IMPACTS OF CHANGING SNOWMELT TIMING
ON NON-IRRIGATED CROP YIELD

by

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The following individuals read and discussed the thesis submitted by student Erin Murray, and they evaluated her presentation and response to questions during the final oral examination. They found that the student passed the final oral examination.

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DEDICATION

This thesis is dedicated to my sisters, Allison and Sarah, for always understanding me and giving me a reason to laugh. I certainly would not have made it this far without a sense of humor—and I attribute that to them.

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ABSTRACT

As climate changes, the final date of spring snowmelt is projected to occur earlier in the year within the western United States. This earlier snowmelt timing may impact crop yield in snow-dominated watersheds by changing the timing of water delivery to agricultural fields. There is considerable uncertainty about how agricultural impacts of snowmelt timing may vary by region, crop type, and practices like irrigation vs. dryland farming. We utilize parametric regression techniques to isolate the magnitude of impact snowmelt timing has had on historical crop yield independently of climate and physiographic variables that also impact yield. To do this, we examine the historical relationship between snowmelt timing and non-irrigated wheat and barley yield using a multiple linear regression model to predict yield in several Idaho counties as a function of snowmelt date, climate variables (precipitation and growing degree-days), and spatial differences between counties. We apply non-parametric techniques to identify controls on this relationship. To do this, we employ classification and regression trees to predict the relationship between snowmelt timing and yield as a function of both climate and physiographic variables (*e.g.*, elevation). Snowmelt timing significantly predicts crop yield independently of climate variables, which also explain yield. Most trends suggest a decrease in non-irrigated wheat and barley yield with earlier spring snowmelt, but a significant opposite relationship is observed in some Idaho counties. Spring and summer precipitation appears to buffer the negative impact of early snowmelt timing on yield, along with several physiographic characteristics (including elevation/latitude of snowmelt and elevation of planting). These controls may assist agricultural producers, land managers, and water managers in decision making as early snowmelt timing occurs in the future.

Keywords: Climate change; snowmelt; water resources; crop yield; dryland farming; agriculture.

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LIST OF ABBREVIATIONS

SWE	Snow Water Equivalent
SNOTEL	SNOwpack TELemetry
SWI	Southwestern Idaho (crop district)
SCI	Southcentral Idaho (crop district)
EI	Eastern Idaho (crop district)
NI	Northern Idaho (crop district)

1 INTRODUCTION

A warming climate impacts the timing of snowmelt, and as a result, the final snowmelt date—the last date in a year at which snow water equivalent equals zero—is occurring earlier in the year in many of the world's snow-dominated basins (Morán-Tejeda *et al.* 2014, Stewart *et al.* 2005, Yamanaka *et al.* 2012). Many of these are semi-arid to arid regions and rely on snowpack to supply stored water during dry summer months when the need is most critical for a number of uses, including agriculture. A shift in snowmelt timing threatens this source of water by shifting peak streamflow earlier in the year, reducing the amount of water available late in the summer (Mote *et al.* 2005, Stewart *et al.* 2005). These changes in water supply particularly impact agricultural producers who rely on snowmelt to provide water for crop production. Changes in snowmelt timing alter both the soil moisture available to crops throughout the growing season as well as the quantity of water available for supplemental irrigation. Non-irrigated crops may be especially susceptible to changes in snowmelt timing, as the timing between peak discharge and the peak of the growing season will impact soil moisture during critical growth periods without the flexibility to add supplemental irrigation water.

Although many studies have investigated the impacts of changing climatic variables on crop yield (*e.g.* Lobell *et al.* 2011, Long *et al.* 2006, Rosenzweig and Parry 1994, Schlenker and Roberts 2009), the crucial relationship between snowmelt timing and crop yield is unknown. Increased temperature projections, one of the main drivers of crop yield, will decrease future yield of most major crops according to the Intergovernmental Panel on Climate Change's Fifth Assessment Report (IPCC 2014). The negative impact of temperature on yield may be underestimated in many existing linear analyses, making temperature a reliable predictor of global decreased yield as climate change continues (Schlenker and Roberts 2009). In contrast, projected precipitation increases in the United States translate to higher average crop yield (IPCC 2014). Regional climate precipitation forecasts are more uncertain than those for temperature, but most models in the western United States predict summer precipitation to decrease (Mote and Salathé 2010), which is arguably the most important water source for dryland crops. In addition to the projected decrease in summer precipitation in the western United States, the potential impact of changing soil moisture at the start of the growing season should not be underestimated. In snowmelt-dominated regions, especially those projecting less summer precipitation, the timing of snowmelt will intrinsically change the timing of water available to crops. We must therefore consider changing snowmelt timing in addition to precipitation/temperature changes as a potential driver of future yield changes.

