1300 Years of Snowpack Change for the Sangre de Cristo Mountain Range

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1300 YEARS OF SNOWPACK CHANGE FOR THE SANGRE DE CRISTO MOUNTAIN RANGE

by

Michael Paul Thornton

A Thesis
Submitted to the Graduate School,
the College of Science and Technology
and the Department of Geography and Geology
at The University of Southern Mississippi
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for the Degree of Master of Science

Approved by:

Dr. George Raber, Committee Chair
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ABSTRACT

New Mexico is heavily dependent on hydrologic inputs along high elevation sites where much of the cool-season precipitation accumulates as snowpack in the lower Southern Rocky Mountains. Snowpack runoff from the Sangre de Cristo (SDC) range provides critical headwater resources for the two major rivers that run through New Mexico and by extension the greater population. Yet, over the past four decades snowpack data from high and mid-elevation sites exhibit a linear trend of declining snowpack in conjunction with earlier seasonal melting. Due to the importance of these cool-season inputs for the region, a decline in montane runoff availability is alarming. Observing hydro-climatic trends over a much broader paleo-historic range is necessary to understand the implications and historical significance of recent snowpack decline in New Mexico and the broader region.

A nested principle components regression was used to reconstruct 1 April snow water equivalent (SWE) along the SDC range from a tree-ring derived dataset. The reconstruction extends from 630–2014 CE and instrumental data has been appended to 2017 for event analysis. The reconstruction is composed of 25 individually nested regression models. All models share a common period of 1955–85 CE with forward (1985–2014 CE) and backward (1955–630 CE) nests extending out temporally. The optimal calibration period (1955–85 CE) explains 64% of the variance in the instrumental record. The instrumental period is statistically representative of the overall range and variability exhibited over the entire historic period; yet, the historic record depicts extended periods of drought which eclipse, in terms of both persistence and intensity, those revealed over the instrumental period.
Based on one event classification scheme, an ongoing drought event (2011–17) ranks third in overall intensity behind the well-known mid-12th century “great-drought” and the late-16th century “mega-drought” and ranks in the 60th percentile regarding overall duration of events. In terms of drought persistence, only two 15-year periods of historic drought extend beyond a 12-year dry period in the 1950s. This 12-year dry period is in the 50th percentile regarding overall intensity of events. An alternative method of classification, targeting extended event periods, reveals five multi-decadal drought periods, all prior to the 17th century.

Numerous pluvial events revealed over the historic record eclipse wet periods observed over the instrumental record in terms of persistence and intensity. The longest and most intense pluvial event over the instrumental record (1983–89 CE) was found to be in the 50th – 60th percentile regarding overall persistence of events, while ranking 7th in overall intensity (85th percentile).

There are more individual anomalous dry years [< -0.5 standard deviations from the mean (SD)] over the instrumental period than wet, a characteristic shared only with the 8th century, most of these occurring during the 21st century. The 20th century is by far the wettest century of the 1385-year record. Although the 1950s drought was severe in terms of persistence it is eclipsed numerous times in terms of intensity. Also, while the current 21st century drought is severe in terms of intensity it is surpassed in terms of duration numerous times. Under predicted climate change scenarios, intense and prolonged droughts, like those revealed over the historic period (e.g., the late-16th century, mid-12th century, and the extended dry period of the early 8th century), would become far more frequent.
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DEDICATION

I would like to dedicate my thesis to my loving wife who supported me in this endeavor. A second dedication is made to my father and mother who provided examples of continued perseverance in working towards one’s goals.
TABLE OF CONTENTS

ABSTRACT.................................................................................................................. iii

DEDICATION................................................................................................................. vi

LIST OF TABLES ............................................................................................................ ix

LIST OF ILLUSTRATIONS .............................................................................................. x

CHAPTER I – INTRODUCTION .................................................................................... 1

1.1 Site description ........................................................................................................ 4

1.2 Research objectives ................................................................................................ 7

CHAPTER II – BACKGROUND .................................................................................... 11

3.1 A general history of dendrochronology ................................................................. 11

3.2 Dendro-climatology in the SW ............................................................................. 13

3.3 Dendro-climatology as a tool to observe paleo-snowpack conditions .................. 14

CHAPTER III – SNOWPACK ALONG THE SDC ...................................................... 18

3.1 SWE data ............................................................................................................... 19

3.2 Streamflow data .................................................................................................... 25

3.3 Precipitation data. ................................................................................................. 28

3.4 Conclusion ............................................................................................................. 32

CHAPTER IV–METHODS ............................................................................................ 34

4.1 Preliminary Model ................................................................................................. 34

4.2 Tree-ring data ......................................................................................................... 35
4.2.1 Targeting tree-data collection sites ................................................................. 36
4.2.2 Collection ............................................................................................................. 39
4.2.3 Data preparation (COFECHA and ARSTAN) ...................................................... 44
4.3 Snowpack data ...................................................................................................... 53
4.4 Calibration and Verification .................................................................................. 55

CHAPTER V–RESULTS AND DISCUSSIONS .................................................................. 61
5.1 Reconstruction model results ................................................................................ 61
5.2 Comparison with other reconstructions ............................................................... 73
5.3 Data distributions, variability, and extremes ......................................................... 79
  5.3.1 Probability densities ......................................................................................... 83
  5.3.2 Anomalies and extreme events ......................................................................... 87
5.3 Extended period classification .............................................................................. 90
5.4 ENSO influence .................................................................................................... 96
5.5 Comparison of event periods to other tree-ring derived paleo-climate records... 103
  5.5.1 Instrumental period (1937-2017) comparison with the overall historic period
   (630-1985) ........................................................................................................... 111
5.6 Conclusion ............................................................................................................. 112

REFERENCES ............................................................................................................ 115
LIST OF TABLES

Table 3.1 SNOTEL and Snow coarse sites used for determining streamflow influence..... 20
Table 3.2 Number of years April 1 represents maximum accumulation (1950-2017) ..... 23
Table 3.3 Streamflow gauges from the upper region of the Pecos River. ................. 25
Table 4.1 Eight chronology sites selected for sampling from the ITRDB.................... 42
Table 4.2 COFECHA output from four sites............................................................. 51
Table 4.3 Snow coarse data sites used to create our PC\textsubscript{1SWE} dataset. ........... 55
Table 5.1 The 25 tree-ring chronologies used in the reconstruction model of SDC 1 April
SWE. .................................................................................................................. 65
Table 5.2 Model calibration and validation statistics with MEBoot medians for 19
backward nests and 6 forward nests........................................................................ 66
Table 5.3 Individual anomalies per century comparison chart..................................... 85
Table 5.4 Anomalous events with a minimum of five consecutive years per event
continued............................................................................................................... 95
Table 5.5 SDC 1 April SWE multi-decadal anomalous events with a minimum of 20
years per event. ................................................................................................... 96
Table 5.6 SDC 1 April SWE reconstruction event comparison with other tree-ring
reconstructions.................................................................................................. 111
LIST OF ILLUSTRATIONS

Figure 1.1 The SDC range contributes essential cool-season inputs to the RGRB and PRB................................................................................................................................. 6

Figure 1.2 SDC Climate Footprint and our selected target area for tree-ring sites. .......... 7

Figure 3.1 Comparison of April, March, and February snowpack (1980-2015) ............. 22

Figure 3.2 Temperature correlation with SDC 1 April and peak SWE data (1950–2015) from the SDC range. ........................................................................................................ 23

Figure 3.3 1 April SWE values against peak annual SWE values................................. 24

Figure 3.4 Streamflow monthly average values from four stations over 34 years (1981–2015). ................................................................................................................................. 26

Figure 3.5 1 April SWE vs. Pecos River streamflow for the upper region of the Pecos River (1981–2015)....................................................................................................................... 27

Figure 3.6 Peak annual precipitation values (1981–2016). ............................................ 30

Figure 3.7 Pecos River streamflow vs. regional gridded precipitation......................... 31

Figure 3.8 Gridded precipitation values at three regions along the PRB....................... 32

Figure 4.1 The regional climate signal for SDC snowpack........................................... 39

Figure 4.2 Field data collection at Burning Bridge Wash, NM with Navajo Forestry guide and Dr. Justin Maxwell............................................................ 43

Figure 4.3 Me with old-growth ponderosa pines at the Rio Pueblo and Fort Wingate sites. ............................................................................................................................ 44

Figure 4.4 Correlation segment and spaghetti plots of COFECHA output. ................. 47

Figure 4.4 Correlation segment and spaghetti plots of COFECHA output. Continued... 48

Figure 4.4 Correlation segment and spaghetti plots of COFECHA output. Continued.... 49
Figure 5.13 ENSO-like pattern influence on regional cool-season hydro-climate for northern NM and the SDC range.
CHAPTER I – INTRODUCTION

The Pecos and Rio Grande Rivers and their tributaries provide the primary source of surface water for New Mexico (NM), while also serving southwestern Texas and regions of northern Mexico. Inhabitants within the Pecos River (PRB) and the Rio Grande River (RGRB) basins have depended historically on these rivers for agricultural and livestock maintenance and today all of NM’s major cities reside within the PRB and the RGRB. The streamflow characteristics of these two important southbound rivers are strongly influenced by snowpack run-off from high elevation sites in the north, beginning in spring [April–June (AMJ)] and typically lasting until late fall [October–December (OND)]. These hydrologic inputs are important to municipal, agricultural, and industrial demands as well as lotic and riparian ecosystems in a region of increasing population growth and anthropogenic demand. As snowpack melts through the season it releases slowly, providing infiltration time for ground-water recharge as well as sustained surface water supply. This rate of release greatly decreases the potential for erosion and helps to maintain related environmental systems. The other dominant form of seasonal precipitation, in NM, occurs during the warm-season [June–September (JJAS)], and largely comes in the form of monsoonal activity, typically delivered as violent flash storms. These monsoon rains often decrease soil stability, pollute streams, and cause flash floods. It is therefore evident that snowpack accumulation from cool-season precipitation, with its consequent rate and timing of annual runoff is an essential feature of a hydrologic cycle for which life within the southwestern arid regions is dependent. Yet as hydrologic demand swells, instrumental snowpack records in the SDC, beginning ca. 1930s, indicate an alarming decline in recent decades. Proxy-records, covering an
extended temporal duration, from surrounding regions in the American Southwest (SW),
have also highlighted this recent decline (Belmecheri et al., 2015; Das et al. 2009; Mote et al. 2005; Pierce et al. 2008) and found the current drought phenomenon to be
significant in scale when compared to the extended paleo-climate record. In conjunction,
a trend towards earlier snowmelt has also been highlighted in numerous studies
throughout the American Southwest (SW) (Cayan et al., 2001; Hidalgo et al., 2009;
McCabe and Clark 2005; Stewart et al., 2005) compounding the issue for inhabitants
dependent on these hydrologic inputs.

Drought persistence and severity during the 21st century, in the American SW, has
been the most extreme since record keeping began in the 1920s (Gregory et al., 2013).
Increasing demand on hydrologic systems, from population growth and a more
industrialized economy put considerable constraints on an already stressed water supply
system. Southern California has received a considerable degree of media attention, as the
primary hydrologic inputs, supplied by high elevation sources to the east (e.g., Sierra
Nevada Mountain range and the Colorado River) have been depleted for large
metropolitan areas such as Los Angeles. Yet, not unlike southern California, NM suffers
from the same modern SW drought phenomenon.

Climate and population growth models throughout the SW predict hydrologic
constraints will worsen as climate change is expected to increase drought potential in arid
regions (Barnett and Pierce, 2008; Cook et al., 2016; Meko et al., 2011; Seager et al.,
2007). As a more industrialized society increases its carbon consumption, our atmosphere
increases its CO₂ ratio, causing global temperatures to rise as radiant energy unable to
exit at previous rates strengthens current climate patterns. These patterns are predicted to
exacerbate already arid conditions in regions like NM. The range of current climatic fluctuations is predicted to expand towards more frequent and extreme events on both ends of the hydrologic spectrum. In conjunction with reduced snowpack due to cool-season drought, increasing peak monsoonal events have already been observed in the SW (Knowles et al., 2006).

Recent hydrologic fluctuations have been attributed partially to a warming climate and specifically to changes in Pacific sea surface temperatures (SST's) (Clow, 2010; Dettinger et al., 2004; Hamlet et al., 2007; Stewart et al., 2005). This increase in frequency, intensity, and duration of both cool-season drought and warm-season pluvial events is a double-edged sword for water planning authorities as extreme pluvial events caused by often violent convective processes can be as problematic as drought – flash floods deliver a source of input that is difficult to contain and can reduce water quality in streams and rivers.

Hydrology has historically been a central issue in NM; battles fought in the name of it, legal and otherwise, continued today (duBuys, 2013). As compounding factors produce a multi-faceted hydrologic dilemma, water issues will become increasingly a central theme in NM. The recent extended and severe drought conditions which began in 2002 give cause to question the ability of current allocation and conservation measures to be sufficient for future needs as the past 18 years have seen some of the lowest annual river flows seen since record keeping began (Gregory et al., 2013; Harley et al., 2017).

Currently in NM, allocation measures rely solely on instrumental data which include the extreme high and low flow parameters present within this time frame. Instrumental hydrologic data may extend back in time as early as ca. 1900. However,
snowpack instrumental periods are generally much shorter in duration. These relatively short windows of observation do not provide long-term perspectives of hydro-climatic variability. The full range of temporal trends (e.g. decadal-to-multi-decadal patterns of variability) are not apparent from an instrumental period perspective, which generally extend, in the case of snowpack, to less than a full century. To realize the full scope of inherent variability, water management authorities require a broader long-term perspective of hydro-variability than these limited instrumentation periods can provide. Currently no long-term perspective of cool-season hydro-variability has been reconstructed for the northern New Mexico (NM) and the SDC region.

Tree-ring drought reconstruction research in the SW has exemplified the ability of extended tree-ring proxy records to assist water management authorities (Bekker et al., 2014; Meko et al., 2001; Rajagopalan et al, 2009; Woodhouse and Lukas, 2006) with water conservation and allocation measures. Visual models produced by quantitative parameters may also be used by the broader public community to better understand the ongoing drought conditions in context of the historical variance.

1.1 Site description

The hydro-climate region under analysis is approached from spatial considerations of the cool-season hydro-climate signal for the SDC range and its larger region. The larger region associated with the cool-season hydro-variability along the SDC range was determined according to a climate “footprint” analysis, which is discussed further in Chapter IV, and considered in conjunction with regional proximity to the SDC range (Fig. 1.2). The resulting climate-region corresponds well to the northern Desert Southwest region where the eastern extent of the Colorado Plateau, the Southern Rockies,
and the northern extent of the Desert Southwest converge along high elevation sites of northern NM and southern Colorado (CO); the climate region also closely aligns with the extent of the Ancestral Puebloans or Anasazi cultural range (Smith, 2002).

The uplift known as the SDC range is comprised of rocks dating back to as far as the Precambrian period (1.8–1.7 billion years ago). The majority of the oldest material, found along the high elevation peaks of the range, typically dates to the Mississippian age (360–320 million years ago). Material gradually reduces in age as one descends into the valleys, west of the range, which are comprised primarily of alluvium and windblown sand materials from the Quaternary period (Lindsey, 2010). The SDC extends from approximately Poncha Springs, CO in the north, to Pecos, NM in the south. Runoff from mountain snowpack is responsible for 50–80% of annual streamflow throughout the western US (NRCS, 2000) and the arid region of the Desert SW is a good example of this. Two major rivers, the Pecos and the Rio Grande, which run from north to south with headwaters in the SDC range and the lower San Juan range, both in southern CO. The Rio Grande begins at 12,000 ft. in south-central CO within the San Juan range flowing some 100 miles east towards the SDC mountain range where the river then flows southward from approximately Alamosa, CO. The Rio Grande travels south nestled against the SDC range to the east for another 100 miles before veering westward. The Pecos River begins at ca. 12,000 ft. in the SDC range, within peaks rising above 13,000 ft. At the Pecos head, the Rio Grande is a mere 24 miles to the west but over 5,000 ft. vertically below it (Dearen, 2016). As these two rivers flow south they eventually descend some two miles in elevation and flow through increasingly arid regions. The
RGRB and the PRB cover a large swath of NM, containing all of its major cities (Fig.1.1).

Figure 1.1 The SDC range contributes essential cool-season inputs to the RGRB and PRB.

SDC snowpack runoff contributes heavily to the Rio Grande River (RGRB) and the Pecos River basins (PRB), the two major rivers basins of New Mexico, which contain all major cities in the region. As these rivers flow from north to south they receive critical headwater resources from the lower Rockies which include the San Juan and the SDC ranges.
Figure 1.2 SDC Climate Footprint and our selected target area for tree-ring sites.

Map created at climexp.knmi.nl (KNMI Climate Explorer, 2017) using instrumental data from the SDC range against girded PRISM precipitation data a climate footprint was defined and used to define an area of investigation. The tree-ring chronology sites used define a radius from which climate analysis for cool-season precipitation can be implemented: here defined by the white circle. Areas of deep crimson have correlation values > 0.60 with 1 April SWE in the SDC range. Although areas along low-elevations have gridded precipitation data (PRISM) that do not possess robust correlations with SDC snowpack, these low areas depend heavily on cool-season inputs in the form of snowpack runoff during the growing season from adjacent high-elevation sites.

1.2 Research objectives.

The primary goal of this research is to develop a long-term perspective of regional cool-season hydro-variability using tree-ring data as a proxy for April 1st snow water equivalent (1 April SWE) measurements from snowpack telemetry (SNOTEL) and snow
coarse data sites. **Placing** the instrumental period (1937–2017) in an historical narrative allows us to determine if modern snowpack variability is within the range of reconstructed values or possibly evident of an altered climate regime. Based on quantitative comparisons generalizations can be made about particular temporal trends and variability. This research presents an examination of temporal trends, on various scales, with an emphasis on drought assessment over the entire extended paleo-record from various quantitative perspectives. Statistical modeling and data visualization techniques were applied with the aid of statistical and data visualization software. Secondary goals of this research include highlighting characteristics of snowpack accumulation and timing of runoff throughout the instrumental period, and the influence of modes of Pacific sea surface temperatures (SSTs) on SDC snowpack, tele-connected through the El Nino-Southern Oscillation (ENSO). A comparison of this reconstruction is made against other reconstructions in the SW and surrounding areas within various zones of SST influence.

