 95 years of data. The upper and lower 10th percentiles are shown with dark shading, 10th-30th and 70th-90th percentiles in medium grey shading, and the 30th-70th percentiles with light grey shading. The median is the heavy black curve. Traces for years that were in the bottom quartile in February are shown in red, and years that were in the top quartile are shown in blue.

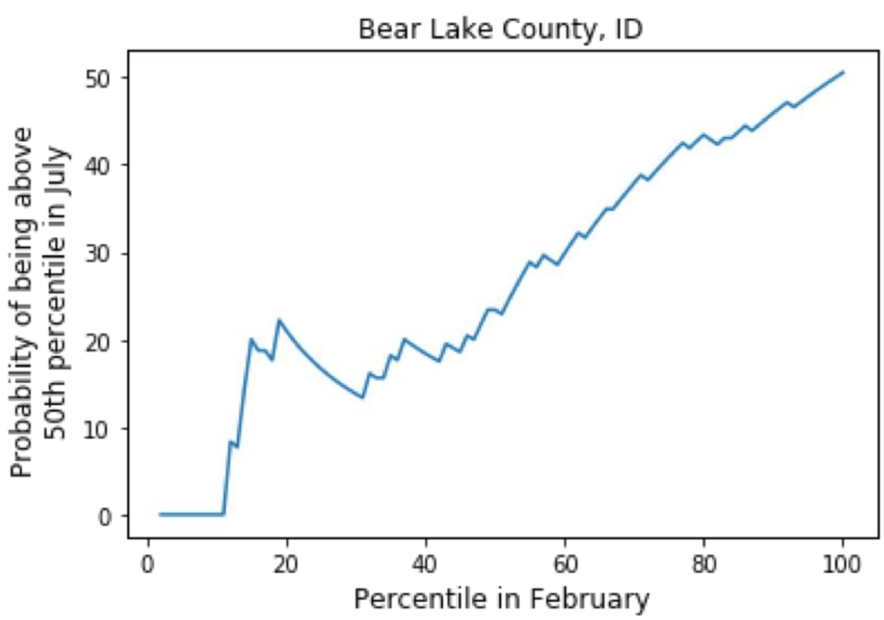

Figure 41: The probability of being above the median in July for Bear Lake County, Idaho for all percentiles as of February.