Speculations on how future changes in snowmelt timing will drive agricultural changes in arid, snow-dominated regions have focused largely on water supply to irrigation systems (Barnett *et al.* 2005). However, the way in which changes in snowmelt timing affect the yields of non-irrigated crops is a critical piece of information that is not well understood. Given that the trend toward earlier snowmelt timing is projected to continue in the western United States (Stewart *et al.* 2004), it is important to quantify the impact of these changes on crop yields. This information is necessary not only to understand impacts of climate change on producers of non-irrigated agriculture, but it is also critically important in predicting how climate change will affect the demand for irrigation water by agricultural producers. An understanding of both changes in the demand for irrigation water and changes in the supply of water for irrigation will support a more accurate assessment of how agricultural producers will adapt to climate change and the associated economic welfare losses that may arise.

In this thesis, we explore the historical relationship between final snowmelt date and non-irrigated agricultural yield. We choose to look at non-irrigated yield in order to quantify changes in the baseline yield of crops that do not receive supplemental irrigation water. About 83% of global farmland practices dryland farming—accounting for 60% of total food production (Fereres and Soriano 2007). Understanding all factors that impact non-irrigated crop yield is critical for assessment of global food security in a changing climate. Sensitivity of baseline crop yield to changing snowmelt timing will also inform how unmanaged ecosystem production might respond to this changing water source. Finally, a change in dryland yield will equate to a change in irrigated yield before water application and could also predict future water demand for irrigated crops with changing final spring snowmelt.

Changes in crop production and irrigation demand in response to changing snowmelt timing are especially of concern in semi-arid production regions that do not receive adequate precipitation throughout the growing season. Idaho is a state of particular interest in this problem, as much of the state depends on snowmelt for water supply with 62% of annual precipitation falling as snow (Serreze *et al.* 1999). According to the 2012 Census of Agriculture, about 32% of farmland in Idaho is non-irrigated

(National Agricultural Statistics Service 2014). Most of Idaho's water diversions are used in irrigation and non-irrigated farmers without the appropriate water rights are prohibited from applying supplemental irrigation water during the growing season. In Idaho, changing snowmelt date is well documented and has become both earlier and more variable within the last 20 years (Kunkel and Pierce 2010), a trend that will likely impact dryland production.

In this paper, we aim to establish the magnitude and direction of snowmelt timing impacts on crop yield in Idaho. Idaho's diverse climate and physiography make it a good place to study how climate and physiographic controls affect the relationship between snowmelt timing and crop yield. Notably, the arid production region of the Snake River Plain (running through Southwest and Southcentral Idaho) receives little precipitation throughout the growing season and primarily subsists on irrigated production. In contrast, Northern and Eastern Idaho receive much more precipitation, thereby supporting more dryland crops. We utilize Idaho's diverse climate and physiographic landscape to test the impact of changing snowmelt timing on yield in different production regions that will likely experience different effects.

We use empirical methods to identify the historical relationship between snowmelt timing in Idaho and county-level agricultural yield. An empirical approach is compelling as we can observe actual changes in a complicated system rather than simplifying simulations. Many empirical studies have successfully investigated climate change impacts on crop yield (Auffhammer and Schlenker 2014; Lobell *et al.* 2007, Lobell and Burke 2010, Sarker *et al.* 2012). In contrast, physical modeling is data-intensive to calibrate and typically produces simplified solutions. The robust historical dataset of reconstructed final snowmelt date produced by Kunkel and Pierce gives us a lengthy time series (spanning 1938-2007) with which to explore the historical impact of changing snowmelt timing on yield. We use two complementary statistical methods and retrospective data to answer the following questions:

(1) Has snowmelt timing impacted crop yield and where are these effects strongest?

(2) What is the direction of impact and what are the climatic and physiographic controls that affect the direction and strength of the relationship?

Complementary parametric and non-parametric estimation techniques allow us to explore the impact of snowmelt timing at sixteen SNOTEL stations in Idaho on non-irrigated wheat and barley yield. We hypothesize that these methods will identify a relationship between snowmelt timing and yield that varies in direction. For example, in Northern (humid) Idaho, an early snowmelt date may increase crop yield by extending the growing season. However, in Southern (arid) Idaho, an early snowmelt date may decrease crop yield by decreasing the total water available to crops over the growing season.