Based on the preliminary analysis, an extensive literature review, and in light of current water concerns the following four central research questions were delineated as an outline: 1.) “What is the historical variability of snowpack in the SDC range, and how does the range of data from the instrumental period (1937–2017) compare to the overall range of values within the reconstructed period?”; 2.) “What are specific characteristics of snowpack variability over the extended paleo-climatic period?”; 3.) “What is the significance of snowmelt runoff for the PRB specifically?”; and 4.) “To what degree do the observed broad-scale teleconnections between patterns of inter-annual to decadal scale coupled ocean atmospheric modes of variability in the Pacific Ocean [i.e. the El
Niño-Southern Oscillation (ENSO) and southwestern snowpack anomalies play a part in modulating the cool-season hydro-climate signal over the reconstruction and instrumental period?”. The following outlines these four central questions:

**Objective 1**

The use of tree-rings to estimate regional hydrologic variability over the past ca. 1000+ years allows for an extended perspective of cool-season water resource variability revealing temporal trends, not apparent in the instrumental period. This research examines instrumental variability and value ranges against the context of the tree-ring derived extended paleo-climatic record. If the instrumental value ranges are significantly outside of the extended range of reconstructed values, this may be evidence of a regime shift brought on by global climate change. If, however, instrumental conditions remain within the overall range of extended variability then water planning authorities might use these results to ask another question: how do current climate prediction models view the expected influence on a climate regime which has been outlined in terms of paleo-record variability? What needs to be understood is the degree of potential that more extreme droughts than those observed over the instrumental period would be expected under an unaltered climate regime and how do these expectations change under the consideration of current climate prediction models for an altered climate regime for arid regions such as the SW.

**Objective 2**

In Chapter V, mathematical assessments of trends in the data over time are depicted and discussed to assess a range of conditions and thereby hydro-climatic events on various scales. Droughts of various intensity and duration are emphasized and
assigned quantitative values for comparison over the full range of the reconstruction period. By comparing the various centuries as well as decadal and sub-decadal trends (e.g., greater than five year extended drought and pluvial periods) captured within the reconstruction period new insight is gained into historic drought conditions for the SW, such as how well-known drought events (e.g., 16th century “mega-drought” and the 1950s SW drought) effect the particular hydro-climate region and relate to the overall range of variability.

**Objective 3**

In Chapter III, an investigation of the timing of annual snowmelt and consequent runoff for the SDC, over the past 40+ years, has been made in order to: a.) access the relevance of using 1 April SWE values to represent annual snowpack accumulation in the SDC range and b.) access the influence of snowpack accumulation and consequent runoff on streamflow for the Pecos River. The Pecos River has its headwaters in the SDC range.

**Objective 4**

In Chapter V.4 analysis performed using the Koninklijk Nederlands Meteorologisch Instituut (KNMI) Climate Explorer (2017) to assess relationships between ENSO-like patterns of variability in Pacific SSTs and sea level pressure (SLP) and 1 April SWE variability in the SDC range is presented and discussed.
CHAPTER II – BACKGROUND

Annual to sub-annual growth increments of tree-rings have been used extensively in the American SW and have been shown to exhibit strong statistical ability for paleo-climate reconstructions (Hardman and Reil, 1936; Schulman, 1945; Fritts et al., 1971; Stockton and Boggess, 1982; Meko and Graybill, 1995). Studies have revealed important characteristics of streamflow variability (Meko et al., 1995; Stockton and Jacoby, 1976; Woodhouse et al., 2001, 2006;) using tree-ring indices. However, reconstructing snowpack values is far less common due to the lack of extensive instrumental data networks. Snowpack data often does not extend past 30–40 years. It may not be possible to successfully statistically validate models with these minimal periods of calibration. Yet, where statistical conditions can be met tree-ring based snowpack reconstructions have been used to produce robust models of hydro-climatic variability (Woodhouse, 2003; Belmecheri et al., 2015) and reveal important insights into the nature of snowpack climate drivers. In this chapter a summary of the evolution of hydro-climatic tree-ring research in the SW from streamflow parameters towards the more recent research of snowpack reconstructions is provided.

3.1 A general history of dendrochronology

The physical rationale for reconstructing hydro-climatic variability with tree rings was founded by Ed Schulman in 1945 to address issues concerning the Colorado River for Los Angeles Power (Meko et al., 2012). Long before this, however, Leonardo da Vinci, in the 16th century, made note of the annual nature of tree-rings. He went on to assert a relationship between hydro-climatic variation and the growth of the tree-ring widths and therefore maintained that tree-rings could serve as indicators for past climatic
conditions (Stalling, 1937). It would be another two centuries however, before an incident of tree-ring science being applied to date a specific climate event is recorded. In 1737, French scientists Du Hamel and De Buffon observed a single conspicuous damaged ring which they determined was due to frost damage (Studhalter, 1956). In 1783, German botanist and forester Burgsdorf applied the first recorded instance of cross-dating to further examine the findings by Du Hamel and De Buffon (Studhalter, 1956). Early instances of dendrochronology were employed and advanced primarily by other German scientists: Julius Ratzburg in 1866 and Robert Hartig in 1897; observing frost, hail, and insect damage (Schweingruber, 1988; Studhalter, 1956; Smith and Lewis, 2007). It wasn’t until an American astronomer, Andrew Ellicott Douglass, realized that Leonardo’s revelation of the relationship between precipitation and tree-ring growth was incredibly applicable in the American SW would tree-ring science be born anew and used to reconstruct hydro-climatic features. The American SW has since played an important and central role to the foundation of the science of dendroclimatolgy. A.E. Douglass also verified Burgsdorf’s crossdating method as an essential tool in the dating of specific climatic events (Douglass, 1909, 1914). Developing low-elevation ponderosa pine chronologies from the SW he created a 500-year chronology to observe regional precipitation patterns (Douglass, 1914) before moving on to focusing primarily on archeological applications of tree-ring science (Dean, 1997). In the past 60 years numerous quantitative statistical techniques have been advanced (Cook, 1985; Cook et al., 1999, 2006, 2013; Fritts, 1976,1991; Schulman, 1945) for better estimation of hydro-climatic variability and it is established that moisture-sensitive trees in the SW contain within their tree-ring widths a signal over time; a growth response to hydro-climatic
events. In the SW this signal is essentially a drought signal, which can be used to successfully reconstruct hydro-climatic variability back in time to the extent of the tree-ring data.

3.2 Dendro-climatology in the SW

Numerous studies beginning with Stockton and Jacoby (1976) – using techniques outlined above – have found that the 20th century contained the wettest multi-decadal period in the past four to six centuries (Bekker et al., 2014; Woodhouse and Lukas, 2006) while a later study found the second half of the 20th century to be the second wettest in the last 1200 years (DeRose et al., 2015). Becker et al., (2014) found the 20th century contained the fewest individual years of extreme drought over the past 576 years. According to these studies and others (Margolis et al., 2011, Meko, and Graybill, 1995; Woodhouse, et al., 2012) the 20th century data created an inappropriate perspective, due to a lack of understanding the natural variability contained in the SW climate regime over an extended period, from which to make hydro-climatic assumptions of variability and most importantly availability. The extreme SW drought events of recent have since been highlighted against the backdrop of extended paleo-perspectives. It stands to reason that a drought event like the current episode which began with the onset of the 21st century has provided incentive for water management authorities to seek an improved knowledge of the hydro-climate variation beyond the instrumental perspective. Since then tree-ring records have been considered by multiple organizations to address sustainable water allocation measures.

Woodhouse and Lukas (2006) observed that water managers had been over allocating water based on high pluvial assumptions of the 20th century instrumental
period. However, these over-allocations were not particularly an issue until the 2002 drought event, as water supply systems were unprepared for drought of this magnitude. The American Southwest has continued to experience intense drought conditions for much of the 21st century to date. Numerous tree-ring proxy analyses have worked directly with water management authorities (Margolis et al., 2011; Woodhouse and Lukas, 2006; Bekker et al., 2014; Woodhouse et al., 2012; DeRose et al., 2015) to assess questions of water supply sustainability and historical flow variation. The data produced from these studies have provided updated input parameters for streamflow models for management purposes.

3.3 Dendro-climatology as a tool to observe paleo-snowpack conditions

One advantage of using snowpack data to assess hydro-climate conditions is the ability to minimize noise from anthropogenic affects. With instrumental streamflow data, many studies require adjusted streamflow to account for anthropogenic depletions and reservoir storage (Meko et al., 2012); models are first performed to assess “natural flow” and then are derived for a proper streamflow analysis using tree-rings. Snowpack however – being the initial source of stream and other surface waters – exhibits minimal direct anthropogenic influence on flow inputs or natural moisture levels.

Woodhouse (2003) produced the first tree-ring reconstruction of snowpack in the American SW. SNOTEL data, from the National Resources Conservation Service (NRCS) recorded as 1 April SWE values, was utilized as a measure of peak yearly snowpack accumulation. To accommodate for minimal missing annual data, the average of all other stations for that year were used as replacement. A Principle component analysis (PCA) was able to explain 77% of the 1 April SWE variance between all NRCS snowpack data sites.
Woodhouse (2003) sampled 28 sites within the Gunnison River basin region of western CO – just north of the SDC climate region under analysis in this project – in the summers of 2000-2001: six chronologies were updated and moisture sensitive species targeted. Out of the 28 sites sampled, 15 were retained and fully developed for modeling. The common period extended from 1938–97 with the tree-ring data explaining 63% of the total variance in 1 April SWE first principle component (PC1) dataset. The reconstruction extended from 1569–1999 CE.

Persistence of low SWE years was evaluated by assessing the periods for which SWE was below average for three or more consecutive years. Woodhouse (2003) found the 16th, 17th, and first half of the 18th century had much higher frequency of persistent (3+ years) drought compared to the later centuries. Unlike numerous other paleo-records from the SW, the 20th century was found to be largely representative of the overall reconstruction in regard to variability and range extremes. Yet, consistent with other reconstructions, the 20th century was found to contain the least amount of extreme low SWE years giving evidence of over-allocation measures based on pluvial period data for that region.

Belmecheri et al., (2015) provides the most current example of a tree-ring snowpack reconstruction. A dataset of 1 April SWE, for the Sierra Nevada (SN) region of California, was compiled from two existing datasets: (1) the NRCS and Water Climate Center and (2) the California Department of Water Resources. The former consists of SNOTEL and snow coarse site data for the western US, while the latter is specific to the state of CA and provides the majority of the data for the reconstruction. 108 stations within the SN range were selected to provide instrumental data for snowpack. The
common period for all datasets was, initially, 1930–2015 CE. Amongst all stations a small amount of data for specific years (< 10% of overall data) was missing and was replaced with average values, as done in the Woodhouse (2003) study. A principle component analysis (PCA) was then applied to all stations. PC1 explained 78% of the common variance. PC1 SWE scores were used in the regression rather than cm values as Woodhouse (2003) had done.

Belmecheri et al., (2015) used tree-ring chronologies solely obtained from a secondary “public” source. Although it is not explicitly stated in the article it may be assumed that these chronologies came from the International Tree-ring Databank (ITRDB) website. This collection of time-series, referred to as a “master-chronology”, contains chronologies from 33 sites in central CA; all blue oak (Quercus douglasii) species. A stepwise multiple linear regression model was then performed, using the tree-ring master-chronology against the PC1 from the 1 April SWE data; as has been conducted in this research. This blue oak time series was able to explain 58% of the variance in the PC1 1 April SWE dataset. In order to verify the ability of the proxy as a predictor of the predictand variable a split-sequence “cross-calibration-verification test” was performed, as Woodhouse (2003) had done.

Total error was discussed as a factor of the (1) detrending error, (2) replication error, and the (3) calibration error combined (Belmecheri et al., 2015). The detrending error, as with all tree-ring reconstructions, is due to the biophysical characteristics of the phenomena under study. Complexity, emergence, and autocorrelation are features in any biophysical phenomenon under investigation. Belmecheri et al., (2015) states the importance of detrending process in dealing with such unwanted noise but recognizes the
removal of potential low-order climate patterns, i.e. variability signal trends at low-frequencies, e.g. at centennial scales, which can be filtered out with the removal of endogenous stand dynamics and age-related noise. The replication error mentioned, applies to the variation of sample depth at varying time scales; typically, a decreasing number of tree-ring series, i.e. sample depth, as the series extend backwards in time, which was accounted for here using the EPS statistic. The calibration error was accounted for as factor of variance not explained by the tree-ring signal. Using bootstrapping of the mean, upper and lower brackets of the 95% confidence intervals (CI) allowed for measurement of the replication error. Here the standardized values of each year were replaced 1000 times and means calculated. A simple standard error (SE) value was given for the calibration period (1930–80), which is simply the remainder of variance not captured by the R² calculation.

Regarding these previous studies, this research project extends beyond the Woodhouse et al. (2012) reconstruction of the Rio Grande River, predating current paleo-hydrological tree-ring proxy data for the RGRB, while also providing novel, annually-resolved, multi-century tree-ring proxy data for the larger region of NM. Currently, observations for the PRB and the SDC Mountains are strictly limited to the instrumental period as no paleo-proxy estimations have been established. This research uses the most up-to-date methods in dendroclimatology research to extend paleo-climatic perspectives for the broader region of northern NM and southern CO, including headwater regions of the PRB, the RGRB, and the SDC range; and updates three sites within the ITRDB, while providing novel tree-ring data from one new site.
CHAPTER III – SNOWPACK ALONG THE SDC

This chapter outlines an investigation of trends in SDC snowpack and its influence on streamflow in the Pecos River over the instrumental period. Hydrological data were collected from 10 snowpack data stations from the NRCS website (NRCS, 2015) within the SDC range in Northern NM, four U.S. Geological Survey (USGS) streamflow gauge stations along the upper regions of the Pecos River, downloaded from the USGS website (USGS, 2015), and gridded Parameter-elevation Regressions on Independent Slopes Model (PRISM) precipitation data from five counties in the region, downloaded from their website (PRISM, 2015). Over the past four decades, SWE data from high and mid-elevation sites within the state exhibit a linear trend of decreasing snowpack in conjunction with earlier seasonal melting. The USGS data also shows a decrease in streamflow discharge over the observed period. However, PRISM data presents an increase in peak annual precipitation values in the form of rainfall brought on by the North American Monsoon (NAM) and is most pronounced in the last decade. This may be consistent with an observed out-of-phase winter-to-summer precipitation relationship over the recorded instrumental period in the region. The analysis presented here signify a streamflow dominated by cool-season hydrological inputs from spring snowpack runoff. A decrease in snowmelt run-off in conjunction with an increase in NAM activity has implications of increasing difficulties for water resource management under a growing-population scenario.

In NM, precipitation, during both the cool and the warm-seasons, primarily occurs in the mountainous regions of the northern part of the state (USGS, 2015). The precipitation signal for this region is characterized as distinctly bimodal in which warm-season and cool-
season events are controlled by separate climate mechanisms (Coats et al., 2015). The cool-
season precipitation in the Arizona (AZ)/NM sector has been recorded to contribute 39% of annual precipitation totals (Serreze et al., 1999). The larger percentage of precipitation, however, is from localized, late-summer, convective storm activity (Gutzler and Preston, 1997; Lo and Clark, 2002; McCabe and Clark, 2005) associated with the prominent NAM system that occurs throughout the southwest but is particularly centered along the Sierra Madre Occidental mountain range in northwestern NM (Grantz, 1997), and yet streamflow is primarily influenced and controlled by snowpack run-off (Margolis et al., 2007) in the SW.

This chapter analyzes dual-season hydrologic climatic impacts on a local scale in the upper PRB region considering broader regional southwestern studies. Snowpack
SWE data from the SDC range is examined against peak precipitation values occurring in late summer as NAM convective storm events in regard to annual Pecos River streamflow values for the period, 1981–2016 water year (WY): a duration provided by USGS streamflow data periods.

3.1 SWE data

To examine cool-season inputs for the PRB nine snowpack data stations were selected based on their temporal and spatial characteristics (Table 3.1) These stations cover a range of high to moderately high elevations, and extend back in time to at least 1980. All selected stations share a common period of 1980–2016.
### Table 3.1 SNOTEL and Snow Coarse sites used for determining streamflow influence.

Data from these sites were collected from the NRCS (2015) website at “Historic Monthly Snow Data” (NRCS; available on line at http://www.wcc.nrcs.usda.gov/snow/). All data sites extend at least far back as 1980 and possess a minimal amount of missing data (<3 years) and are located within the SDC range were selected. These sites were found to exhibit a high amount of common variance ($R^2 = 0.81$).

A PCA was ran on all ten snowpack stations using the statistical software package RStudio (2017) to determine common variance. The first eigenvector retained all ten stations along the first PC axis and explained 81% ($R^2 = 0.81$) of the variance common to all stations (1980–2017) (Table 3.1). The PC1 dataset was used here to compare to precipitation and stream flow gauge data as described. Another subset of data was comprised from this dataset, where five instrumental stations (Table 3.2) possessing an extended duration (1950–2017) where analyzed for correlation. Both datasets contain monthly snowpack data for SWE in inches. From the (1950–2017) dataset two subsets of data were derived: 1.) 1 April SWE, and 2.) Peak annual SWE. A comparison of these two datasets is shown in Fig 3.2. The majority of data used for the study presented in this chapter is provided over a period of 30 or 37 years: 1981–2010 and 1980–2016 respectively, depending on the comparison made in each regression and/or correlation.
assessments. This time frame was used to fit the USGS 30-year “normals” precipitation dataset for download on their website (USGS, 2015), as well as being a time frame suitable to many of the snowpack instrumental durations along the SDC. However, for the plot in Fig. 3.2 the extended dataset is applied (1950–2017) to allow for an extended perspective of snowpack accumulation and concurrent timing of runoff when comparing peak and 1 April SWE values.

From the plot below (Fig. 3.1) it is evident that 1 April SWE records often capture the maximum accumulation of annual snowpack based on monthly observations during a pluvial year, yet during warmer years it is often well below the maximum annual record. 1 April SWE values exhibit a far more robust and inverse relationship with temperature than peak SWE (Fig. 3.2). From this observation it is most probable that warmer temperatures are partially the cause of the larger gaps between the two data line plots depicted in Fig. 3.3. Warm wet (i.e. high values of cool-season inputs) years as well as warm dry years are likely to cause earlier seasonal melting and inputs delivered as rain fall rather than snow even when cool-season inputs are relatively high. Any increased warming trend would produce far earlier snowmelt dates and thus 1 April may lose some validly under a warming scenario as an indicator of overall snowpack for the year in the SDC range yet still remains a good indicator of tree-growth due to correspondence with the growing season.

Table 3.2 shows the relation of 1 April SWE to overall annual snowpack accumulation over the last 68 years (1950–2016) in tabular format. Taos Canyon exhibits the earliest melting timing of all sites (Table 3.2) as is evident from the low percentage of years where 1 April SWE data represent the annual maximum. Other stations exhibit
much higher frequencies of snowpack accumulation lasting later in the season (i.e. until the 1st of April) providing better hydro-reserves during the growing season in conjunction with decreased evapotranspiration rates.

Figure 3.1 Comparison of April, March, and February snowpack (1980-2015)

Snowpack is often at its peak for 1 April SWE data when snowpack is high. Years of early snowmelt is most likely due to warmer temperatures, such as in 1999 and 2002; years known as very dry years for the SDC and larger climate region. Since 2011 NAM activity has been high while cool-seasons inputs have been low. Snowmelt is generally early during this period as well. Created in Excel (2016).
Figure 3.2 Temperature correlation with SDC 1 April and peak SWE data (1950–2015) from the SDC range.

Map created using KNMI Climate Explorer (2017) tools at climexp.knmi.nl. Maximum temperature was ran against peak (left) and 1 April (right) SWE values for the period 1950-2017.