To test the relationship between snowmelt timing and yield, we first estimate a parametric multiple linear regression model that controls for climatic variables (*e.g.,* precipitation and growing degree-days) and spatial differences between counties (*e.g.,* elevation) that also impact crop yield. This parametric regression allows us to extract the partial impact of snowmelt timing on historical yield, and establish the direction and magnitude of its influence. As this methodology imposes an assumption that the relationship between snowmelt timing and yield is linear, we additionally utilize non-parametric techniques to identify non-linear controls on the direction of the relationship.

Together, these techniques reveal the underlying relationship between snowmelt timing and yield, as well as the factors that control the direction of impact.

Using these two statistical techniques, we find that snowmelt timing has significantly impacted non-irrigated wheat and barley yield independently of climatic and physiographic characteristics. Early snowmelt generally reduces both wheat and barley yields; however, in some regions early snowmelt corresponds with increased crop yields. Despite most regions experiencing lower yield when snow melts early, several variables identify the regions that appear to benefit from early snowmelt. Notably, spring and summer precipitation may buffer the negative impact of early snowmelt timing on yield. In addition to precipitation, several biophysical characteristics of the county and SNOTEL stations (such as latitude, elevation, and topography) predict the varied direction of impact. Identification of climatic and physiographic controls on this relationship gives producers in snow-dominated regions a pertinent piece of information for navigating their expected yield changes in response to climate change. A decrease in baseline yield in arid production regions under future early snowmelt timing will almost certainly increase demand for irrigation water—a result with serious implications for water managers in the West.

2 STUDY REGION

Idaho’s diverse climate and physiography provides a range of different regions to study the relationship between snowmelt timing and crop yield. Historical crop yield data exists at the county level proximal to SNOTEL stations for which historical snowmelt timing also exists (Figure 2.3), giving us a robust dataset with which to test controls on this relationship. Below, we discuss how agricultural production and climatic/physiographic characteristics vary spatially across Idaho

2.1 Agricultural Landscape

Barley and wheat are two of the most abundant dryland crops produced for harvest in Idaho, with non-irrigated acres making up about 55% of total wheat production and 36% of total barley production (National Agricultural Statistics Service 2014). Four major crop districts in Idaho (Figure 2.1) represent broadly different crop choices, production practices, and climatic/soil conditions (Patterson and Painter 2013): 1) Northern Idaho (NI); 2) Southwestern Idaho (SWI); 3) Southcentral Idaho (SCI); and 4) Eastern Idaho (EI). Table 2.1 summarizes how several production metrics vary by crop district including the total acres of production, percentage of non-irrigated land, average wheat yield, and average barley yield. Crop district summary statistics are calculated by averaging county-level summary statistics. Detailed summary statistics by county are presented in Appendix A, Tables A.4 (Wheat) and A.5 (Barley).

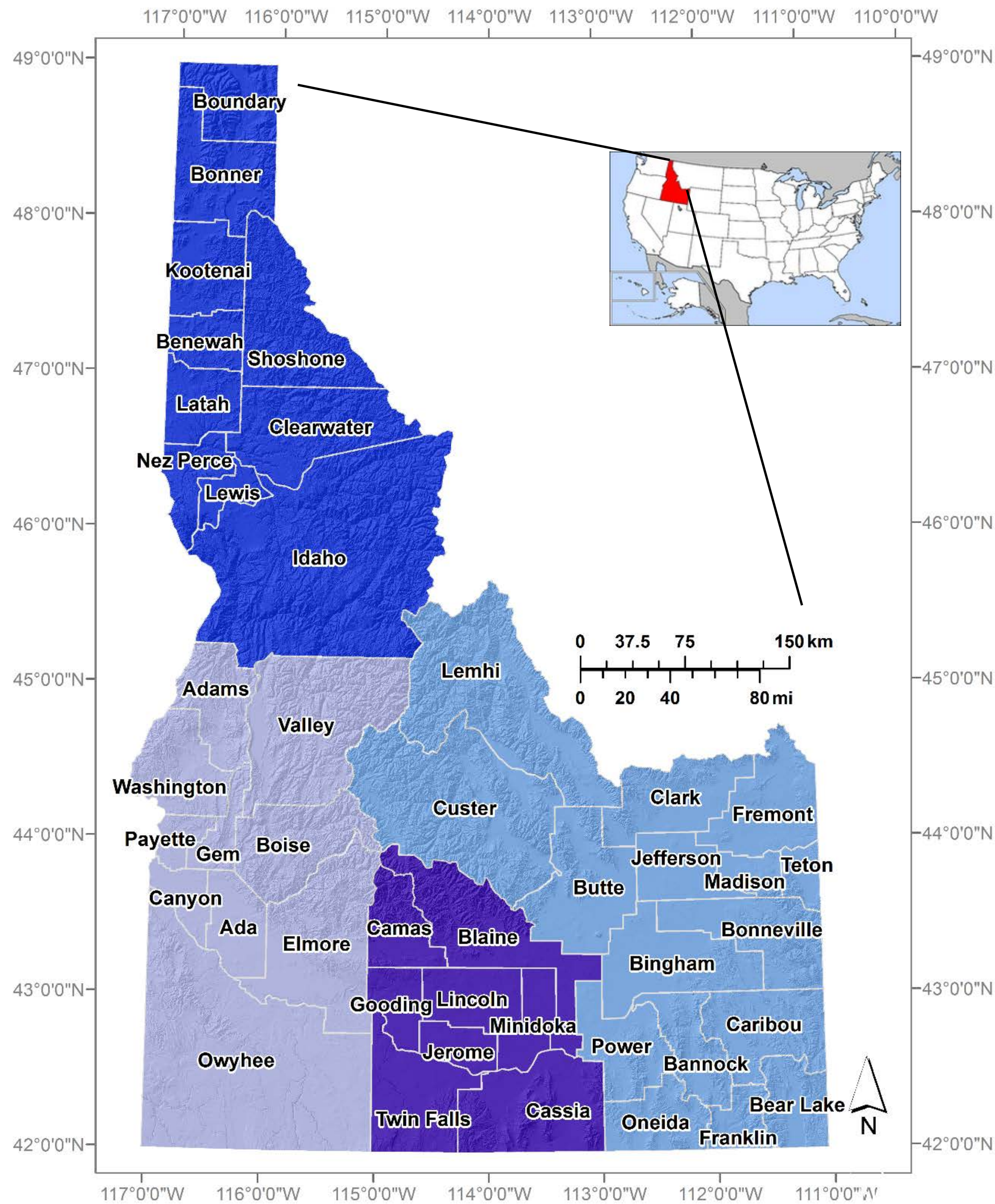


Figure 2.1. **Map of the four Crop Districts that characterize the agricultural landscape of Idaho (Patterson and Painter 2013): 1) Northern Idaho (NI); 2) Southwestern Idaho (SWI); 3) Southcentral Idaho (SCI); and 4) Eastern Idaho (EI).**

Table 2.1. **Non-irrigated production statistics by crop district from the 2012 Census of Agriculture (National Agricultural Statistics Service 2014). Crop yield is in units of bushels per acre [bpa]. Crop districts are labeled in Figure 2.1.**

Crop District	Harvested Acres	Non-Irrigated land	Dryland Wheat Yield [bpa]	Dryland Barley Yield [bpa]
NI	828,000	95%	49	44
SWI	621,000	19%	45	45
SCI	1,171,000	13%	23	26
EI	1,900,000	24%	24	28
Idaho Total	**4,505,000**	**34%**	**29**	**30**

2.2 Climate and Physiographic Landscape

The climate variable of primary interest in this study, precipitation falling as snow, differs in distribution across the state with the most snow falling in the mountainous regions of central Idaho. Climate and elevation gradients diversify the state’s landscape (Figure 2.2) and Table 2.2 summarizes several climate variables by crop district. Köppen-Geiger climate zones classify Northern and Eastern Idaho as a “fully humid snow climate” whereas Southwest and South central Idaho is arid (Kottek *et al.* 2006). In addition to being arid, the Snake River Plain (area of low elevation crossing Southwest and South central Idaho) is classified as “summer dry with hot summers” (Kottek *et al.* 2006). The fully humid classification of Northern and Eastern Idaho indicates that they receive more summer precipitation relative to the Snake River Plain. Many of the climate and physiographic characteristics in Idaho (Figure 2.2) are correlated with snowfall, making it necessary to consider the climate and physiographic landscape when teasing apart the partial impact of snowmelt timing. Also, the diversity of climate and physiographic characteristics give us a range of conditions across the state for investigating controls on the relationship between snowmelt timing and crop yield.