<table>
<thead>
<tr>
<th>Site Name</th>
<th>Elevation (ft)</th>
<th>Apr 1 = Max</th>
<th>Apr 1 &lt; Max</th>
<th>Apr 1 = Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rio en Medio</td>
<td>10300</td>
<td>37</td>
<td>31</td>
<td>54%</td>
</tr>
<tr>
<td>Hematite Park</td>
<td>9500</td>
<td>36</td>
<td>45</td>
<td>44%</td>
</tr>
<tr>
<td>Taos Canyon</td>
<td>9100</td>
<td>8</td>
<td>73</td>
<td>10%</td>
</tr>
<tr>
<td>Tres Ritos</td>
<td>8600</td>
<td>31</td>
<td>49</td>
<td>32%</td>
</tr>
<tr>
<td>La Veta Pass</td>
<td>9440</td>
<td>44</td>
<td>36</td>
<td>55%</td>
</tr>
</tbody>
</table>

Table 3.2 Number of years April 1 represents maximum accumulation (1950-2017)

The third column shows the number of years where 1 April SWE values represented annual maximum per station. The fourth column shows number of years per station where Apr 1 values where less than annual maximum and the fifth column shows the percentage of years per station where Apr 1 SWE values represented annual maximum.
Figure 3.3 1 April SWE values against peak annual SWE values.

A regression plot showing a comparison of two extended SWE datasets (1950-2017) for the SDC range: The maximum annual SWE value is compared to the 1 April SWE values. Blue line represents 1 April SWE data while the red line represents peak or maximum annual values. The pluvial maximums are much better preserved by the 1 April SWE values than dry maximums. Post 2010: a deviation from the norm is evident. 1 April shows to be a good estimate of accumulation and snowmelt timing as in dry years the snowpack is significantly reduced prior to April 1st. Plot created in RStudio (2016).
3.2 Streamflow data

Streamflow discharge data were obtained from the U.S. Geological Survey (USGS, 2015). Four stations were selected for analysis based on logistics to headwater streamflow. All stations are upstream from damming and other potential anthropogenic effects (Table 3.3). The downloaded data consists of monthly values of streamflow in cubic feet per second (cfs). From these data, two subsets were derived: 1.) annual water year (WY) peak value (cfs) and 2.) annual WY mean value (cfs). Each of these were normalized to compare against normalized SWE and precipitation data. In addition to the monthly values downloaded and averaged to create the annual datasets, a dataset of 30-year (WY: 1981–2010) “normal”, which consists of mean monthly values over a period of 30 years, was created for comparison with USGS precipitation data (Fig. 3.4).

<table>
<thead>
<tr>
<th>Stream gauge ID</th>
<th>Station name</th>
<th>Start date (WY)</th>
</tr>
</thead>
<tbody>
<tr>
<td>08378500</td>
<td>PR near Pecos</td>
<td>1910</td>
</tr>
<tr>
<td>08379500</td>
<td>PR near Anton Chico</td>
<td>1910</td>
</tr>
<tr>
<td>08328650</td>
<td>PR near Santa Rosa</td>
<td>1976</td>
</tr>
<tr>
<td>08383500</td>
<td>PR near Puerto de Luna</td>
<td>1928</td>
</tr>
</tbody>
</table>

Table 3.3 Streamflow gauges from the upper region of the Pecos River.

Gauges were selected based on logistics: such as being upstream from damming and proximity to headwaters source. All streamflow data was obtained from http://wcc.sc.egov.usda.gov/nwcc (USGS, 2015).

Snowmelt runoff begins accumulating during the spring (AMJ) and runs through the growing season as reserves and timing of melt is sufficient. Fig. 3.4 shows that for the four stations above Sumner Dam this input contributes heavily to peak streamflow levels. The NAM inputs occurring from July to September are secondary in contributing to peak flows. It is noted that gauge stations further downstream are influenced to a lesser extent than those further upstream by snowmelt runoff and maintain high to moderate levels of flow for sustained periods relative to the shorter pulse of rapid flow upstream.
Figure 3.4 Streamflow monthly average values from four stations over 34 years (1981–2015).

All streamflow data was obtained from [http://wcc.sc.egov.usda.gov/nwcc](http://wcc.sc.egov.usda.gov/nwcc) (USGS, 2015). Streamflow gauge stations are represented as histogram clusters at each month. On the far right overall annual flow is represented. These boxes represent data from stations from further upstream to further downstream, left to right respectively. The black line represents the overall average across stations, calculated monthly, and is applied to a secondary y-axis on the right-hand side. It is evident that peak flow occurs in May due to snowmelt runoff, while the NAM season pulse is secondary and peaks in August. Created in Excel (2016).

From the visual interpretation provided in Fig 3.4 it would be assumed a robust statistical relationship between 1 April SWE values and peak annual WY streamflow could be established. Yet, while both annual peak or maximum WY flow and mean WY flow exhibit some relationship with 1 April SWE values ($R^2 > 0.27$), 1 April SWE was found to a possess a more robust relationship with the mean annual WY streamflow rather than with peak flow ($R^2 = 0.37$) (Fig. 3.6). It should be noted that no significant
relationship could be established, visually or statistically, between PRISM data (i.e. monsoonal warm-season inputs) and streamflow peak or mean flow.

Figure 3.5 1 April SWE vs. Pecos River streamflow for the upper region of the Pecos River (1981–2015)

WY annual flows are ran against Apr1SWE. Normalized data are presented the above plots. Top: April 1 SWE normalized values are compared to WY annual peak flow average for all five gauges ($R^2 = 0.23$). Bottom: April 1 SWE normalized values are compared to normalized WY annual mean flow from all five gauges ($R^2 = 0.37$). Created in RStudio (2016)
3.3 Precipitation data.

Gridded precipitation data values, produced by the PRISM Climate group at Oregon State University (PRISM, 2015) were downloaded to assess the summer NAM signal (Table 3.4). Monthly climate data for the period WY 1981–2016 were available for download on a county wide basis. Five counties in the upper PRB region were assessed. From these data, a peak annual precipitation dataset was derived. These annual peak values occur during June or August. These county wide data were used to create three separate datasets representing an upper, middle and lower region for the upper PRB (Fig. 3.8) to assess regional precipitation patterns. The Santa Fe and San Miguel county data were averaged to comprise the upper region dataset. This region represents the headwater USGS gauge near Pecos. The middle region consists of averaged Guadalupe, San Miguel and Torrance county data. This region influences the two middle gauges at Anton Chico and Santa Rosa. The lower region consists of averaged Guadalupe and De Baca county data. These counties represent the lower gauge at Puerto de Luna above Sumner Dam. Also downloaded was a 30-year normal (1981–2010; WY) dataset as mentioned above (Fig. 3.7).
<table>
<thead>
<tr>
<th>Month</th>
<th>De Baca</th>
<th>Guadalupe</th>
<th>Torrance</th>
<th>San Miguel</th>
<th>Santa Fe</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oct</td>
<td>1.45</td>
<td>1.30</td>
<td>1.33</td>
<td>1.34</td>
<td>1.29</td>
</tr>
<tr>
<td>Nov</td>
<td>0.49</td>
<td>0.62</td>
<td>0.64</td>
<td>0.68</td>
<td>0.80</td>
</tr>
<tr>
<td>Dec</td>
<td>0.62</td>
<td>0.73</td>
<td>0.80</td>
<td>0.70</td>
<td>0.88</td>
</tr>
<tr>
<td>Jan</td>
<td>0.47</td>
<td>0.44</td>
<td>0.46</td>
<td>0.51</td>
<td>0.59</td>
</tr>
<tr>
<td>Feb</td>
<td>0.37</td>
<td>0.44</td>
<td>0.45</td>
<td>0.51</td>
<td>0.54</td>
</tr>
<tr>
<td>Mar</td>
<td>0.54</td>
<td>0.64</td>
<td>0.59</td>
<td>0.77</td>
<td>0.88</td>
</tr>
<tr>
<td>Apr</td>
<td>0.70</td>
<td>0.74</td>
<td>0.52</td>
<td>0.83</td>
<td>0.69</td>
</tr>
<tr>
<td>May</td>
<td>1.18</td>
<td>1.38</td>
<td>1.02</td>
<td>1.50</td>
<td>1.07</td>
</tr>
<tr>
<td>Jun</td>
<td>1.34</td>
<td>1.55</td>
<td>1.18</td>
<td>1.81</td>
<td>1.26</td>
</tr>
<tr>
<td>Jul</td>
<td>1.96</td>
<td>2.38</td>
<td>2.54</td>
<td>2.69</td>
<td>2.09</td>
</tr>
<tr>
<td>Aug</td>
<td>2.25</td>
<td>2.62</td>
<td>2.50</td>
<td>3.15</td>
<td>2.19</td>
</tr>
<tr>
<td>Sep</td>
<td>1.83</td>
<td>1.89</td>
<td>1.74</td>
<td>2.18</td>
<td>1.55</td>
</tr>
</tbody>
</table>

Table 3.4 PRISM precipitation data for four counties in New Mexico.

Gridded precipitation data values, produced by the PRISM (2015) Climate group at Oregon State University (available online at http://www.prism.oregonstate.edu) were downloaded to assess the summer NAM signal.

A peak pulse in precipitation, occurring in late summer, represents NAM activity and is shown to exert less influence on streamflow for the upper Pecos River region than snowmelt runoff (Fig. 3.4, Fig. 3.7). The rationale for this includes considering long term water table fluctuations, and soil moisture availability. Evapotranspiration rates increase during warmer months and inherent temporal characteristics of strong convective storm release, which often result in flash flooding, provide little time for proper infiltration of these hydrologic inputs into the deep layers of the soil and the proliferate limestone features found in the RGRB and the PRB valley regions. Due to insufficient recharge time, warm-season precipitation has less influence in terms of the input amounts to the long-term (annual) water table ratio. Fig. 3.6 depicts NAM activity as peak summer precipitation (1981–2016).
Figure 3.6 Peak annual precipitation values (1981–2016).

Five stations are shown individually in light gray while the mean of all five is depicted by the black line. The green dotted line shows the overall linear trend of the mean value. A strong divergence from normal conditions is evident around 2012: a significant increase in NAM activity. Plot created in Excel (2015).

Interestingly, an out-of-phase summer-to-winter relationship has been established (Griffen et al., 2013) for precipitation events over the instrumental period for the SW and these findings are consistent with this pattern of increasing monsoonal activity in conjunction with decreasing snowpack reserves and streamflow found here. This out-of-phase relationship has been most pronounced in the last few years beginning in 2012 (Fig. 3.6, Fig. 3.5) which incidentally was the beginning of a strong El-Niño event.

Fig. 3.8 further establishes that peak precipitation does not coincide with peak streamflow over the instrumental period (Fig. 3.7). Again, this phenomenon is a result of precipitation over the cool-season period being stored as snow and released slowly over
time beginning in spring. However, it should be mentioned that the influence of the NAM is likely to increase further downstream, while the influence of snowmelt is most pronounced upstream. However, while the NAM precipitation signal appears to gain in significance further from the headwaters source, the annual peak precipitation values, i.e. NAM inputs, are increasingly higher in northern regions near the headwaters. Using grouped PRISM (2015) data based on a three-part regional delineation Fig. 3.8 shows a substantial increase in overall precipitation further upstream.

Figure 3.7 Pecos River streamflow vs. regional gridded precipitation

All precipitation data was obtained from www.prism.oregonstate.edu/explorer (PRISM, 2015). A precipitation PRISM dataset of 30-year (WY: 1981-2010) “normals”, where average monthly conditions over a 30-year period (1981-2010) are compressed into a single 12-month dataset, is represented by the grey histogram. This dataset is overlaid with a histogram of 30-year streamflow “normals” over the same period. Plot created in Excel (2015).
Figure 3.8 Gridded precipitation values at three regions along the PRB.

Here, the “Upper” region consists of precipitation averages over San Miguel and Santa Fe counties; the “Middle” region consists of precipitation averages over Guadalupe, Torrance, and San Miguel counties; the “Lower” region consist of southern Guadalupe and De Baca precipitation averages. An increase in precipitation primarily influenced by summer convective inputs as peak precipitation occurs in June-August in all counties is evident in more northern regions of the headwaters. Plot created in Excel (2015).

3.4 Conclusion

Thus it should be recognized that tree-ring proxy reconstructions may be better estimators of 1 April SWE values and thereby temperature and cool-season hydro-climate signal convergences. This would still be representative of overall soil moisture availability regardless of This chapter establishes the importance of cool-season hydrology inputs as snowpack accumulation and subsequent runoff are primary drivers of streamflow. A decrease in snowpack since 1980 in conjunction with a slight increase in NAM activity has been shown. Since 2012, significant fluctuations in the overall patterns
of data were evident in both the cool-season (SWE) and warm-season (peak precipitation) datasets, as sharply decreasing and increasing trends, respectively. Also, an interesting divergence is seen in the SWE peak and 1 April datasets regression plot during these last few years. These suggest implications for future research on a potentially changing climate regime.

Earlier snow melt – exhibited here by divergences from peak and 1 April SWE values – could potentially indicate shortages later in the growing season. This study has also shown that 1 April SWE values are typically good indicators of snowpack accumulation but less so in dry years; however, this feature may be useful as a quantitative measure of early snowmelt which has potential impacts on tree growth as well as streamflow parameters and overall watershed conditions. Future studies might analyze various SWE parameters for potential in tree-ring reconstructions if this trend in divergence between peak accumulation and 1 April values continues.
CHAPTER IV–METHODS

Tree-ring derived indices were used as a proxy to reconstruct cool-season hydro-climatic variability for the SDC range. Statistical models have been produced from step-wise multiple regression analyses, using tree-ring indices derived from pre-determined species within a specified region as a proxy record for snowpack, i.e. cool-season precipitation, variability. In order to estimate the ability of this model to capture the regional climate signal the tree-ring time series rendered indices serve as the predictor variables and are regressed onto instrumental records, the predictand variables, over a common period of overlap. Methods used here, e.g. PCA, and step-wise regression, are common tools for paleo-climatology (Cook et al., 1999; Cook et al., 2013; Meko, 1997; Salzer and Kipmueller, 2005; Woodhouse 2003;). Here the most current methods are applied to build statistical and visual models of cool-season precipitation for the SDC range.

4.1 Preliminary Model

To estimate the ability of tree-rings to capture the cool-season climate signal a preliminary model was constructed. Data were obtained from five regional snow coarse data sites using the United States Department of Agriculture’s NRCS (2015) website. These five stations possess snow coarse data from the SDC range extending into the 1930s; four in NM and one in CO. Preliminary analysis showed a high degree of fidelity amongst the five SWE data stations, as determined by a principle components analysis (PCA) using SPSS software ($R^2 = 0.83$). Through further statistical analysis it was possible to determine the relevancy of a proxy reconstruction for snowpack along the SDC range by comparing the existing tree-ring data obtained from the ITRDB website
within the region to the first principle component (PC$_1$) dataset of instrumental snowpack. All available tree-ring chronologies were obtained from the ITRDB for the entire state of NM (ITRDB, 2015). The ITRDB Google Earth Map (2017) link was used to assess locations of tree-ring sites in range in southern CO. After running all chronologies through ARSTAN (2015) to obtain residual output files, all standardized indices were ran against the PC$_1$ of SWE

1 April SWE instrumental data (PC$_{1SWE}$), using the program PCReg (2017). The ARSTAN residual chronologies achieved an $R^2 = 0.68$. A total of 128 chronologies were uploaded with 62 retained for modeling. All chronologies were “pre-whitened” in ARSTAN and only lag 0 chronologies pulled into the model with two exceptions of chronologies pulling in at lag + 1. The preliminary orthogonal eigenvector-based PCA model explained a significant amount of the variance in the 1 April SWE dataset over the common period (1937–85) and exhibited potential for building a robust model of snowpack variability.

4.2 Tree-ring data

Trees selected for this study were sampled along altitudinal gradients of the species elevation range limits where montane conifer forest zones transition to subalpine fir and grasslands along talus deposits of montane regions and canyon slopes. In order to update and collect new chronologies, moisture-sensitive species were targeted at locations based on geophysical features, such as well-drained thin soils, appropriate spatial range to the instrumental data, i.e. within the climate footprint, and statistical relevance.
4.2.1 Targeting tree-data collection sites

Tree-ring chronology sample sites expand throughout the American SW. Determining which chronologies sites to target for best potential predictors requires intimacy with geophysical processes involving the trees and climate. Appropriate species selection for this study required targeting species known to be moisture sensitive and growing on south facing rocky scree slopes within arid regions. Lower elevation pines are typically targeted for SW drought reconstructions as moisture sensitive species (Fritts, 1976; Hidalgo et al., 2001; Salzer and Kipfmueller 2005; Schulman 1956). South facing slopes are favorable as they receive more radiation on average and subsequently are more prone to drought. In addition, trees are sampled along ecotonal boundaries where trees are growing along the furthest extent of their biogeographical range. Selection of specimens at the edge of their latitudinal, longitudinal, and elevational range further maximizes response to exogamous environmental stressors. The pine species selected for this study were sampled along altitudinal gradients of the species elevation range limits where montane conifer forest zones transition to subalpine fir and grassland zones.

In addition to selection based on specific species growing in ideal conditions statistical supplementation was provided from the preliminary analysis to narrow in on best potential predictors. Adding existing potential predictor chronologies from the ITRDB into statistical modeling software, allows for insight into which sites and what species correlate well with the instrumental data. According to Tobler’s First Law (Tobler, 1970) the sites nearest to the station instrumental data should on average be the best indicators. However, geo- and bio-physical variation between tree species, site characteristics, and climate fluctuations on micro-to-regional scales produce multifaceted
connections of various strengths between the climate variable of interest and the trees within the region.

To reconstruct moisture availability in semi-arid regions involves trimming the various contributions to the growth patterns in individual trees in order to reveal the limiting environmental signal at the appropriate scale. Often distortions to the influence of the primary driver are limited in influence only when considered over the certain scales of time and space. Local scale influence, e.g., will typically diminish at broader scales of analysis. As long as one or more environmental factors remains significant over an extended spatial and temporal scale cross dating and subsequent averaging over space and time will bring out the dominant regional signal which is revealed to be the controlling factor on seasonal ring-width growth for that region. Thus, spatial filtering often involves simply targeting the appropriate number for trees over an appropriate range for that particular climate signal of interest. Temporal filtering often involves reducing the effect of confined events found at low frequency scales in order to highlight the higher frequencies produced by a seasonal climate driver.