Over the period of record for crop yield data in Idaho (starting in 1938), the final snowmelt date is becoming earlier over time (Figure 2.3). The diverse crop districts of Idaho will almost certainly be impacted by this projected early snowmelt timing in different ways. Agricultural production in Idaho relies on snowmelt as a water source in all crop districts and we expect changes in the timing of snowmelt to influence all regions, even those where snow comprises a minor percentage of the total annual precipitation.

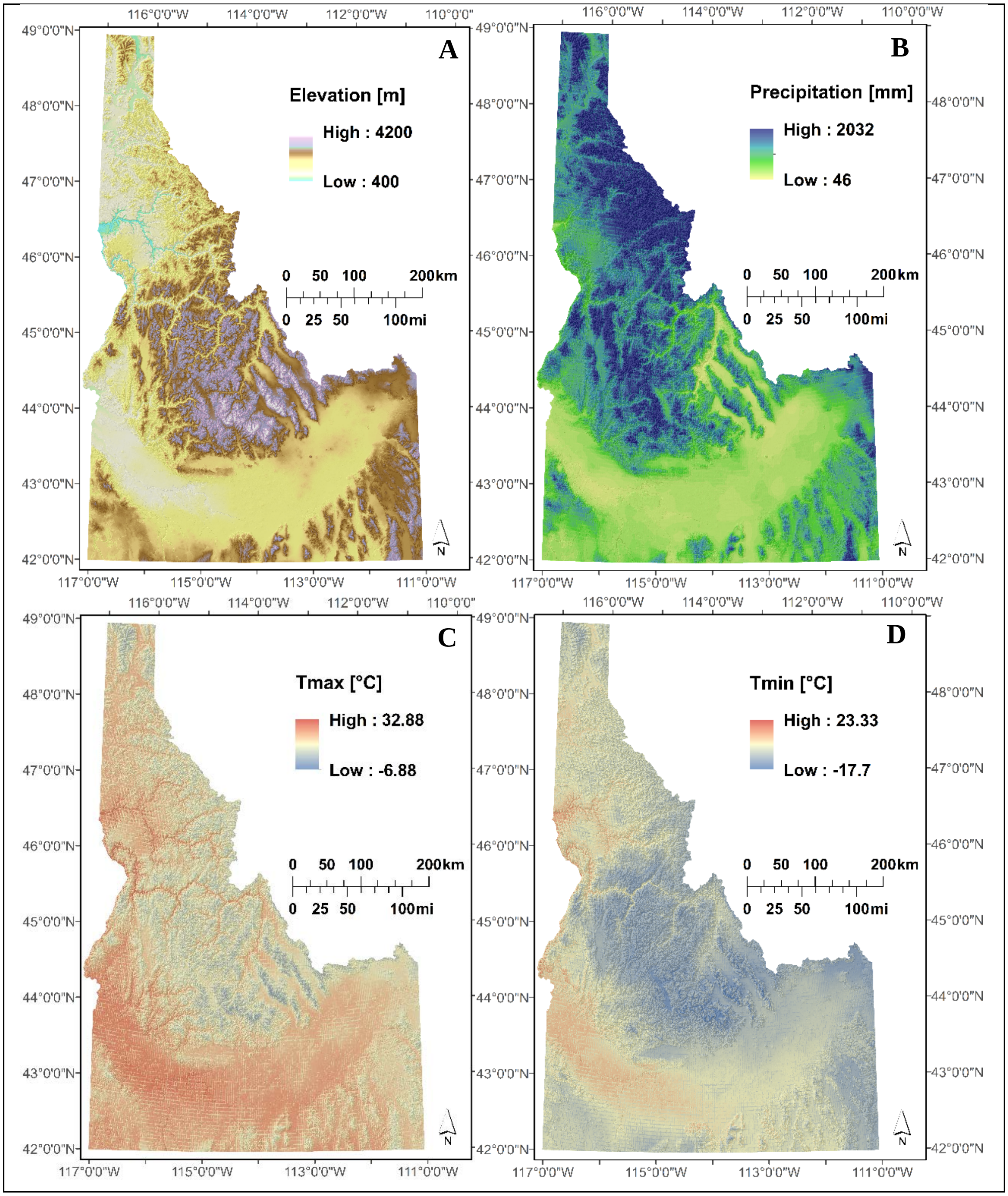


Figure 2.2. **Climate and physiographic characteristics of Idaho. All presented climate data is the annual 30-year climate normal from 1981-2010 (PRISM Climate Data): (A) Elevation (800-m DEM), (B) Precipitation, (C) Maximum temperature, (D) Minimum temperature.**

Table 2.2. **Climate summary statistics by crop district—Northern Idaho (NI), Southwestern Idaho (SWI), Southcentral Idaho (SCI), Eastern Idaho (EI), and State Total—for minimum temperature [°C], maximum temperature [°C], precipitation [mm], and total snowfall [cm].**

Region	**Variable**	**Mean**	**StDev**	**Min**	**Max**
NI	Minimum Temperature	2.8	0.8	1.6	3.7
	Maximum Temperature	15.5	1.5	14.0	17.4
	Precipitation	54.6	10.9	35.0	71.8
	Total Snow	9.3	2.2	6.9	12.3
SCI	Minimum Temperature	1.8	3.0	-3.8	5.1
	Maximum Temperature	16.9	2.3	12.3	20.0
	Precipitation	32.2	14.7	15.1	56.1
	Total Snow	6.5	8.6	1.2	29.2
SWI	Minimum Temperature	0.3	2.0	-2.9	2.5
	Maximum Temperature	15.3	1.4	13.4	17.3
	Precipitation	23.2	3.1	19.8	28.2
	Total Snow	6.5	3.8	3.0	14.8
EI	Minimum Temperature	-0.9	1.4	-2.9	2.1
	Maximum Temperature	13.9	1.2	11.6	15.6
	Precipitation	27.5	6.4	20.2	40.8
	Total Snow	9.1	3.9	5.3	18.8
State	Minimum Temperature	0.7	2.4	-3.8	5.1
	Maximum Temperature	15.2	1.9	11.6	20.0
	Precipitation	33.5	14.6	15.1	71.8
	Total Snow	8.0	5.1	1.2	29.2

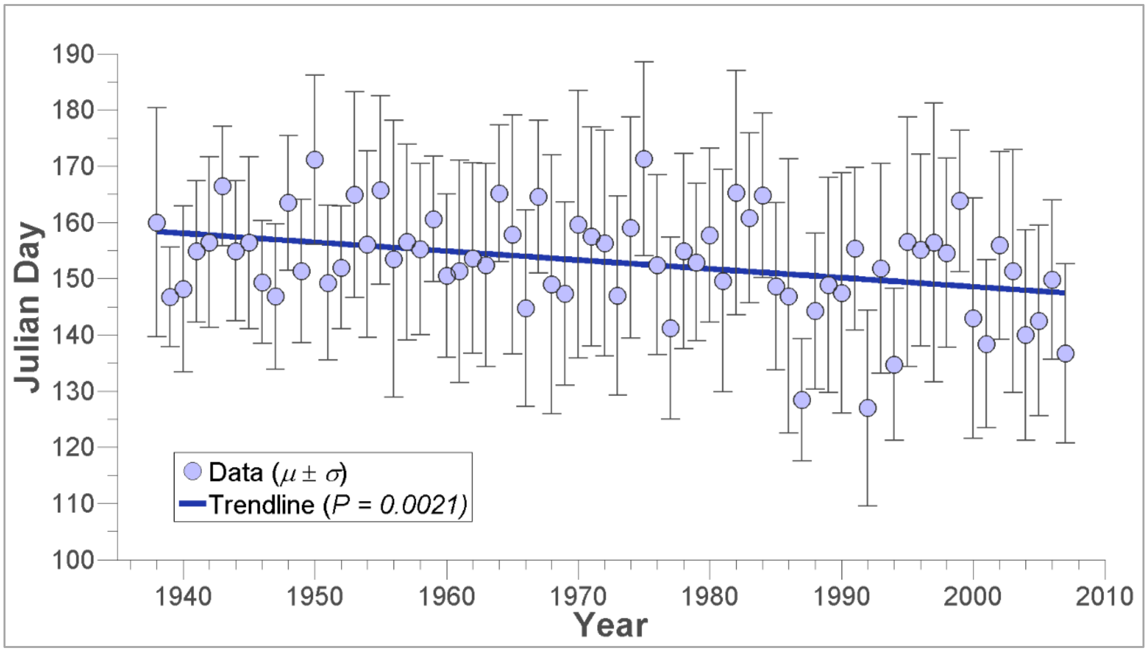


***Figure 2.3*. Historical reconstructions of snowmelt timing at Idaho SNOTEL stations (Kunkel and Pierce 2010). Each data point represents the mean of snowmelt timing at 16 SNOTEL stations within each year, ± the standard deviation between stations.**

3 DATA

This section describes the data used in estimation, including data sources and variable calculations. Detailed data sources are presented in Appendix A, Tables A.1 – A.3. Detailed summary statistics by county and SNOTEL station are reported in Appendix A, Tables A.4 – A.12.