To better understand the appropriate spatial scale of the regional cool-season signal a *climate footprint* (Harley et al. 2016) overlay of the region was constructed. A climate footprint designates regions of robust statistical correlation which correspond to a continuous range of similar climatic conditions. In the case of modeling precipitation, interpolative equations are applied to rain gauge data to generate a gridded field of similar hydro-climatic features which is then ran against the instrumental data to determine the spatial scale of the instrumental climate signal.
The KNMI Climate Explorer (2017) tool was used to determine the climate footprint for cool-season precipitation over the SDC range for the extent of the instrumental data (1937–2017). A field of gridded PRISM (2015) data points was evaluated against our PC1SWE data for correlation analyses (Fig 4.1). An inner-basin tree-ring proxy data collection may be compared against a broader regional collection, where the former targets trees within an a priori set boundary, i.e. a watershed, based on arbitrary geophysical assumptions, while the later targets trees within a spatial boundary, typically broader in region, derived from the footprint analysis which incorporates a quantitative measure of the climate signal into a spatial field of consideration, statistically. It is hypothesized that the later will produce a more descriptive model (Cook et al., 1999).
Figure 4.1 The regional climate signal for SDC snowpack.

Tree-ring sites used to reconstruct Apr 1SWE were selected from highly correlated regions in close proximity to the upper RGRB and the PRB regions. Map created from data derived from an analysis ran using the KNMI Climate Explorer (2017) tools at climexp.knmi.nl. PRISM gridded precipitation data is correlated against Apr1SWE values: the color coded gradient of correlation is shown in the legend. Map created in ArcMAP (ESRI, 2017).

4.2.2 Collection

The overlap of data from the preliminary analysis of ITRDB tree-ring sites and NRCS snowpack data allowed a for a common period of forty-eight years (1937–85). Due to a lack of tree-ring data sites in the ITRDB extending beyond 1985 into the present statistical relevance diminished after this period. However, forward nests have been run and statistics shown for all forward models extended beyond 1985 to 2014.
Of the 3000 plus tree-ring chronology data sets on the ITRDB website at least 809 of them terminate between 1950–80, while another 856 are truncated in the 1980s (Grissino-Mayer and Fritts 1997; Larson et al., 2013). Updating chronologies to a more current date allows for a broader window of overlap between the predictor (tree-ring data) and the predictand (instrumental data). This may add skill to the model, by reducing error and by producing more robust relationships between the variables. A temporal increase in data would also allow for extended reservation of data over the “common period” to be used in error analysis by way of verification statistics. Updating sites also allows for extension of data into the past. In targeting sites for updating two goals were considered: 1. extend the reconstruction model back in time as far as possible and, 2. extend the statistically validated common period overlap forward beyond 1985.

Eight chronology sites, based on the statistical relationships observed from the preliminary analysis and accessibility, were visited in the summer of 2016 for sampling and updating (Table 4.1). Using standard dendrochronology methods (Stokes and Smiley, 1968) seven established sites were collected along with one new site previously unsampled. Using a screw-tip bore to extract pencil size cores from 15–30 trees per site is standard (Fritts, 1976), yet when updating previously established sites 10–20 trees per site is standard. Two cores were extracted from 12–15 living trees at all seven sites and from 20 living trees at the new location. The selected location for the development of a novel chronology was a canyon on private land near El Moro national monument with steep rocky slopes and numerous old-growth ponderosa pine [Pinus ponderosa (PIPO)] and pinyon pine [Pinus edulis (PIED)]. Permission was granted by owner; for all other sites permits were obtained from the Carson National Park service, El Morro National
Monument, and the Navajo Forestry service. All new sites sampled were comprised of PIPO and PIED.

A diversity of tree ages was sampled to filter out physiological variance. Young growth often exhibits relatively large ring-widths as spurious growth is an adaptation of trees born from competition for open canopy or as an adaptation for escaping mortality caused by fire and/or grazing. For much older trees, ring-widths often decrease with increasing years up to some asymptotic limit (Cook et al., 1995). Therefore, both size and age are seen to affect the ring-width patterns particularly at the inner and outer boundaries of the individual tree-ring segments.
Table 4.1 Eight chronology sites selected for sampling from the ITRDB.

<table>
<thead>
<tr>
<th>r</th>
<th>Beginning Year</th>
<th>End Year</th>
<th>Investigator</th>
<th>Site Name</th>
<th>Species</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.802</td>
<td>1392</td>
<td>1972</td>
<td>Dean</td>
<td>Satan Pass</td>
<td>PSME</td>
</tr>
<tr>
<td>0.758</td>
<td>1629</td>
<td>1976</td>
<td>Dean</td>
<td>Burning Bridge Wash</td>
<td>PIED</td>
</tr>
<tr>
<td>0.752</td>
<td>1595</td>
<td>1972</td>
<td>Dean</td>
<td>Turkey Springs</td>
<td>PIPO</td>
</tr>
<tr>
<td>0.731</td>
<td>1477</td>
<td>1972</td>
<td>Robinson/Dean</td>
<td>Fort Wingate</td>
<td>PIED</td>
</tr>
<tr>
<td>0.721</td>
<td>1662</td>
<td>1972</td>
<td>Dean</td>
<td>Cebolleta</td>
<td>PIED</td>
</tr>
<tr>
<td>0.714</td>
<td>1304</td>
<td>2007</td>
<td>Touchan</td>
<td>Fenton Lake</td>
<td>PSME</td>
</tr>
<tr>
<td>0.707</td>
<td>1570</td>
<td>1978</td>
<td>Cleaveland</td>
<td>Peublita Canyon</td>
<td>PSME</td>
</tr>
<tr>
<td>0.696</td>
<td>620</td>
<td>2011</td>
<td>guiterman</td>
<td>canyon del potro</td>
<td>PIPO</td>
</tr>
<tr>
<td>0.686</td>
<td>1411</td>
<td>1972</td>
<td>Dean</td>
<td>Turkey Springs</td>
<td>PIED</td>
</tr>
<tr>
<td>0.686</td>
<td>1638</td>
<td>1972</td>
<td>Dean</td>
<td>El Morro</td>
<td>PIED</td>
</tr>
<tr>
<td>0.752</td>
<td>1594</td>
<td>1971</td>
<td>Dean</td>
<td>Pueblita Canyon</td>
<td>PSME</td>
</tr>
<tr>
<td>0.752</td>
<td>1594</td>
<td>1971</td>
<td>Dean</td>
<td>Pueblita Canyon</td>
<td>PIED</td>
</tr>
<tr>
<td>0.68</td>
<td>1621</td>
<td>1981</td>
<td>Swetnam</td>
<td>Garcia Park</td>
<td>PIPO</td>
</tr>
<tr>
<td>0.678</td>
<td>1295</td>
<td>2007</td>
<td>Touchan</td>
<td>Echo recollection (Dean)</td>
<td>PSME</td>
</tr>
<tr>
<td>0.677</td>
<td>1760</td>
<td>1978</td>
<td>Cleaveland</td>
<td>Peublita Canyon</td>
<td>PIED</td>
</tr>
<tr>
<td>0.674</td>
<td>1572</td>
<td>1986</td>
<td>Swetnam</td>
<td>Cat Mesa</td>
<td>PIPO</td>
</tr>
<tr>
<td>0.674</td>
<td>644</td>
<td>2007</td>
<td>Touchan</td>
<td>Mesa Alta</td>
<td>PSME</td>
</tr>
<tr>
<td>0.672</td>
<td>1687</td>
<td>1976</td>
<td>DEAN</td>
<td>Ned Tanks</td>
<td>PIED</td>
</tr>
<tr>
<td>0.67</td>
<td>1362</td>
<td>1972</td>
<td>DEAN</td>
<td>Echo Park</td>
<td>PSME</td>
</tr>
<tr>
<td>0.666</td>
<td>1536</td>
<td>1972</td>
<td>Dean</td>
<td>El Morro</td>
<td>PIPO</td>
</tr>
<tr>
<td>0.64</td>
<td>1291</td>
<td>1987</td>
<td>Graybill</td>
<td>Black mountain</td>
<td>PSME</td>
</tr>
<tr>
<td>0.618</td>
<td>1600</td>
<td>1997</td>
<td>Ryerson</td>
<td>Terrace Lake Pines, CO</td>
<td>PIPO</td>
</tr>
<tr>
<td>0.613</td>
<td>1675</td>
<td>1997</td>
<td>Ryerson</td>
<td>Wilson Ranch</td>
<td>PIPO</td>
</tr>
<tr>
<td>0.602</td>
<td>1543</td>
<td>1986</td>
<td>Swetnam</td>
<td>Rio Pueblo</td>
<td>PIPO</td>
</tr>
</tbody>
</table>

Eight sites (blue highlight) were selected based on statistical relevance and logistics and successfully collected. Due to time constraints, only three of these (Burning Bridge Wash, Garcia Park, and Rio Pueblo) were processed to completion for statistical analysis.
Figure 4.2 Field data collection at Burning Bridge Wash, NM with Navajo Forestry guide and Dr. Justin Maxwell.

Pictured are Dr. Justin Maxwell (Dendrochronologist @ the University of Indiana) and Navajo Forestry team member Tim Jim standing in the canyons at Burning Bridge Wash, NM. Many Pinyon pines (PIED) were sampled at this site (photo courtesy of Michael Thornton: 2016).
4.2.3 Data preparation (COFECHA and ARSTAN)

Four sites were developed in the lab; three updated sites: Garcia Park (GAR) and Rio Pueblo (RIO) within Carson National forest; and Burning Bridge Wash (BBW), located on Navajo land; and one new site: Maquis Canyon (MCE). Samples from the field were mounted and sanded using increasingly finer-grit sandpaper until the transverse plane was finely polished for viewing purposes under a low magnification light reflecting microscope. Sanding core-samples of living trees, with progressively finer grit sandpaper, is standard and allows for proper delineation of the tree-ring boundaries. Specimens were examined and analyzed for crossdating purposes. The “memory method” (Douglass, 1941) was utilized by examining all cores under the microscope numerous
times, using a pencil to mark conspicuous rings and to assign numeric decades on the core. All cores were scanned at 1,200 dpi and measured using WinDendro (Regent Instruments Canada Inc., 2009). Rings were measured to the nearest .001 mm. Microscope and scanned computer image perspectives of cores were used concurrently with WinDendro to assess ring boundaries.

After initial measurements, COFECHA (Grissino-Mayer, 2001; Holmes, 1983) was used for crossdating quality control. This software performs statistical analyses and reports correlation values. It also assesses and flags potential crossdating errors and makes suggestions accordingly. This program was used simultaneously with WinDendro and microscope analyses to ensure proper crossdating based on statistical probabilities and repeated observations.

COFECHA detrends and standardizes all tree-rings to factor out age-related growth trends and low frequency noise using a 32-year cubic smoothing spline, with a 50% frequency response cut-off, i.e. a minimum of 50% variance remains. Core samples were examined over 50-year segments with 25-year overlap. Autoregressive (AR) modeling removes autocorrelation to produce residual chronologies used to produce a master chronology of the site combining all data from each successively correlated core from that particularly site. Pearson correlation analysis was used with a 90% confidence interval ($p = .10$). Interseries correlation values for all four sites ranged from .077 to 0.81 while mean sensitivity values, a measure of complacency, ranged from 0.4 to 0.63. The output files are plotted below for visualization purposes. There are eight plots: two for each site. A spaghetti plot shows line frequencies the raw ring index, while a correlation plot shows crossdating correlation skill for each core (Fig. 4.4). New and existing data
are shown together. New data extends into the present while older ITRDB data do not. With the exception of the MCE plot which consists entirely of newly collected data.
Figure 4.4 Correlation segment and spaghetti plots of COFECHA output.
Figure 4.4 Correlation segment and spaghetti plots of COFECHA output. Continued.
Figure 4.4 Correlation segment and spaghetti plots of COFECHA output. Continued.
Figure 4.4 Correlation segment and spaghetti plots of COFECHA output. Continued.

Spaghetti plots of all four cross-dated chronologies are exhibited (a1, b1, c1, d1) followed by correlation segment plots (a2, b2, c2, d2) for (a) Burning Bridge Wash, (b) Garcia Park, (c) Maquis’ Canyon, and (d) Rio Pueblo. In the spaghetti plots each black line represents an individual tree-ring core and is labeled appropriately. In the correlation plots each 50-yr. segment is color coded based on correlation with the “master” or overall chronology. Areas in red show areas which failed to statistical cross-date. Created in RStudio (2016).
<table>
<thead>
<tr>
<th>Site Name</th>
<th>Site Code</th>
<th>Inter-Series Corr.</th>
<th>No. of Dated Series</th>
<th>Time Span</th>
<th>Number of Flags</th>
<th>Mean Sensitivity</th>
<th>Mean length</th>
</tr>
</thead>
<tbody>
<tr>
<td>Garica Park</td>
<td>GPK/GPP</td>
<td>0.782</td>
<td>46</td>
<td>1621-2015</td>
<td>0</td>
<td>0.399</td>
<td>180</td>
</tr>
<tr>
<td>Rio Pueblo</td>
<td>RIO/RPP</td>
<td>0.808</td>
<td>60</td>
<td>1543-2015</td>
<td>1</td>
<td>0.482</td>
<td>263</td>
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<tr>
<td>Burning Bridge Wash</td>
<td>BBW</td>
<td>0.811</td>
<td>61</td>
<td>1629-2015</td>
<td>2</td>
<td>0.622</td>
<td>235</td>
</tr>
<tr>
<td>Maquis Canyon</td>
<td>MCE</td>
<td>0.770</td>
<td>21</td>
<td>1602-2015</td>
<td>3</td>
<td>0.634</td>
<td>292</td>
</tr>
</tbody>
</table>

Table 4.2 COFECHA output from four sites.

Depicted are four low-elevation conifer species chronologies from Northern NM. The new site (MCE) depicts less individual cores collected then the other three updated sites due to requirements of new site data collection. Rio Pueblo dates back in time further than other chronologies however MCE possesses the longest mean chronology length, which is a measure of average age/length of individual time series. MCE also possesses the highest mean sensitivity, a measure of complacency from one year to the next, indicating a high degree of stress on trees at sites with higher mean sensitivity values. Naturally sites with higher sensitivity typically have a higher number of flags, as missing rings and an overall wide range of variability from year to year is likely to cause complications cross-dating procedure. Inter-series correlation, a measure of overall agreement between individual time-series and the master chronology is also given.

In addition to raw ring-width values derived from existing chronologies downloaded from the ITRDB new raw ring-width values output from WinDendro were detrended in batch mode using the program ARSTAN (Cook 1985; LDEO TRL, 2006); a widely used program for dendrochronological analysis. ARSTAN removes signal noise, e.g. local scale influence, to obtain a stand level or regional scale climate signal. The signal expressed should define the linear controls of the limiting factor on tree-growth for that particular region and/or species. Assuming appropriate species and site selection, the limiting factor controlling tree growth should be the climate variable of interest. ARSTAN was used to standardize all tree-ring text files in order to obtain an estimation of the mean value function and thereby reduce unwanted signal noise. Standardization involves detrending and transformation of data. Detrending removes age-related growth
trends and non-climatic frequencies by applying a smoothing spline to the data. The low-frequency fluctuations, i.e. decadal to multi-decadal scale, are assumed to be unwanted environmental noise and removed (Cook et al., 1995) where as high-frequency variability, i.e. year to year fluctuations, are retained. This method is appropriate when considering drought and pluvial events in a data set. In general, the transformation of data in the standardization process refers to indexing and detrending all tree-ring values for comparison. After standardization, an approximation of the mean value function is applied to the tree-ring indices in order to highlight the regional stand level variance while diminishing the unique variance within individuals and nearest neighbors over common time intervals (Cook, 1999).

ARSTAN outputs four types of output. First a “raw” ring-width chronology, which is mean annual values in mm. without detrending or standardization. The detrending is then applied with empirical curve fitting. A negative exponential curve is typically used to remove the age-related growth trend, though if negative values occur a straight-line fit may be used. Both result from a least-squares method which reduces the sum of the residuals (Cook, 1985). Further detrending and standardization divides the ring width values by the fitted curve value (Cook, 1985). Here, a 2/3 of the mean segment length cubic smoothing spline with a 50% frequency-response was applied to all data transformations (Cook and Peters, 1981). This double-detrended ring-width indices result in a “standard” chronology with a mean of 1.0.

The following outputs produced are the “residual” chronology (crns.res) and the “ARSTAN” chronology (crns.ars). The crns.res removes low-order persistence using residual autoregressive (AR) modeling (Box and Jenkins 1976). This low-order
persistence in ring growth patterns is considered to be of biological origin where a pervious wet or dry year would affect the growth of the following year(s) by reducing or increasing carbon stores (Cook, 1985). This biological inertia needs to be filtered out in order to obtain the annual influence of climate (Cook, 1987). AR modeling considers the current year’s ring index value is a function of the previous year(s) value. Residual values are produced and retained for modeling where predicted values are subtracted from the actual values of the current year. The crns.res is the result of a statistical process termed “pre-whitening” or removal of “white” noise (Cook, 1985). The final crns.ars chronology factors the removed persistence back into the model by “reddening” the crns.res.

The residual chronology indices were used as predictor variables for the reconstruction model as residual chronologies are typically better predictors for stochastic hydro-climatic data (Griffin, 2007) since autocorrelation from biological inertia within the tree-ring data structure is removed. A user defined lag is applied to all tree-ring indices and these lagged variables with a subset of non-lagged variables is ran against the annual SWE predictand variables. If there is significant autocorrelation in the instrumental data lagged variables will be pulled into the model.

4.3 Snowpack data

The United States Department of Agriculture NRCS National Water and Climate Center produces monthly historical SNOTEL and snow coarse data for snow water equivalent (SWE) and snow depth by state. Data was collected from the NRCS (2015; 2017) website for NM and CO for the SDC range as described in section 1.2. 1 April SWE data was used as it is a good estimator of annual snowpack accumulation and seasonal snowmelt timing on average. Five stations possessed the necessary temporal
duration for statistical regression analysis with the tree-ring time-series. To calculate missing values for all stations an average of standardized values was used. For any missing annual record at a station all other station values for that year were standardized per station, column-wise. Next the average of all these standardized values at that year over each station was used to estimate the value of the missing year:

\[ S\mu_i = (\sum Pzi) / N \]

\[ Pzi = (x - \mu) / \sigma \]

\[ \mu = (\sum X) / N \]

\[ \sigma = \sqrt{\sum (Xi - \mu)^2 / N} \]

Such when a missing value is located, z-scores at year i (zi), the year of the missing value, are calculated for each non-missing data station (P) using the standard deviation (σ) and the mean (μ) of each station (P). Next, Sμ i is calculated; the average of all Pzi values at year i. Next an average of the nearest neighbor original values (i.e. non-standardized) is placed in the empty cell representing the year of missing data and then this value is adjusted until a standardized version of the value is a closest match estimate of the averaged previously calculated standardized value (Sμ i). This method takes into account the relationship that a particular year (a year with a missing value) has with all other years for each station and then by finding the average value of each stations standardized index for that year, the missing value adjusts until its standardized form matches this estimate so that a more correct relationship is implied. This should produce a more accurate estimate than a nearest neighbor average. Using the method described here allows for detection of high frequency patterns such that the substitutes of missing
values take into account the relationship of that particular stations entire dataset and is based on the other stations fluctuations for that year as well.