3.1 Agricultural Yield

Non-irrigated wheat and barley yield is compiled in 43 Idaho counties from United States Department of Agriculture survey data 1938-2008 as a county-level, annual estimate in units of bushels per acre [bpa] (National Agricultural Statistics Service 2014). To account for yield increases over time due to technological advances, we detrend each yield series and use the negative residual yield in all statistical analyses. Zhu *et al.* (2011) debates the varying methodologies in detrending yield data; for the purposes of this study, we use a linear model to detrend yield by year. The following steps produce our annual, detrended yield data.

(1) Estimate a best fit line (Y_{fit}) through observed yield (Y_{obs}) over time using the method of ordinary least squares (Equation 3.1).

$$Y_{fit} = \beta * \text{Year} + \alpha \qquad \text{(Eq. 3.1)}$$

(2) Calculate detrended yield ($Y_{residual}$) using the negative residual between the best fit yield (Y_{fit}) and observed yield (Y_{obs}) (Equation 3.2).

$$Y_{residual} = -(Y_{fit} - Y_{obs}) \qquad \text{(Eq. 3.2)}$$

For the remainder of analyses, the detrended yield data ($Y_{residual}$) from Equation 3.2 is used to represent county-level yield. Figure 3.1 shows yield changes over time graphically; including the observed yield data, the linear fit to the raw data, and the subsequent detrended data in four counties that represent each crop district of Idaho. Table 3.1 lists the slope (β) of each best fit line from Equation 3.1.