A PCA was then ran on all five stations along the SDC range that extend to or beyond 1938 with missing values estimated extending the time period (1937–2016) using IBM’s SPSS statistical analysis software (Table 4.3). PC1 explained 83% of the variance between stations and retained all five stations from the SDC Range on the first axis. As is evident from a strong amount of common variance on the first PC axis, PC$_{1\text{SWE}}$ strongly represents regional snowpack variation for the SDC range.

<table>
<thead>
<tr>
<th>Site name</th>
<th>State</th>
<th>Elevation</th>
<th>Start year</th>
<th>Latitude</th>
<th>Longitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hermatite Park</td>
<td>NM</td>
<td>9500</td>
<td>1937</td>
<td>36.67</td>
<td>-105.37</td>
</tr>
<tr>
<td>Taos Canyon</td>
<td>NM</td>
<td>9100</td>
<td>1937</td>
<td>36.41</td>
<td>-105.33</td>
</tr>
<tr>
<td>Tres Ritos</td>
<td>NM</td>
<td>8600</td>
<td>1938</td>
<td>36.13</td>
<td>-105.53</td>
</tr>
<tr>
<td>Panchuela</td>
<td>NM</td>
<td>8400</td>
<td>1937</td>
<td>35.83</td>
<td>-105.67</td>
</tr>
<tr>
<td>La Veta Pass</td>
<td>CO</td>
<td>9440</td>
<td>1938</td>
<td>37.6</td>
<td>-105.02</td>
</tr>
</tbody>
</table>

Table 4.3 Snow coarse data sites used to create our PC$_{1\text{SWE}}$ dataset.

4 sites from NM and 1 from CO are used as the only sites extending back in time to 1938 and beyond along the SDC range. These sites all load on the first PC axis and 83% of the variance is explained.

4.4 Calibration and Verification

The program PPR (Point-by-Point Regression) developed by Ed Cook was used to produce the final reconstruction model. PPR has been shown to work well in drought reconstructions (Cook et al., 1999) that require a multiple-predictor-multiple-predictand scenario but also work as well for a single-predictand scenario as demonstrated by Cook et al., 1999. Here multiple-predictors, i.e. standardized tree-ring chronologies, are used against the PC$_{1\text{SWE}}$ data. PPR is based on a principle component regression (PCR) analysis to produce estimates of instrumental data using multi-dimensional proxy data, i.e. tree-rings chronologies. This is a method of reducing complexity and dimensionality.
in data and accounts for the maximum amount of variance while minimizing inflation from covariance. A regression constant (bo) is defined as the intercept of the y value when x = 0. A matrix of regression coefficients is also calculated (B) to be applied to each tree-ring index. The tree-ring index (U) at year i is derived of a matrix of orthogonal tree-ring principle component scores created to eliminate compounding covariance issues which extend from multidimensional-multivariate datasets. Finally, error in the form of a vector of regression residuals or model errors (e) is calculated and added to the equation. 

\[ Y_i = bo + \sum \Sigma BU_i + ei \]

This is the common equation used in PCR for linear regression of multivariate analysis in tree-ring drought reconstructions. However, PPR has an automated nested reconstruction feature not found in other software programs, to account for sample depth variance over time as well as rigorous error assessment statistics built in.

When reconstructing back in time, differences in the size and the composition of the time-series proxy data result in various degrees of inherent error and thus the ability of the data to accurately estimate climate phenomenon changes as well whenever significant changes in the time-series data occur. The most recent period, used for calibration with the instrumental data, typically contains the largest sample size and thereby often the highest estimation ability, and this skill with sample size generally decreases as the data composition changes back in time. Thus, validation statistics calculated from this most recent period, which includes data from all of the youngest and oldest trees, should not apply to regions of the time-series where the composition and the
sample depth of the data has changed significantly. This potential for bias can be largely eliminated by using a nested approach where multiple reconstruction models are assembled, each possessing a unique temporal and spatial representation (Cook et al., 1999), such that whenever sample depth and subsequently data composition significantly changes through time a separate reconstruction model is produced, based on new parameters, with its own correlation and validation statistics.

Overestimations in reconstruction skill have historically been accounted for with the subsample signal strength (SSS) statistic which addresses increasing error from changes in sample depth (Cook and Pederson, 2011; Wigley et al., 1984). Yet when at any particular site there is relatively large amounts of tree-to-tree variance of the signal strength inherent in the growth response increases in sample depth can drown out the signal where few trees possess a stronger signal comparatively and make SSS statistics invalid (Meko, 1997). Furthermore, as predictors are typically on a site by site basis where entire site chronologies produce indices based on mean value functions calculated over each particular site, individual trees containing important signal trends may be diluted or cut short of their early period data.

Instead of taking site chronologies, PPR takes in indices of individual trees from all sites at once (Cook et al., 2013; Meko, 1997). Then the separate regression models are estimated and validated for all trees. This method allows for the entire time series of each tree to be utilized from beginning to end. A user defined lag function determines how many potential predictors enter the model by lagging the tree-ring data + or – in years for each year of the climate variables. Our model retained only lag 0 indices. This is expected as it is less likely that lagged predictors will enter a hydro-climate model when
“pre-whitening” is performed before hand (Meko and Graybill, 1995), as was accomplished in the ARSTAN procedure, unless the climate variable contains significantly autocorrelated data itself. Thus time-filtering is applied once more, and is the first step in the model building process which reverses the effect of potential multicollinearity of the data (Meko, 1997).

Next $k$ subsets of tree-ring data are produced where the beginning years of the oldest trees are represented by the smallest, typically single-tree, subset, while the model containing the most recent years will be represented by a subset of a relatively large number of trees (Meko, 1997). From these data subsets of individual trees is formed a matrix of $x$ years for $n$ trees. Models are fitted by entering tree-ring indices stepwise in decreasing order of contribution to the reduction of residual variance calculated by the leave-one-out method, until they fail to increase the adjusted $R^2$ (Cook et al., 2013; Weisberg 1985). These subsets create a ‘nested suite’ of reconstructions, separated by at least ten years (Cook et al., 2013). Each reconstruction overlaps the instrumental data completely during the “common period” and has its own calibration and verifications equations for model assessment and cross-validation purposes. The full reconstruction is created by appending each subset back in time. After separate models are produced scaling the separate subset reconstructions accounts for variance differences over all models (Cook et al., 2013). The resulting stats calculated include the average variance explained over the calibration period (CRSQ) or coefficient of multiple determination which indicates the goodness of fit of the model. This is calculated by subtracting from 1 the total sum of errors over the total sum of variance found in the calibration model. In
theory this can also be achieved by subtracting the amount of unexplained variance from one.

Next the reduction of error (CVRE) for the calibration period is calculated using the leave-one out method. A validation period, i.e. verification period, \( r^2 \) is computed as the square of the Pearson correlation value. Next is the verification period measure of error statistics: verification reduction of error statistic (VRE) and verification coefficient of efficiency (VCE). These stats have quotients with identical numerator equations which contain a measure of error by way of the sum of squares of the residuals (SSres), i.e. the unexplained variance. The denominator equations on the other hand, containing a measure of total observed data variance by way of the sum of squares of the total variance (SStot), diverge where the observed calibration period data mean is substituted for the verification period mean in the VRE statistic but retained in the VCE equation. Otherwise these equations are analogous to the calibration \( R^2 \) (CRSQ) equation yet applied to a separate subset of data, i.e. the verification period. However, while CRSQ has finite range of 0–1, VRE and VCE have a theoretical range of infinity - 1.0 and thus much more difficult to pass.

As for VCE and VRE, VCE is the more difficult to pass. If calibration mean and verification mean are equal then \( RE = CE \) yet otherwise \( RE \) will always be > \( CE \) as it uses a substitution mean from another dataset which will always produce a larger denominator in the equation thus reducing the value to be subtracted from 1. A positive value of \( RE \) and \( CE \) are considered to show skill in the reconstruction model. A value <0 is considered to have no skill or not enough skill to accurately represent the predictand variables over time.
Limitations from these statics include a lack of theory based testing which is largely accounted for here by the use of the maximum entropy bootstrap (MEBoot) method (Cook et al., 2013). Uncertainties in the form of regression prediction intervals are provided where direct estimates are constructed from MEBoot pseudo-reconstruction parameters. MEBoot differs from traditional bootstrap methods in that MEBoot does not disrupt the time order sequencing of data when resampling with replacement (Cook et al., 2013). The MEBoot method is applied to both the predictor and the predictand variables to account for error on both sides of the regressions models. As a replacement for traditional test statistics (t-tests) an empirical density function produced from 300 MEBoot runs is applied. The traditional parametric prediction intervals (Olive, 2007) using t-tests values is preserved here but this method applies non-parametric data from the MEBoot application which results in semi-parametric prediction intervals (Cook, et al., 2013). This produces 300 calibration and verification statistics measures. The average of these is shown in Table 4.2
CHAPTER V–RESULTS AND DISCUSSIONS

5.1 Reconstruction model results

The nested suit of reconstructions was developed from a 37 tree-ring site chronology subset of best candidate predictors retained from preliminary analysis and includes updated and new chronologies. Although only 25 were retained for modeling. All tree-ring chronologies had beginning years from 10 to 1675 CE and end in years from 1985 to 2015 CE.

The best model was constructed from a calibration period of 1955–85 (30 years) with the verification period, 1937–84 (17 years), withheld for independent validation statistics (Cook et al., 2013; Fritts, 1976). This model explained 64% of the variance in the PC_{SWE} dataset. Although, updated sites were included there was not enough statistical significance in the added data to maintain this high level of explained variance in the forward nests (see Table 5.2). The relatively short validation period is compensated through comparison of our reconstruction to other fully independent reconstructions in the region, a method proposed by Cook (2013). Error results are shown in Fig. 5.2 and Table 5.2. A split sequencing calibration/verification test was also performed (Fig 5.3), where the entire overlap period (1937–85) was used as the calibration period ($R^2 = 0.60$) and then a split calibration/validation period sequence produced stats for each half (Meko and Graybill, 1995) based on predictability of the reserved half.

For model building each chronology was analyzed against the PC_{SWE} for both year $t$ and $t + 1$, a total of 74 chronologies, and only those with significant correlation values ($p < 0.01$, 2-tailed) were retained in the model (Cook et al., 1999). The screening procedure reduced the predictor pool from 74 to 25 tree-ring chronologies retained. With
the exception of two chronologies, all chronologies retained consisted of the three most common low-elevation pine species used in the SW for drought reconstructions: Douglass fir \([Pseudotsuga menziesii (PSME)]\), PIED, and PIPO. Of the two exceptions, one was produced from Juniper \([Juniperus scopulorum (JUSC)]\)—the oldest and consequently the longest chronology—and derived from trees growing in a lava field near the El Malpais National Monument, and the other collected at Bear Canyon, derived from Southwestern white pine \([Pinus strobiformis Engelm (PISF)]\). The robust climate correlations with low-elevation conifers is due to a relationship between cool-season precipitation and the growth response in these species at specific geographical locations (Cook, 1985; Fritts, 1976; Hidalgo et al., 2001; Salzer and Kipfmueller, 2005). All chronologies were positively correlated with \(PC_{\text{SWE}}\) at year \(t_0\) (i.e. no lag). Residuals from the regression plot were found to be evenly distributed.

The spatial distribution of the chronologies used for modeling is shown in Fig. 5.5. The chronologies are size-coded to reveal correlation strengths. The spatial pattern of chronologies used can be explained by the KNMI Climate Explorer (2017) climate footprint map where areas of high correlation from the relationship of PRISM gridded precipitation data with hydro-fluctuations in the instrumental snowpack data reveal more robust relationships between tree-ring growth response and snowpack measurements. Chronologies fall within this climate footprint and follow the climate footprint patterns in correlation strength (Fig. 5.5). Locally trees are located on south facing rocky scree slopes and at particular elevations. Regionally there is a western lag from the SDC range where precipitation variance is highly similar. This is partially explained by the prevailing westerly movement of storm activity from the Pacific Ocean; a prominent
feature of the cool-season hydro-climatic system. Regions east of the SDC range would be less influenced by storms from the Pacific due to orographic depletion of moisture reserves by the SDC range which contains the highest peaks in the state of NM.

From the 25 tree-ring chronologies retained 25 nested reconstruction models were assimilated spanning the period, 630–2014 CE (Table 5.2). Figure 5.4 shows the appended reconstructions extending back and forward in time, with decreasing subsets of individual tree-ring data, from the optimal calibration period (1955–85). The final reconstruction is depicted twice in Fig. 5.1. The upper figure depicts a reconstruction based solely on proxy tree-ring data spanning from 630–2014. The lower figure depicts a reconstruction based on proxy tree-ring data spanning from 630–1985 with instrumental data appended post-1985 (1986–2016). These plots also include the semi-parametric MEBoot 2-tailed 90% prediction intervals described in the previous section where proxy data are used. The MEBoot intervals use 5% and 95% quantiles as replacement for t-test statistics (Cook et al., 2013). Below the reconstruction plots an error plot is depicted showing the validation statistics for each reconstruction model produced as the chronology sample size and composition changes through time (Fig. 5.2). Notice the decline in data sample size post-1985, partially driving the inability of this model to maintain the robust relationship exhibited by the 1955–85 calibration period past 1985.

The model calibration and validation statistics are shown in Table 5.2. In addition to the calibration data: CRSQ, CVRE; and the validation data: VR2, VRE, VCE; are added estimates of calibration and validation statistics from 300 nested MEBoot pseudo-reconstructions (Cook et al., 2013)—here the median of all 300 MEBoot runs is shown.
As all statistics show positive correlation the model is considered valid for the entire reconstruction interval (Cook et al., 2013).
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Table 5.1 The 25 tree-ring chronologies used in the reconstruction model of SDC 1 April SWE.

The Pearson correlation values are depicted in the final right-hand column such that chronologies are placed in a descending order, with more robust relationships on top. Candelaria and Amole Canyon have not yet been added to the ITRDB and therefore have not been assigned ID numbers.


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Table 5.2 Model calibration and validation statistics with MEB medians for 19 backward nests and 6 forward nests.

Depicted are all 25 nested models with calibration/validation statistics for the reconstruction. The first year of each interval is indicated under IFY while the last year of the interval is indicated under ILY. All backward nests end in 1985 and all forward nests begin in 1955 extended out from the 1955-1985 calibration period. The number of chronologies used in each model is indicated under NTR.

The five calibration and validation statistics CRSQ, CVRE, VRSQ, VRE, and VCE are described in the text. For each statistic the MEB median value is listed to the right and is based on 300 MEB pseudo-reconstructions. It is evident that all nests have extremely stable statistics even where the number of chronologies (NTR) is reduced to 3. These reconstruction values have been appended forward and back in time to create the plot below.
Figure 5.1 The full SDC 1 April SWE reconstructions: 630–2014 (top) / 630–2016 (bottom).
Figure 5.1 The full SDC 1 April SWE reconstruction: 630–2014 (top) / 630–2016 (bottom). Continued.

The entire reconstruction spanning from 630–2014 is depicted in light blue with a 20-year low pass filter applied and shown as the dark blue line (upper). Next, a reconstruction spanning from 630–1985 is depicted with instrumental data tacked on after 1985 (i.e. 1986–2016) to show relationship. Visually these two are similar during the instrumental period. However, it is shown that tree overestimate drought when compared the instrumental data.
Figure 5.2 Changes in calibration/validation statistics with sample composition changes over time (630–2017).

Each line indicates a separate statistic each calculated for all 25 models where abrupt increases and decreases represent separate model statistics, the new and shortest in duration models overly the longer models. The red line depicts the sample depth changes over time and is represented on a separate y-axis. A sharp decline in statistical relevance is evident around 1985. Also available chronologies drop significantly (red-line) after this period. Plot created in SigmaPlot (Systat Software, San Jose CA)
Figure 5.3 Instrument vs. tree-ring derived data with split calibration/validation sequencing statistics.

Depicted is the tree-ring indices used in the reconstruction (black line) against PC₁SWE (dashed line) over the “common period”. In addition to the 1955-1985 calibration model used in the PPR reconstruction, statistics were run for a full 1937-1985 calibration period with subsequent split sequencing of verification statistics shown. The full period calibration is R² = 0.60. This period is split and the first half (1937-1960) achieves an R² = 0.64 while the latter half (1961-1985) is used for verification of the first half achieving a verification R² = 0.56, the reverse is done for the latter half where R² = 0.64 and verification R² = 0.55. There is no significant difference in either half of the model to capture the climate signal or to predict the outcome of the other half of the data. Plot created using SigmaPlot (Systat Software, San Jose, CA)
Figure 5.4 Time-span of the 19 reconstruction models used to reconstruct 1 April SWE.

The overall reconstruction model is comprised of 25 subset-reconstruction models extending back and forward in time by appending each subset model after appropriate scaling. Depicted is the earliest model on top towards the latest and most temporally extensive model on the bottom. Plot created in RStudio (2016).
Figure 5.5 Map of 25 regional chronologies and 5 snow coarse data sites with the corresponding climate footprint.

Trees-ring sites used to reconstruct 1 April SWE were selected from highly correlated regions determined using the KNMI Climate Explorer (2017) tools at climexp.knmi.nl. Specific species located in specific geographical locations were used to successfully reconstruct cool-season precipitation based on gauges within the SDC range. Green triangles represent trees and are size-coded to reveal correlation strengths. Blue and white circles represent NRCS instrumental data (1 April SWE). PRISM gridded precipitation data is correlated against PC_{SWE}: correlation values run from white to red to yellow and finally green from higher to lower correlations respectively. Map created in ArcGIS (ESRI, 2017).
5.2 Comparison with other reconstructions

In order to assess the ability of the model beyond statistics calculated from data within the limited temporal range of the validation period our reconstruction model is compared to two 1 April SWE reconstructions and one cool-season precipitation reconstruction from the American SW.

The cool-season precipitation reconstruction used here for comparison was modeled from multiple low-elevation pine species, \((\text{Pinus ponderosa, Pinus edulis, and Pseudotsuga menziesii})\), derived from the southern extent of the Colorado Plateau in AZ (Salzer and Kipmueller, 2005). A millennial length expression of precipitation with complete overlap of our reconstruction was produced from chronology sites in locations near and within the KNMI Climate Explorer (2017) climate footprint region of our own SDC snowpack hydro-climate correlations. This reconstruction tracts relatively well with our reconstruction: \(R^2 = 0.52\). Fig. 5.7 shows an 11-year smoothing spline comparison of the two reconstructions. The close relationship of these two reconstructions is explained by considering that both reconstructions are provided from low elevation pine species over a region of similar climatic conditions. Within this region selected species are responding to the cool-season hydro-climate signal (Salzer and Kipmueller, 2005).

The Salzer and Kipmueller (2005) southern Colorado Plateau precipitation reconstruction is indicated by the blue line while the SDC reconstruction data is depicted by the red line. Although the two reconstructions tract impressively well some notable differences occur. Decadal to multi-decadal drought periods, \(ca.\ 830, 1200, \) and \(1450\) are exhibited as intense and prolonged events in the AZ however are relatively non-events in
the SDC data. The 16th century and the 1950s droughts are clearly evident in both datasets and expressed similarly. The AZ data expresses more variability in the overall range matching the SDC data in the majority of pluvial events while expressing more prominent drought signals throughout. One pluvial event ca. 950 is expressed as much larger rings in the SDC data when compared to the AZ data. This event is the most intense pluvial event in the SDC record but relatively unimpressive event in AZ data. The most notable difference is a pluvial event, ca. 1330, where the AZ data shows a sharp increase in ring widths which surpasses all other regions of the dataset, while the SDC data shows no significant increase in data. All other pluvial regions match relatively well.

The two 1 April SWE reconstructions from the SW used for comparison correlate less well with the SDC data (Fig. 5.6). The data sites are from within the American SW yet apply to regions with separate and unique climate signatures and therefore contain less agreement among them. The Woodhouse (2003) reconstruction uses the same three species which comprise the Salzer and Kipmueller (2005) reconstruction data, (Pinus ponderosa, Pinus edulis, and Pseudotsuga menziesii), as well as the majority of data used in our SDC reconstruction. The weaker relationship between Woodhouse (2003) and our reconstruction might be expected due to documented regional differences of influence from Pacific teleconnections. Studies have shown that Pacific variability is responsible for 10-60% of SWE variability (Mote, 2005). The Woodhouse (2003) reconstruction is within a transition zone with respect to ENSO’s influence and on the edge of the significant correlation zone in respect to PNA’s influence, while the SDC range is firmly south of this transition zone in a region of significant correlation with both PNA and ENSO influence (Cole and Cook, 1998; Woodhouse, 2003). Stahle et al. (1998) used
these same three species of low-elevation conifers from NM and regions of southern Colorado to reconstruct ENSO, yet found the Gunnison River basin, reconstructed by Woodhouse (2003), to be north of regions found to correlate well. Numerous other studies have shown differences in Palmer Drought Severity Index (PDSI) reconstructions for these two regions (Cole et al., 2002; Fye et al., 2003; Woodhouse et al., 2009).

The second SWE reconstruction (Belmecheri, 2015) uses a single species of Blue Oak (Quercus douglasii) from central California. These samples are collected throughout central California and used to reconstruct Sierra Nevada (SN) snowpack. While the effect of El Niño at times for the SDC and the SN ranges is similar the effects of La Niña are quite divergent (NOAA 2017) therefore the similarity of ENSO effects is minimal. However, numerous similarities are present among all three 1 April SWE datasets.

The prominent 16th century drought, well preserved in paleo-records from the central and western US (Meko et al., 1995, Stahle et al., 2000; Stahle and Cleaveland, 1988; Stockon and Jacoby, 1976; Stockon and Meko, 1975; Woodhouse, 2003), is present in all three 1 April SWE reconstructions but is most pronounced in the SDC reconstruction. The pluvial which follows into the 17th century is depicted in all three as well but much less pronounced in the Sierra Nevada reconstruction (Belmecheri, 2015). A mid-17th century drought is evident in both the Woodhouse (2003) data and the SDC data, but absent altogether in the Sierra Nevada data. A strong mid-18th century drought is evident in the Belmecheri (2015) data but represents another strong divergence from the other two reconstructions. Overall, the Woodhouse (2003) and SDC data track similar events on a 20-year scale with often large divergences on an annual scale, e.g. the early 19th century. A common theme in many SW reconstructions (Stockon and Jacoby, 1976;
Stockon and Meko, 1975; Stahle et al., 2009), the 1840s dry-period is similarly evident in both the Woodhouse (2003) data and the SDC data. The 1930s drought is well depicted in the SDC data, as well as in the Belmecheri (2015) data but absent from the Woodhouse (2003) data, however an overall dry period for the early 20th century is evident in all three data sets with an increasing pluvial trend into the later period of the 20th century as well.
Figure 5.6 A comparison of three 1 April SWE regional reconstructions from the western US.

Figure 5.7 Comparison of two cool-season low-elevation pine reconstructions from the SW(630–1985).

5.3 Data distributions, variability, and extremes

A Box and Whisker plot is used to show median, interquartile range (IQR), outlier, and extreme outlier values from the SDC reconstruction data per century (Fig. 5.8). The instrumental period is contrasted against the reconstruction (i.e. historic proxy records) centennial data subsets. It should be noted that the 7th century only contains 70 years of data (630–699). The instrumental period also contains less than a full century of data: 81 years (1937–2017). The 17th, 19th, and 20th centuries exhibit median values well above this overall trend; the highest among them at 0.331 in the 17th century. The 20th, 16th, and 12th centuries also exhibit relatively large IQRs, far above the overall-run IQR. Overall there is a noticeable change in the size of the IQRs, evident after the 15th century. The 18th century exhibits the highest maximum values (i.e. high-whisker mark) of all centuries, outliers excluded, followed by the 10th and the 15th centuries. The 19th century exhibits the lowest minimum value range (i.e. low-whisker mark), followed by the 16th and the 10th centuries. The 19th century exhibits the largest overall range of data, outliers excluded, followed by the 10th, 16th, and 18th centuries. The 8th century contains the overall most compact datasets, outliers excluded.
Figure 5.8 SDC 1 April SWE box and whisker plot for centennial data comparison.

Fourteen centuries are depicted to allow for a comparison of data distribution. The Instrumental period is also depicted for comparison: a dataset of 80 years (1937–2016). The overall reconstruction distribution is depicted on the far left-hand side. Created with SigmaPlot (Systat Software, San Jose, CA).

Fig. 5.9 depicts two data distribution plots: a plot showing the distribution of all proxy data from 630–2014 (top), and a plot showing the distribution of proxy data with instrumental data appended post-1985 (1986–2016). A fairly normal distribution is evident in both plots. The most extreme dry years are marked with red-dotted lines and read from left to right: more extreme to less. Where the forward nests are used and tree-ring proxy data represent the entire distribution of data, 2002 is revealed as the 5th direst year on record over the last 1384 years. The four most extreme dry-years in both plots are
somewhat clustered within a 169-year period (1579–1748) while the ten driest years on record appear within only a slightly larger cluster: (1579–1861), with the expectation of 2002 in the forward nest. 1951 ranks in the top 15 driest years on record. The 18th century contains three of the five lowest values on record as well as the second driest year on record. Concerning extreme pluvial outliers (values > 2 SD) the 18th century contains the highest amount on record: six years, while the 10th century ranked 2nd: three years.

Concerning extreme dry years (values < -2 SD) the 19th century ranked 1st: 7 years, while the 18th century ranked 2nd: four years and the 10th century 3rd: three years. The 18th and the 19th centuries each contained the highest number of extreme outliers (< -2 or > 2 SD) on record: 10 years, while the 18th contained the highest number of extreme dry years and the 19th the highest number of extreme wet years.
Figure 5.9 SDC 1 April SWE data distribution plot.

The y-axis displays the number of times a value occurs. The x-axis displays the values as they appear in the reconstruction. This plot includes the reconstruction values from tree-ring estimates (630-1985) and instrumental data (1986-2017). Created in RStudio (2016).
5.3.1 Probability densities

A probability density function (PDF) figure is used to further compare distributions and data clusters per century (Fig 5.10) with two plots: one (top) representing entirely proxy tree-ring data (700–1999), and another (bottom) with the 20th century containing 86 years of proxy data (1900–85) from tree-ring estimates augmented with 14 years (1986–99) of instrumental PC1SWE data. The 7th century which contains only 70 years of data is not depicted. The instrumental data (PC1SWE), an 80-year period (1937–2016), is depicted as well, as a dotted black line. Table 5.3 depicts an easy visualization of the discussion below: anomaly characteristics of each century.

The 20th century (purple) contains a high number of wet years. Over 23% of data from this century has values $> 1.0$ SD, and 41% $> 0.5$ SD. Also, with the 17th century, contains the highest number of years $> 1$ and $> 0.5$ SD of any century. The 19th century (bisque) exhibits a pulse of extremely dry years, with 7 years of data $<-2.0$ SD, however 40 years are $> 0.5$. Thus the 19th century contains the highest number of years per century $> 0.5$ SD as well as the highest number of extreme dry years as discussed in the last section. The 18th century (green) contains 12 years of data $> 1.5$ SD, and 35 years $> 0.5$ yet the peak density data for this century is slightly dry. The 17th century (olive) exhibits peak pluvial densities near 0.5 SD above the mean with 46 years of data above this threshold, making it an extremely wet century. The 16th century (turquoise), exhibits a wide range of high density probabilities, i.e. numerous extreme years with 68 years
outside of mean conditions (> -0.5 and < 0.5) and the highest number of years < -1 SD (22) yet the majority of its data is cluster around -0.2 SD. The 15th century (peach) exhibits a moderate dataset with equal numbers of wet and dry years (>0.5 and < -0.5) yet with a pulse of drier years (< -1.0) that outweighs the wet (>1.0): there are 19 < -1.0 and only 15 > 1.0. Only the 16th century has more than 19 years < -1.0. The 14th, and the 13th centuries (robin-egg blue, midnight-blue, respectively) exhibit middle of the road compact datasets, with the 13th century containing the majority of its data (>40%) hovering very close to the mean of 0 is the most compact dataset. The 12th century contains a moderate range of values with a fairly even number of values on both ends of the spectrum: the primary pulse is slightly wet with a wide slope in out towards the most extreme values, yet a secondary pulse of strong dry years is evident as well. The 11th century (red) has the majority of its data around 0.5 SD. The 10th century (orange-rust) exhibits a distinct pulse of very dry years with 12 years around -1.5. The 9th century (brown) is fairly normally distributed with the peak of its data hovering slightly below the mean, with a secondary pulse of pluvial values as well yet the data reveals an overall wet century (35 yrs. > 0.5, 25 yrs. < -0.5: 18 yrs. > 1.0, 16 yrs. < -1.0). The 8th century (pink orange line) is one of the driest centuries sharing with the 15th and the 16th century the highest number of years (32) < -0.5 SD and 18 years < -1, but with far fewer years towards the wet side to counteract these low values (26 > 0.5, and 10 > 1), exhibiting the widest range between extreme dry and wet years on both the 1.0 SD and the 0.5 SD from the mean scale. This scenario fits well with the Fig. 5.8, as the 8th century is particularly dry with the lowest high whisker value and 2nd lowest median value. The instrumental period leans conspicuously into the dry end of the spectrum. A large amount (32) of dry years
Overall the 8th century and the instrumental period appear to be the driest, as the only two centuries with more dry years (<-0.5) than wet (>0.5): a total of 7(6) years more dry than wet for the 8th(instrument). The 8th century had the lowest number of years overall per century >1 SD (10 years). The instrumental period had as many dry years (<-0.5) as any other period (32 years) and it contains 20 less years than the century long datasets. The wettest centuries are the 20th, 19th, and 17th. The 20th century contains 39(24) wet to 29(16) dry years on the 0.5(1.0) SD from mean scale. The 19th century contains 40(20) wet to 28(15) dry years on the 0.5(1.0) SD from mean scale. The 17th century contains the largest range, weighted to the pluvial end of the spectrum, of differences with 46(21) wet to 27(16) dry years on the 0.5(1.0) SD from mean scale. The 18th and 11th centuries are also notable wet by this way of analysis [18th: 35(19) wet to 30(12) dry., 11th: 33(18) wet to 26(15) dry].

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Table 5.3 Individual anomalies per century comparison chart.

Each century is depicted in a comparison table format for easy reference. The numbers represent number of individual years containing values corresponding to each column. The 20th and 17th centuries exhibit the most individual anomalous wet years (> 0.5 and > 1.0) and relatively few anomalous dry years (< -0.5 and < -1.0), as well as the highest number of overall wet years across all anomaly
categorizations. Other comparisons can also be made. The 8th century has the fewest amount of wet anomalies (> 0.5 and > 1.0) and relatively high numbers of dry years.

Figure 5.10 SDC 1 April SWE probability density function plot per century.

The x-axis shows drought and pluvial years in the form of standard deviations from the mean. The y-axis shows the percentage of values for each century. All centuries contain 100 years of annual data. The instrumental period is also depicted (dotted-black line) containing only 78 years of annual data. Created in RStudio (2016).
5.3.2 Anomalies and extreme events

Extreme snowpack anomalies are defined here as years with values more than 1.1 SD or z-scores (plus or minus) away from zero, a value proposed by Dean (1998) to distinguish climatic episodes significant to the physical environment and human populations. It should be reiterated here that the mean value of the SDC reconstruction PC1 scores is 0.035, so standardization has a minimal transformational effect on the data. When graphed [Fig. 5.11 (top)], clusters of extreme years can be assessed. For the two plots contained in Fig. 5.11 the entire proxy record (630–2014 CE) is used with no amended instrumental data.

The 21st century, containing 15 years (2000–2014), is highly significant in terms of drought, there is little to no relief during this period in terms of extreme individual wet periods. With the onset of the 20th century a cluster of dry years is evident yet there is also a fair number of pluvial anomalies within. Extreme drought values with little or no relief from extreme pluvial years occur: 1651–91, a 40-year period with no pluvial anomalies and consisting of seven individual dry anomaly years over this period; 1573–93, a 21-year pluvial anomaly free period with eight dry anomalies; 1272–1309, a 38-year pluvial anomaly period with five dry anomalies; 734–67, a 33-year period
containing six dry anomalies but no pluvial anomalies. The late 10th century exhibits relatively high densities of extreme drought years with few pluvial anomalies. Overall the first nine centuries (7th–15th) have noticeably less extreme dry years < -2 SD but no conspicuous difference concerning pluvial extremes.

The lower graph depicts a 20-year low pass filter applied to the original reconstruction data. Drought events occurring in the early 8th century stand out here as well as being a relatively dry century. Other dry periods include ca. 850–925, ca. 975–1050, a large extensive drought in the mid-12th century, and a late 13th century dry period. All these periods appear temporally extensive with little relief from pluvial events compared to the less severe, in terms of duration, droughts post 13th century. Even the “mega-drought” of the 16th century, although the most intense drought, appears less severe in terms of temporality. Comparing both plots in Fig. 5.11: the early 20th century drought is significantly reduced in severity when considering an overall 20-year signal whereas the 1950s drought appears to be much more significant. These differences in appearance of drought and pluvial significance results from distinct scales used in each plot considering how the data is categorized and classified. The upper plot highlights individual years of extreme drought without taking into consideration preceding or following years, while the lower plot takes an overall 20-year signal into account, which exhibits heavy influencing on individual points from preceding and following data points. The two plots taken together: the mid-12th century drought is most significant in temporal duration, the 8th century is the overall driest century, while the 16th drought is most significant in terms of intensity. The late 10th and early 11th century is also shown to be a long-term dry period with little relief until ca. mid-11th century.
Figure 5.11 Two SDC 1 April SWE anomalous events plots derived from individual deviations from the mean (top) and a 20-year low pass filter (bottom) (630–2014).

Top: Anomalies are defined as events >1.1 or < -1.1 SD (values are standardized around the mean of 0). Bottom: A spline is defined with a 20-year low pass filter and plotted around a mean of 0 with negative values in red and positive values in blue. Post-1985 data is derived from instrumental 1 April SWE data from the SDC range; pre-1986 derived from tree-ring estimates. Created in RStudio (2016)
5.3 Extended period classification

To classify extended hydro-climatic events, drought and pluvial, by considering intensity and duration together a five-year minimum event plot was created (Fig. 5.12). The techniques used here are a combination of techniques used by Salzer and Kipmueller (2005) and Woodhouse (2003). Like Woodhouse (2003), who assessed three-year minimum drought periods, original data is considered, yet like Salzer and Kipmueller (2005) events are considered over time at five-year minimums and assessed depending on their relation to previous conditions. Drought events are depicted as red boxes while pluvial events are depicted as blue. To classify extended hydro-climatic events, by considering intensity and duration together, a five-year minimum event plot was created.

Events are considered over time at five-year minimums and individual annual values are assessed in relation to previous conditions. All events have average values significantly deviated from the mean [i.e., > 0.5 (wet) and < -0.5 (dry)]. The data file used for this image was created in a self-created python program that takes in chronological data with individual annual values and checks them against specified criteria to determine the extent of event periods. Once an individual dry year occurs [< -0.5 SD(dry) or > 0.5 SD (wet)] that year is logged as an event, wet or dry, which continues through time until specified criteria is met to exit the event period, thus setting the beginning and ending dates. Criteria for ending a dry period, are defined under various circumstances. One criteria considers the average of all values for that event over time. Averages must remain < -0.5 for a dry period, while the opposite sign value is true for wet periods. In addition
to averages over time, values that have returned to mean conditions (> -0.5 and < 0.5 SD) for more than three consecutive years or significantly deviate in the other direction (e.g., for dry periods: > 0.5 SD) for two consecutive years would qualify as criteria for ending an event period. Any combination of these values could potentially end an event period. This method was accomplished by creating a bracket variable to accept values assigned to brackets of SD data, such that a return to mean conditions (> -0.5 and < 0.5 SD) after a dry or wet period had begun would determine the bracket variable receive a value of 1, while values substantially deviating in the other direction (> 0.5 SD for drought periods and < -0.5 for wet periods) once a period had begun, receive a bracket variable value of 2, and a value > 1.0 SD (dry period) or < -1.0SD (wet period) would be determine that the bracket variable value receive a value of 3. Yet, once a successive value of < -0.5 (dry) or > 0.5 (wet) occurs the bracket object value is returned to 0. In order to exit an event period the calculated average over time must cross the assigned threshold or the bracket object value must equal 4. If the event was > or = 5 consecutive years in duration while meeting all the specified criteria the average value over that period is used to represent the intensity for that particularly event.

There were 47 wet and 41 dry events (Fig. 5.7). Dry events range from five to 15-year periods with the average at seven years. Wet events range from five to 21-year periods, with the average at eight years. The most intense pluvial event is a nine-year period (960–68) with an average SD value of 1.38 for the nine-year period. The longest pluvial event by duration is a 21-year period event with an average SD value of 0.85. There are 16 pluvial periods which extend to or beyond nine years, which are considered decadal events for this analysis. There are 10 drought periods which extend to or beyond
this period. The 1950s drought (1950–61), a 12-year period, with an SD value of -0.64, is included among these. The most extreme drought, in terms of duration and intensity, is the 16th century “mega-drought” (1573–87), a 15-year period, with an SD value of -1.0. The current ongoing drought (2011–17) is ranked third in intensity with a value of -0.85, after the infamous mid-12th-century, and 16th century mega-droughts. Decadal scale drought periods are evident in the 8th (2), 12th, 13th, 16th, 18th (2), and 20th centuries. The early 8th century contains a relatively high number of dry periods of significance, containing the 4th ranked in intensity, a nine-year period; also including a 12-year period drought which is ranked 3rd in terms of duration. The 10th and 19th centuries contain the highest number of drought periods (5), yet all of minimal duration. All periods are shown in Fig. 5.12 and Table 5.4.
Figure 5.12 Drought and Pluvial events classified as five or more consecutive years of values meeting specified criteria.

Red histogram boxes depict drought events; blue boxes depict pluvial events. All events have values > 0.5 (wet) or < -0.5 (dry) which derived from averages of individual years. Created in RStudio (2016).
<table>
<thead>
<tr>
<th>Duration</th>
<th>Years</th>
<th>Avg.Value</th>
<th>Duration</th>
<th>Years</th>
<th>Avg.Value</th>
</tr>
</thead>
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<td>1573-1587</td>
<td>15</td>
<td>-1.00</td>
<td>960-968</td>
<td>9</td>
<td>1.38</td>
</tr>
<tr>
<td>1146-1152</td>
<td>7</td>
<td>-0.86</td>
<td>1484-1488</td>
<td>5</td>
<td>1.19</td>
</tr>
<tr>
<td>2011-2017</td>
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<td>-0.85</td>
<td>800-806</td>
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<td>1.19</td>
</tr>
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<td>738-746</td>
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<td>-0.84</td>
<td>1866-1870</td>
<td>5</td>
<td>1.11</td>
</tr>
<tr>
<td>1899-1905</td>
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<td>-0.82</td>
<td>1490-1494</td>
<td>5</td>
<td>1.00</td>
</tr>
<tr>
<td>991-995</td>
<td>5</td>
<td>-0.82</td>
<td>1194-1204</td>
<td>11</td>
<td>0.93</td>
</tr>
<tr>
<td>1283-1289</td>
<td>7</td>
<td>-0.81</td>
<td>1983-1989</td>
<td>7</td>
<td>0.87</td>
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<tr>
<td>660-665</td>
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<td>1720-1724</td>
<td>5</td>
<td>0.87</td>
</tr>
<tr>
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<td>-0.76</td>
<td>1602-1622</td>
<td>21</td>
<td>0.85</td>
</tr>
<tr>
<td>1999-2004</td>
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<td>-0.75</td>
<td>1758-1762</td>
<td>5</td>
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</tr>
<tr>
<td>1623-1628</td>
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<td>-0.75</td>
<td>1162-1167</td>
<td>6</td>
<td>0.81</td>
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<tr>
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<td>1553-1559</td>
<td>7</td>
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</tr>
<tr>
<td>1773-1783</td>
<td>11</td>
<td>-0.73</td>
<td>1831-1842</td>
<td>12</td>
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<td>1664-1672</td>
<td>9</td>
<td>-0.72</td>
<td>1309-1315</td>
<td>7</td>
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<td>1790-1795</td>
<td>6</td>
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<tr>
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<td>1052-1067</td>
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<tr>
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<td>1764-1772</td>
<td>9</td>
<td>0.77</td>
</tr>
<tr>
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<td>5</td>
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<td>1526-1531</td>
<td>6</td>
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<td>1633-1637</td>
<td>5</td>
<td>0.76</td>
</tr>
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<td>1950-1961</td>
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<td>1991-1995</td>
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<td>1229-1233</td>
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<td>1710-1714</td>
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<tr>
<td>951-955</td>
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<td>1906-1922</td>
<td>17</td>
<td>0.72</td>
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<tr>
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<td>946-950</td>
<td>5</td>
<td>0.71</td>
</tr>
<tr>
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<td>1639-1644</td>
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<td>-0.60</td>
<td>896-900</td>
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</tr>
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<td>-0.60</td>
<td>1511-1516</td>
<td>6</td>
<td>0.67</td>
</tr>
<tr>
<td>1542-1549</td>
<td>8</td>
<td>-0.60</td>
<td>1884-1892</td>
<td>9</td>
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<td>1090-1095</td>
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<td>-0.59</td>
<td>673-677</td>
<td>5</td>
<td>0.66</td>
</tr>
<tr>
<td>1276-1280</td>
<td>5</td>
<td>-0.59</td>
<td>1688-1695</td>
<td>8</td>
<td>0.65</td>
</tr>
<tr>
<td>1360-1369</td>
<td>10</td>
<td>-0.58</td>
<td>727-735</td>
<td>9</td>
<td>0.65</td>
</tr>
<tr>
<td>1097-1101</td>
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<td>-0.57</td>
<td>666-671</td>
<td>6</td>
<td>0.64</td>
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<tr>
<td>1845-1849</td>
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<td>-0.57</td>
<td>1699-1703</td>
<td>5</td>
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</tr>
<tr>
<td>1805-1810</td>
<td>6</td>
<td>-0.57</td>
<td>1112-1125</td>
<td>14</td>
<td>0.61</td>
</tr>
<tr>
<td>721-726</td>
<td>6</td>
<td>-0.57</td>
<td>1594-1600</td>
<td>7</td>
<td>0.61</td>
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<td>1861-1865</td>
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<td>852-865</td>
<td>14</td>
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<tr>
<td>878-882</td>
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<td>-0.55</td>
<td>784-795</td>
<td>12</td>
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</tr>
<tr>
<td>1728-1742</td>
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<td>1209-1213</td>
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<td>0.56</td>
</tr>
<tr>
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<td>1076-1084</td>
<td>9</td>
<td>0.56</td>
</tr>
<tr>
<td>1399-1404</td>
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<td>1743-1751</td>
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<tr>
<td>1338-1345</td>
<td>8</td>
<td>-0.51</td>
<td>1331-1335</td>
<td>5</td>
<td>0.55</td>
</tr>
</tbody>
</table>
<pre><code>     |      |           |              |      |           |
</code></pre>
<p>| 1237-1245    | 9     | -0.52     | 842-846      | 5     | 0.51      |
| 1426-1435    | 10    | -0.50     |              |      |           |</p>

Table 5.4 Anomalous events with a minimum of five consecutive years per event.
Table 5.4 Anomalous events with a minimum of five consecutive years per event continued.

Events are shown from most extreme in intensity to least based on SD value. Dry events are depicted on the left (first 3 columns) while wet anomalous events are depicted on the right-hand side (last 3 columns). There are more wet \( n = 47 \) periods than dry \( n = 41 \). The instrumental period (1937–2017) is representative of dry events in respect to both intensity, with the period 2011–17 ranking in the 98\(^{\text{th}}\) percentile for overall intensity of events, and duration, with the 12-year 1950s drought ranking in the 95\(^{\text{th}}\) percentile for overall extent of duration of events. Wet periods are less well represented over the instrumental period as this period (1937–2017) contains events ranking no higher than the 60\(^{\text{th}}\) percentile for both intensity and duration. The most intense wet period (1991–95) ranks in the 50\(^{\text{th}}\) percentile for intensity, and the longest period of duration (1983–89: \( n = 7 \)) ranks in the 60\(^{\text{th}}\) percentile for extent of duration.

A second classification method was used to reveal extended periods of drought and pluvial event (Table 5.5). The criteria are less restrictive to allow more years to follow during primarily dry or wet events to assess multi-decadal periods of conditions. These periods begin as in the first classification system when a value veers from mean conditions \((> -0.5 \text{ and } < 0.5)\) the first ten years must consist almost entirely of negative or positive values only allowing for single year exceptions which do not exceed 0.5 SD in the other directions. Overall no consecutive periods more than three years of reverse sign values, no more than two values 0.5 SD in the other direction and no more than one value 1 SD in the other direction. The period ends abruptly at the last value of that sign (– or +) before the signs reversed. The end period must contain three years of consecutive values of that sign for the period. All events are of 20 years or longer. Drought periods extend from 21 to 25-year periods and pluvial events are of 20 and 23 years.

There are five multi-decadal dry and two pluvial events. The 8\(^{\text{th}}\) century contains three of all seven events: two dry and one wet. There are two long term dry events
between 1131–1296. There is a cluster of one multi-decadal dry and followed by one multi-decadal wet event between 1573–1621. There are no multi-decadal events after this period.

<table>
<thead>
<tr>
<th>Period</th>
<th>Duration (yrs.)</th>
<th>Sign</th>
<th>SD average</th>
</tr>
</thead>
<tbody>
<tr>
<td>703–724</td>
<td>22</td>
<td>Dry</td>
<td>-0.5</td>
</tr>
<tr>
<td>735–760</td>
<td>26</td>
<td>Dry</td>
<td>-0.48</td>
</tr>
<tr>
<td>784–806</td>
<td>23</td>
<td>Wet</td>
<td>0.62</td>
</tr>
<tr>
<td>1131–1151</td>
<td>21</td>
<td>Dry</td>
<td>-0.54</td>
</tr>
<tr>
<td>1273–1296</td>
<td>24</td>
<td>Dry</td>
<td>-0.41</td>
</tr>
<tr>
<td>1573–1593</td>
<td>21</td>
<td>Dry</td>
<td>-0.83</td>
</tr>
<tr>
<td>1602–1621</td>
<td>20</td>
<td>Wet</td>
<td>0.92</td>
</tr>
</tbody>
</table>

Table 5.5 SDC 1 April SWE multi-decadal anomalous events with a minimum of 20 years per event.

5.4 ENSO influence

Large scale climate forcing on precipitation and temperature anomalies through tele-connections of the ENSO is well established (Ropelewski and Halpert, 1986, 1987; Redmond and Koch, 1991; Gershunov and Barnett, 1998; McCabe and Dettinger, 1999; Higgins et al., 2000; Gutzler et al., 2002; Ciancarelli et al., 2014). To assess the influence
of interacting Pacific SSTs and SLPs, specifically of regions associated with ENSO-like patterns, on our hydro-climate-region, our tree-ring derived (PC_{1Recon.}) and PC_{1SWE} data were run separately against various indices typically used as approximations of ENSO phases. This was accomplished using the KNMI Climate Explorer (2017) tool described in Chapter V. Fig. 5.13 shows the relationship of SSTs and 1.) our PC_{1SWE} data [Fig. 5.8 (top: right)] for the period 1936–2017, and 2.) our PC_{1Recon.} data [Fig. 5.8 (top: left)] for the period 1870–2017. There is a clear relationship between southern-equatorial Pacific SSTs and the hydro-climate region. This is representative of an ENSO like influence on the hydro-climatic region, as the Nino 3.4 region, a region of Pacific SST’s used to identify ENSO phases, is positively correlated with both instrumental SWE data and tree-ring growth increments. Furthermore, the Da Silva SLP dataset also derived from the climexp.knmi.nl. website is compared to our tree-ring derived data to assess relationships between another ENSO indicator and our climate region. A clear relationship between SLP variability and the climate region over the period 1945–93 is shown in Fig. 5.8 (bottom).

ENSO has been observed by numerous studies to drive precipitation anomalies in the western US, specifically in the Pacific NW and the SW, which exhibit an inverse relationship to ENSO phase events (McCabe and Dettinger, 1998; Dettinger et al., 1998; Cayan et al., 1998; Rajagopalan, 2000). ENSO is an interannual to decadal scale mode of variability and has been described as a coupled ocean-atmospheric system, demonstrating quasiperiodicity and producing global scale teleconnections (Battisti and Sarachik, 1995; Rajagopalan, 2000). ENSO primarily influences wintertime precipitation in the SW (Gershunov, 1998; Gershunov and Barnett, 1998; Cayan, 1996; Stahle et al., 1998)
although modulating effects on the NAM have been observed as well (Seager et al., 2009; Coats et al., 2015). However, as ENSO phases typically peak in December or January the most pronounced effects on precipitation are seen as winter and early spring anomalies (climas.arizona.edu) in the SW. Winter time influence from ENSO on intra-seasonal extreme precipitation and temperature (Gershunov 1998; Gershunov & Barnett 1998) is well observed.

When conditions are normal in the eastern Pacific equatorial ocean an overlying atmospheric pressure gradient, measured between Tahiti and Darwin, Australia, is observed, where a low-pressure system of convective uplift over Australia draws thermal energy from a high-pressure cell of sinking cool air over the Tahiti region, enforcing an easterly flow of winds over the equatorial Pacific. The well-known Trade Winds of equatorial prevailing easterlies drive westward bound waters which are replaced by cold nutrient-dense water from the depths along the equatorial South American western coast, thereby creating a “cold-tongue” region in the eastern Pacific; a relatively cold and narrow equatorial region of SSTs bound from the eastern Pacific. However, periodically this pressure gradient weakens slowing down westward bound flows, flattening out the thermocline and thus leaving warm surface waters undisturbed. This warming of the Pacific cold-tongue exhibits far reaching teleconnections on a global scale, by altering otherwise stable pressure systems and influencing the mid-latitude jet streams. This “warm-phase” is referred to as El Niño. Hence the El Niño – Southern Oscillation, ENSO. When the cold-tongue region warms low pressure systems in the Pacific enlarge, e.g. the Aleutian low expands southward. This enhances the Pacific or subtropical jet-stream and increases the flow of the prevailing westerlies bringing moist air during
winter months over the SW which interacts with topographic features, e.g. orographic processes convective energy substantially increases precipitation levels (climas.arizona.edu; earthguide.ucsd.edu). Jin et al., (2014), observed wind field anomalies of the lower atmosphere at the 500 mb geopotential height that led to increased snowpack in the SW which correspond to ENSO-like SST patterns, where a low-pressure system initially in the Pacific south of the Aleutian Islands expands southwest affecting the jet stream, keeping it over the SW, but also pulling in moisture from the Gulf of Mexico.

The less frequent pole of this dual-phased ENSO system is known as La Niña and results in a cold phase along the equatorial Pacific, where normal SLP-STT interacting conditions are enhanced, with significant influence on regional precipitation and temperature fluctuations, over North America precipitation and temperature anomalies, particularly for the Pacific North West (NW). This cold phase of the ENSO results a pronounced high-pressure system over the southern Pacific shifting poleward towards the location of the typical Aleutian low (Jin et al., 2014). This process also enforces a low-pressure cyclone over central Canada pulling the pacific jet-stream northward and bringing moist Pacific air to the Pacific NW bypassing the lower latitudes. This decrease of westerly storm movement over the SW can produce significant drought anomalies. However, Jin et al. (2014) found that shifts of southern Pacific high-pressure systems eastward over the SW, likely caused by a strong warm season precipitation regime peaking later in the NAM season, e.g. in September, resulted in the most significant decreases in winter precipitation and was not associated with tropical Pacific SSTs. Although no significance was found with La Niña and drought, increased snowpack was
found to correlate well with El Niño-like patterns of SST variability. Cole et al., (2002) found La Niña-like patterns of SSTs have a tendency to cause drought in the SW, a tendency which may be modulated by extratropical SSTs, such as those associated with the Pacific Decadal Oscillation (PDO). Negative PDO phases in conjunction with a La Niña phase is likely to increase drought in the SW whereas a positive PDO would dampen effects caused by La Niña conditions. Cook et al. (2007) describes La Niña-like SST conditions as drought inducing for North America but does not necessarily equate to drought in the SW. While ENSO variability typically works on timescales of 2–7 years the strength of these events depends on interactions with other large-scale systems which operate on separate time scales; e.g. extratropical SSTs (PDO), and geopotential height anomalies (PNA).

ENSO conditions have been approximated with various indices to determine specific intervals. While no comprehensive ENSO index exists, SST anomalies over the Nino3.4 region have been shown as the most prominent feature of ENSO (Stahle et al., 1998). Temperature changes and gradients over the Nino3.4 region are used to create a standardized index of anomalous events, measured as five consecutive three-month averages, defined by an exit of normal conditions (> -0.5 degrees C and > 0.5 degrees C).

To examine ENSO-like patterns of SST variability the Hadley Centre Global Sea Ice and Sea Surface Temperature (HadISST: 1871–present) index was used. The cold tongue region is noticeably correlated along with other regions found to correspond to ENSO phases. A warmer tropical eastern Pacific in conjunction with a colder extratropical central North Pacific is indicative of an El Niño event (Zhang et al., 1997). Here, wintertime SSTs (December–March: DJFM) are shown to correspond positively to the
following spring season where annual 1 April SWE values represent winter precipitation accumulation and also to the growing season as is evident in a positive correlation with tree-growth indices.

Since ENSO is a coupled mode of SST and SLP variability SLP indices are also evaluated here for relationship potential with our data. The winter southern oscillation index (SOI) is commonly used (Svoma, 2011) and has been reconstructed with tree-rings (Stahle et al., 1998). The SOI applies to SLP side of ENSO which is a standardized index derived from observed sea level pressure differences between Darwin, Australia and the island of Tahiti. Our correlation with Da Silva SLP data shows a clear relationship. A negative correlation between pressure measured over Tahiti is evident while a positive correlation with pressure values along the eastern Australian coast is also evident. The island of Tahiti can be seen conspicuously as an area of inverse correlation with our PC$_{1Recon}$ data. An inverse relationship here suggests that during normal conditions and an area of high pressure is located over the Nino3.4 region, synonymous with the western extent of the Pacific cold-tongue and the eastern extent of inversely related water temperatures in the western Pacific, the tree-growth and 1 April SWE values are constrained, however during an El Niño event as the waters warm due to lower pressure over Tahiti the trees grow more and the SWE values increase.
Figure 5.13 ENSO-like pattern influence on regional cool-season hydro-climate for northern NM and the SDC range.

Top: A dataset titled HADSST1 (Dec–Mar averaged) is run against 1 April SWE instrumental annual values (PC$_{1SWE}$) [top(left)] and our PC$_{1Recon}$ data [top(right)]: correlation field values > 40% are evident. The lower plot shows the relationship SLP from October–July, winter and spring of that WY, on our PC$_{1Recon}$ data: values > 60% are evident. Created in KNMI Climate Explorer (2017).
5.5 Comparison of event periods to other tree-ring derived paleo-climate records.

The following is a discussion of event periods and characteristics of each century and a comparison of event periods to other regional paleo-hydro-climate records is also made. For a quick and easy comparison, Table 5.6 is exhibited at the end of this section.

Large-scale drought signals present in the reconstruction data are centered along regions of the western US. Long-term drought signals here are primarily representative of southwestern regional phenomena. Droughts like the dust-bowl 1930s drought, which is not a southwestern phenomenon, do appear as single or more years of intense drought on occasion, as the most extreme years are often expressive beyond the spatial range of the overall term of these drought periods. Particularly western California and the more SW region, e.g. four-corners region, will often share similar signals whereas drought signals in the mid-west or regions of the Great plains and northern Rockies are less evident in the SW. E.g., Droughts like the late 1500s and late 1200s are centered more strongly in the Southwest and Pacific west coast regions, respectively, but are evident in reconstructions from both regions. Table 5.5 depicts how event periods overlap with other records in the region.

Overall, the 20th century, with the exception of the 1950s drought, has been primarily wet. An extensive pluvial event of 17 years, occurred in the early century (1906-1922) and overlaps well with a pluvial event (1905–17) described by Fye et al., (2003). This event is evident in the PDSI record and has a spatial extent expanding the majority of the larger western US (Fye et al., 2003), excepting the far Pacific Northwest where often an inverse signal is depicted for large scale climate events. This event occurred immediately following a strong seven-year drought (1899–1905) that ranked 4th among all droughts in the overall PC_{SWE} data. This event also overlaps an event described by the PDSI (1897–1904) as a large-scale drought
stretching SW from the Great Plains along the Colorado Plateau to the Pacific and into Northwestern Mexico (Fye et al., 2003). This drought is spatially similar in scale to the 1950s droughts but centered slightly westward. The 1950s drought is centered over the SDC range, yet our climate region is along the eastern edge of the region affected by the 1897–1904 drought. However, for the 20th century, pre- and post-1950s drought, a primarily wet [Fig 5.11 (bottom)] period is evident. As discussed 24 years were > 1 SD from the mean; more than in any other century and individual wet years (>0.5) far outnumbered individual dry (< -0.5) years. This century also contained a high median value and a very large IQR. The Dust Bowl (1930–36) was largely absent from our record, as it was largely a phenomenon of the Great Plains, and the northern Rockies (Fye et al., 2003). However, numerous paleo-drought-records in the west have recorded both 1956 and 1934 to be the driest years of the 20th century (Guttmann, 1991, Cook et al., 1996, Woodhouse and Overpeck, 1998). For our record 1934 registers at -1 SD, by far the driest year of that, while 1956 registers at -1.5 SD. The lowest value of that century in 1951 is -2.25 SD. The 1950s drought is described as a 12-year period (1950–61) in our data and by the PDSI data as an 11-year event (1946–56) (Fye et al., 2003). This dry period is well documented in SW reconstructions (D’Arrigo and Jacoby, 1991; Salzer and Kipmueller, 2005; Fye et al., 2003). Cook et al (2016) describes it as a 10-year period (1948–57).

The 19th century was also largely wet, exhibiting two of the most significant pluvial events, the first being a 12-year wet period (1831–42) with a mean of 0.8 SD, which also overlaps an event described by Fye et al., (2003), (1825–40). The second period is ranked as the fourth most intense pluvial period on record with an average SD value of 1.1, yet over the minimum of five years (1866–70). Another nine-year pluvial was evident at the end of the century (1884–92). Yet these pluvial events are offset by a relatively large number of small
drought periods. There are five drought periods revealed in the event classification, all of minimal duration and exhibiting relatively low SD values < -0.6. This century possessed far more individual wet years (> 0.5) than dry (< -0.5): 40 to 28. However, this century also possesses five of the 11 lowest individual values over the entire record and the largest number of extreme dry outliers (< -2.0, n = 7). Possessing a pluvial median value, the highest top whisker value (Fig. 5.3) per century, and the largest overall range (outliers excluded) of data overall it is a highly variable but overall wet century. Droughts recorded by other proxy-records over this period include events in the 1890s, 1880s, 1860s, and 1820s. The 1890s drought appears mainly in records from the central plains (Stockton and Meko, 1983; Lawson and Stockton, 1981; Weakly, 1965; Woodhouse and Overpeck 1998). Yet this drought is evident here in two periods: 1893–96, with and SD average of -0.67, and another period from 1899–1904 with an SD average of -1.1. Meko and Graybill (1995) describe a dry period (1879–83), that exactly matches our own. An 1860s drought is well documented in reconstructions with a strong Dust Bowl signal (Stahle and Cleaveland 1988; Wedel 1986). While Blasing et al., (1988), a southern Great Plains reconstruction, as well as a Kansas newspaper (Woodhouse and Overpeck 1998) document 1860 as being the driest year of that century. Our records indicate 1861 as the lowest value (-2.48) of the 19th century and the 6th driest for the overall reconstruction. Incidentally, this low year is during a documented La Niña event (1855-1963) (Cole et al., 2002). The 1820s-drought, a strong signal in the Great Plains and SW region (Fye et al., 2003), is evident in our record as a period from 1818–24 with an average SD of -0.93. Yet due to a strong three-year pluvial period from 1815–17 this event does not register in the five-year minimum event classification due to persistence in the averaging. This period is recorded in numerous tree-ring reconstructions in the Plains (Fritts, 1983; Stockton and Meko, 1983), while Meko et al. (1993) shows a five-year
period (1818–22) period for the Gila River. The Fye et al. (2003) PDSI reconstruction describes a dry period that matches our own (1818–24).

The 18th century is also largely wet, although less so in some regards compared to the 19th and 20th centuries. A highly variable century containing many of the driest years on record and possessing the second highest number of extreme dry outliers, yet also possessing the highest number of extreme pluvial outliers (>2.0 SD, \(n = 6\)) overall. Two decadal scale droughts are evident during this period: 1.) a 15-year drought (1728–42) in the second quarter, which overlaps a period described in Smith and Stockton (1981) reconstruction of the salt River, AZ, as a 20-year event (1721–40). This event was also described in Cleaveland and Duvick’s (1992) reconstruction (1735–44) over the Midwest. Although possessing a minimal SD average (-0.55), it shares the rank of longest drought on record, along with the 16th century drought; and 2.) an 11-year drought (1773–83) heralding-in the last quarter (-0.73 SD) of the century. This 11-year drought shows up in Stahle and Cleaveland’s (1988) June PDSI reconstruction over Texas as a 10-year period (1772–81), as well as in western and SW reconstructions (Hardman and Reil 1936; D’Arrigo and Jacoby 1991; Woodhouse et al., 2010; Woodhouse and Overpeck 1998). Overall the first and third quarters of the 18th century are extremely wet, with a very large number of extended pluvial events (\(n = 5\)).

The 17th century, like the previous three discussed, is largely wet and highly variable, while it contained the second driest period on record (Fig. 5.4) it also possesses the highest median value on record (Fig. 5.3). A strongly pluvial period overall with 46 years > 0.5 SD. It contains the longest pluvial on record at 21 years (1602-22) by the first classification method which includes consideration of persistence in determining the number of years in period and exhibits a relatively high average SD value of 0.85. This period matches the Fye et al., (2003)
21-year period. While the second method which ends immediately once dry or wet individual values subsist records a 20-year event (1602–21) and an increased SD average value of 0.92. A longer pluvial period by this second method of classification exists in the late 8th century.

The 16th century contains the widest spread of data overall and the worst drought on record [15-year period (1573–87) at -1.0 average SD, by the first method of classification and a 21 year (1573–93) overall dry period by the second, with an SD average of -0.83 is evident]. Not the longest drought by the second method of classification but by far the most intense. This “mega-drought” has appeared in numerous paleo-climate records from the SW and the western US, although largely a southwestern phenomenon (Woodhouse and Overpeck, 1998; Fye et al., 2003). Reconstructions from northern NM and the four-corners region have documented the late 1500s drought (Stockton and Jacoby, 1976; Rose et al., 1982; D’Arrigo and Jacoby 1991, Meko et al., 1995; Grissino-Mayer 1996, Stahle et al., 2000; Fye et al., 2003; Salzer and Kipmueller, 2005; Cook et al., 2016). The Stockton and Jacoby (1976) Colorado River at Lee’s Ferry reconstruction found a 23-year period (1573–1595) to be the longest and most severe periods of drought on record. This drought was also persistent throughout the western US in precipitation, drought, and flow reconstructions (Hughes and Graumlich 1996; Haston and Michaelsen 1997; Hughes and Brown 1992; Hardman and Reil 1936). Fritts (1965) found a dry period beginning in 1565 and spreading out into the entire western US by 1585. Lake sediments in Minnesota (Dean et al. 1994), old growth-conifers in the SW (Swetnam and Betancourt 1998), and eolian deposition (Muhs and Holiday 1995) records all reveal a severe drought in late 1500s (Woodhouse and Overpeck 1998). Yet, the first half of the 16th century was primarily wet with three significant pluvial events. A pluvial event described by Fye et al., (2003): (1549–58), overlaps with our record of a seven-year pluvial (1553–59).
The 15th century contained the 2nd and 5th ranking pluvial events and significant high pluvial outliers. However, while the last quarter century was indeed largely wet, the first three quarters of the 15th century were moderately dry. In common, the last five centuries (15th – 20th) were all of relatively high variability with wide ranging fluctuations yet also with relatively high-whisker and median values all higher than those exhibited by the first seven centuries (7th-14th).

The 14th century contained the most compact dataset (Fig. 5.3) with one large pluvial early on (1309–15, average SD = 0.78), and another nine-year pluvial event late in the century (1380–88). However, this century also contains three significant droughts including one on a decadal-scale (1360-69).

The 13th century is noticeable dry in the second half, exhibiting one of the longest dry periods in the record: a 24-year period (1273–96), classified using the second method, is primarily dry and has an average SD value of -0.41 and contains two drought events classified with the first method: 1276–80, and 1283–89. A decadal-scale drought event in the first quarter is also evident. The late 1200s drought period, referred to as the “great drought” (Woodhouse and Overpeck, 1998), has been connected with the abandonment of the Anasazi or Ancestral Pueblo societies around Mesa Verde and the four corners region (Douglas, 1935; Dean, 1994; Woodhouse and Overpeck, 1998; Cook et al., 2016). Stine (1994) found underwater tree-stumps which recorded low lake levels in the SNs, CA. A southwestern Arkansas chronology show a period from 1276–1313 (Weakly 1965). This drought is also evident as a significant event in SW known (Rose et al., 1982; Grissino-Mayer, 1996) and the White mountains of California (Hughes and Graumlich, 1936; Woodhouse and Overpeck, 1998). This period has been found to be more severe than the 16th century drought along the CA mountains and the Great Plains.
(Weckly 1965). Like the 14th century, the 13th exhibits a relatively small data range, for both the IQR and the overall range.

The 12th century contains three decadal scale events: two pluvial events and one drought. The dry period includes a drought lasting from 1132-1142 with only a slight reprieve; a three-year period with only one value >0.5 SD, before entering back into another dry period (1146-1152) of strong intensity (SD average = -0.86), a period ranked 3rd highest intensity in the overall record. The second method of classification exhibited in Table 5.2 describes a 21-year dry period from 1131–51 with an average SD value of -0.54. The mid-1100s drought is described in Southwestern archaeological data (Euller et al., 1979; Dean et al., 1985) as a forerunner to the great drought of 1200s. The event is evident in tree-ring records from the White Mountains and the four-corners regions (La Marche, 1974; Rose et al., 1982, Woodhouse and Overpeck, 1998). The latter half of the 1100s is moderately wet. However, there are 6 strong droughts between 1122–1299, a period designated by Stine (1994) as an overall extended dry period.

The 11th century contains two decadal scale events: nine and 16-year pluvial events. A century exhibiting a pluvial median and pluvial outliers with no dry outliers (Fig. 5.3). The 10th century possess the highest ranked, by intensity, pluvial event on record at 1.38 SD average, a nine-year period. However, much of the century was dry with 5 significant droughts ranging from -0.61 to -0.82 SD average.

The 9th century contains two large pluvial events: a 14-year mid-century pluvial event (SD average = 0.58) and seven-year pluvial (SD average = 1.19) which is ranked 3rd in intensity overall. The 8th century is conspicuously dry and possessing a very compact dataset. All droughts events are contained in the first half. There are four decadal events evident: two droughts and two pluvials. The 20-year spline [Fig. 5.6 (bottom)] shows a very dry century while
the box and whisker (Fig. 5.3) plot shows the lowest median outside of the instrumental period overall. Grissino-Mayer (1996) records the 8th century as dry overall. Archaeological evidence from the four-corner region, shows a dry period beginning ca. 750 and lasting several decades. A giant sequoia reconstruction in central CA shows a dry period from 699-823 (Hughes and Brown, 1992; Woodhouse and Overpeck 1998). Using the second classification scheme (Table 5.2) three long term events, two dry and one wet, are described in the 700s: 1.) a 22-year dry period (703–24) with an SD average value of -0.5, 2.) a 26-year dry period (735–60) with an SD average value of -0.48, and 3.) a 23-year wet period (784–806) with an SD average value of 0.62.

To step back and summarize: From the 1500s to present the data consists of far more wet than dry years in terms of individual anomalies, i.e. years < -0.5 SD or >0.5 SD. The 8th century is the driest century in the reconstruction in terms of individual anomalies; the only century possessing more dry anomalies (<-0.5 SD) than wet (>0.5). However, the instrumental period also exhibits this phenomenon as well as possessing a median value far below the 8th century. The largest pluvial by intensity is contained in the 900s which is otherwise a moderately dry century and the longest by duration is contained in the early 1600s. The 1500s “mega-drought” lasting 15 years although the period 1573-1593 is exceptionally dry with only a small two-year relief of values <1 SD.

The instrumental period a 78-year period which overlaps with possibly the wettest century overall contains some of the driest data trends on record along with the 8th century.

<table>
<thead>
<tr>
<th>SDC</th>
<th>Event</th>
<th>Overlap periods</th>
<th>Record</th>
</tr>
</thead>
<tbody>
<tr>
<td>1906–22</td>
<td>Wet</td>
<td>1905–17</td>
<td>Fye et al. 2003</td>
</tr>
<tr>
<td>1899–1905</td>
<td>Dry</td>
<td>1897–1904</td>
<td>Fye et al. 2003</td>
</tr>
<tr>
<td>1879–83</td>
<td>Dry</td>
<td>1879–83</td>
<td>Meko and Graybill 1995</td>
</tr>
<tr>
<td>1831–42</td>
<td>Wet</td>
<td>1825–40</td>
<td>Fye et al. 2003</td>
</tr>
<tr>
<td>1773–83</td>
<td>Dry</td>
<td>1772–81</td>
<td>Stahle and Cleaveland 1988</td>
</tr>
<tr>
<td>1728–42</td>
<td>Dry</td>
<td>1721–40; 1735–47</td>
<td>Smith and Stockton 1981; Cleaveland and Duvick 1992</td>
</tr>
<tr>
<td>1664–72</td>
<td>Dry</td>
<td>1664–72</td>
<td>Fye et al. 2003</td>
</tr>
</tbody>
</table>
Table 5.6 SDC 1 April SWE reconstruction event comparison with other tree-ring reconstructions.

<table>
<thead>
<tr>
<th>Period</th>
<th>Type</th>
<th>Event</th>
<th>Source References</th>
</tr>
</thead>
<tbody>
<tr>
<td>1623–28</td>
<td>Dry</td>
<td>1622–28</td>
<td>Fye et al. 2003</td>
</tr>
<tr>
<td>1602–22</td>
<td>Wet</td>
<td>1602–22</td>
<td>Fye et al. 2003</td>
</tr>
<tr>
<td>1573–93</td>
<td>Dry</td>
<td>1570–87; 1573–95</td>
<td>Fye et al. 2003; Stockton and Jacoby 1976</td>
</tr>
<tr>
<td>1553–58</td>
<td>Wet</td>
<td>1549–58</td>
<td>Fye et al. 2003</td>
</tr>
<tr>
<td>1542–49</td>
<td>Dry</td>
<td>1542–48</td>
<td>Fye et al. 2003</td>
</tr>
<tr>
<td>1273–96</td>
<td>Dry</td>
<td>1276–1313</td>
<td>Weakly 1965</td>
</tr>
</tbody>
</table>

Evident are events in our record that match or overlap periods in other records of SW drought reconstructions. Included are PDSI and streamflow reconstructions. The column “Overlap periods” shows event time periods of overlap with our own record. The column “Record” shows the source of the overlap periods.

5.5.1 Instrumental period (1937-2017) comparison with the overall historic period (630-1985)

The recent 21st century and 1950s SW drought phenomena are documented in instrumental records across the Western US. Studies have used these anomalous periods as standards to characterize anomalies revealed in paleo-records against (Cook et al, 2016; Fye et al., 2003). As expected, for this study these two periods present the worst cases of drought over the instrumental record. To contrast these periods as well as wet instrumental periods in the light of the overall historic period an in-depth comparison was made of period events. A t-test was conducted for the observed or instrumental PC\textsubscript{1SWE} data and the tree-ring derived PC\textsubscript{1Recon} data, to test for significance of difference. The range and characteristics of variability inherent in the PC\textsubscript{1Recon} data are fully captured by the PC\textsubscript{1SWE} data. This implies that data within the instrumental period is representative of historic variability over the reconstruction period. There is no evidence of an altered climate regime. However, some important features of the data over the historic reconstruction period (630-1985) are not exhibited during the PC\textsubscript{1SWE} data period (1937–2017). Duration and intensity of drought and pluvial events during the historic period eclipse periods found in the instrumental period. However, drought is much better represented over the instrumental period than pluvial events and extremes.
Droughts in the instrumental period 2011–17 and 1999–2004 exhibit relatively considerable intensity, with the 2011–17 period ranked 2nd in overall intensity and 1999–2004 ranking 10th in overall intensity. Only the 16th century “mega drought” surpasses the intensity of the 2011–17 drought period, although the comparison is made between a 15-year and a seven-year period, respectively. Furthermore the “mega-drought” period is calculated from tree-ring derived data while the ongoing drought period is calculated from the instrumentally observed data.

Concerning duration of drought events, the 1950s 12-year drought event, the longest period of drought during the instrumental period is surpassed in duration by two 15-year periods: 1728–42 and 1573–87. The 1950s drought exhibits the median SD average value for droughts events. However, for pluvial events there is nothing in the instrumental record similar to the numerous extended events during the historic period. There are three pluvial events during the instrumental period. Two of which are closely clustered together and express a moderately wet period (1983–95). The periods 1941–45 and 1983–89 possess SD average values of 0.54, and 0.53, respectively and are in the 15th percentile with the lowest overall SD average value being 0.51. The 1991–95 period has an SD average of 0.68 and is in the 50th percentile. There are 10 pluvial events throughout the historic period >10 years in duration. Only the instrumental period and the 15th, 13th, and 9th century contain no pluvial events > 10 years in duration. The 1983–89 period is longest of the instrumental record and is in the 50th percentile for duration of events. Furthermore, the second classification system used to estimate extended periods with overall wet or dry averages, reveals no multi-decadal wet or dry events during the instrumental record.

5.6 Conclusion
While the ongoing drought period (2011–present) is of significant intensity even when compared to the most extreme droughts in the overall historic period, it is not nearly as long as other events (e.g., 10-, 12-, and 15-year periods) revealed in the historic record. However, of decadal-scale events, such as the 1950s 12-year period, only two 15-year periods (1773–83 and 1573–87) surpass the duration of this drought event. Drought is well represented by the instrumental period yet eclipsed only rarely in terms of duration and intensity. The 2011–17 event is in the 97th percentile in terms of intensity while the 1950s event is in the 95th percentile in terms of duration. The most extreme pluvial events over the instrumental period register at the 85th percentile in terms of intensity and 50th – 60th percentile in terms of duration. It is interesting that the 20th century was the wettest century on record yet intermittent dry years have prevented long term pluvial swings seen elsewhere in the historic record. There may be less influence from multi-decadal scale climate drivers.

Water expectations formed over the 20th century, as seen in other SW paleo-records, was short-sighted and based on a highly pluvial period—the wettest century on record. However, with the onset of the 21st century the instrumental record now reveals intense drought that is not outside the range and variability exhibited throughout the historic period. The 21st century drought intensities are matched and even surpassed in the historic record. Intense drought in the 8th, 10th, 12th, 13th, 16th, and early 20th centuries rival the intensity seen over the 21st century record. Furthermore, more prolonged droughts than what has been seen over the instrumental period with equal intensity and beyond are revealed. Therefore, droughts of the current intensity should be expected on longer time-scales without any climate regime alterations, yet with predicted climate change scenarios considered droughts of increased intensity and persistence.
should be expected to become more frequent than what has been depicted over the historic record.
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