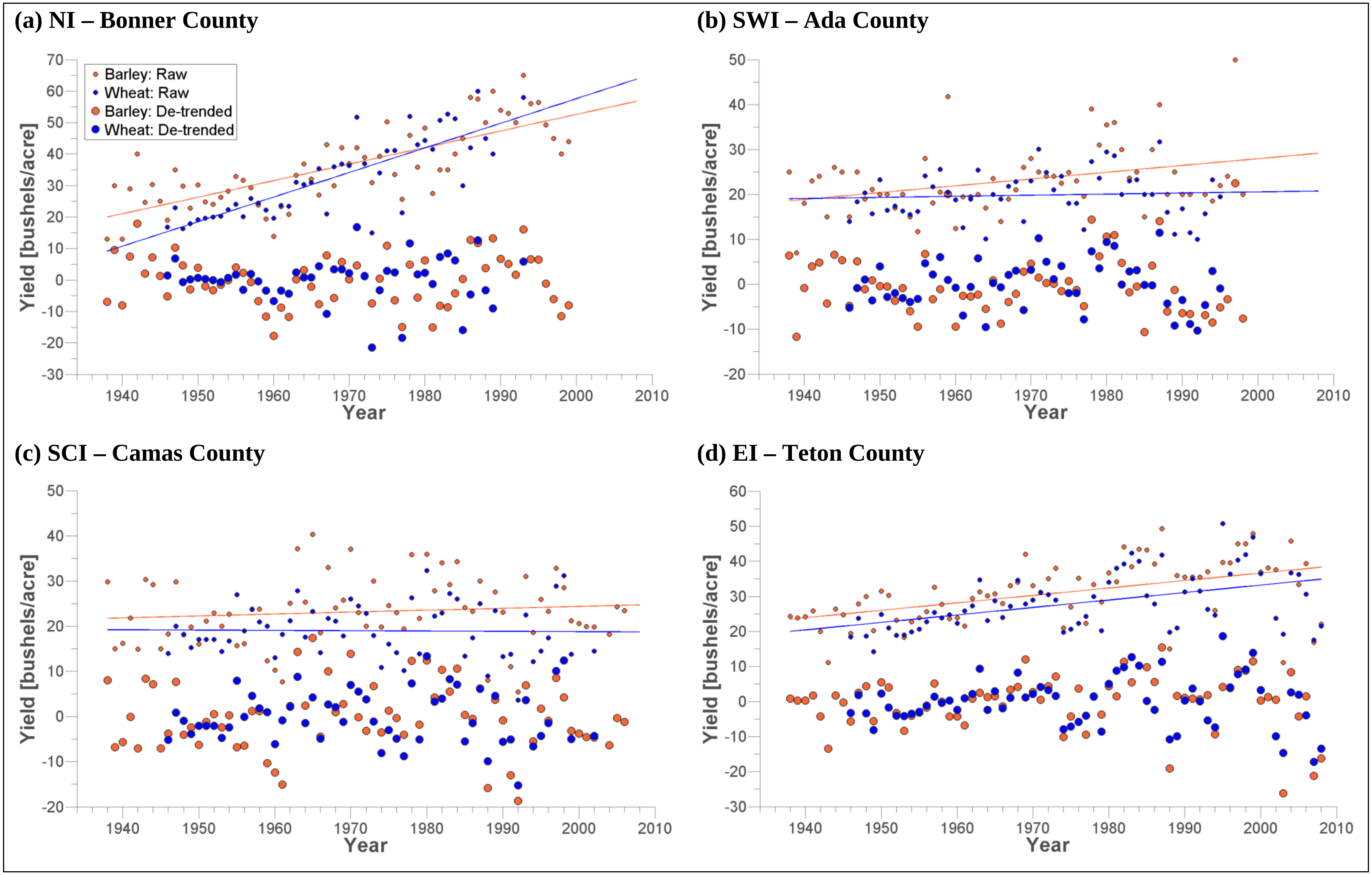


Figure 3.1. **Yield increases over time in four Idaho counties representing the four crop districts of Idaho: (a) Northern Idaho represented by Bonner County, (b) Southwestern Idaho represented by Ada County, (c) Southcentral Idaho represented by Camas County, and (d) Eastern Idaho represented by Teton County. "Raw" and "Detrended" estimates are those before and after detrending, respectively.**

Table 3.1. **Slopes (β) used in de-trending analysis, calculated from Equation 3.1.**

County Number	County Name	Barley Slope	Wheat Slope
1	Ada	0.15	0.02
2	Adams	0.25	0.29
3	Bannock	0.04	0.14
4	Bear Lake	0.05	0.05
5	Benewah	0.63	0.67
6	Bingham	0.06	0.10
7	Blaine	0.27	0.09
8	Boise	0.29	0.28
9	Bonner	0.53	0.78
10	Bonneville	0.16	0.20
11	Boundary	0.77	0.78
12	Butte	0.09	0.39
13	Camas	0.04	-0.01
14	Canyon	0.14	0.10
15	Caribou	0.31	0.26
16	Cassia	0.22	0.16
17	Clark	0.28	0.25
18	Clearwater	0.42	0.53
19	Custer	0.02	0.50
20	Elmore	0.29	0.06
21	Franklin	0.05	0.13

22	Fremont	0.35	0.29
23	Gem	0.20	0.23
24	Gooding	0.25	0.08
25	Idaho	0.49	0.70
26	Jefferson	0.33	0.42
27	Jerome	0.05	0.10
28	Kootenai	0.56	0.74
29	Latah	0.58	0.74
30	Lemhi	0.23	-0.10
31	Lewis	0.51	0.61
32	Lincoln	0.31	0.22
33	Madison	0.21	0.19
34	Minidoka	0.32	0.34
35	Nez Perce	0.61	0.66
36	Oneida	0.06	0.10
37	Owyhee	0.08	0.31
38	Payette	0.23	0.40
39	Power	0.04	0.18
40	Teton	0.21	0.21
41	Twin Falls	0.16	0.28
42	Valley	0.31	0.40
43	Washington	0.25	0.24

3.2 Climate Characteristics

The date of final spring snowmelt is historically reconstructed from streamflow records as the last Julian day in a water year that snow water equivalent (SWE) becomes zero (Kunkel and Pierce 2010). In this study, we use final spring snowmelt date from 16 SNOTEL stations throughout Idaho (Figure 3.1) with a period of record beginning as early as 1901 at some SNOTEL stations. The average length of record is 65 years, and we use data beginning in 1938 to span our length of crop yield data. We disregarded data from SNOTEL stations outside of Idaho.

Daily precipitation [mm], maximum and minimum temperature [°C] are collected in 24 counties from Global Historical Climate Network (GHCN) sites (Peterson and Vose 1997). Each GHCN site is used to estimate average county-level climate (see Table A.1 for pairings). Cumulative precipitation is summed over three different periods—annual ($Pann$), summer ($Psum$), and spring ($Pspr$). Cumulative precipitation is calculated if the annual time-series has at least 360 days of complete data.

(1) Cumulative annual precipitation ($Pann$) occurs over a calendar year.

(2) Cumulative summer precipitation ($Psum$) occurs in May, June, and July.

(3) Cumulative spring precipitation ($Pspr$) occurs in April and May.

The three calculations of P are used in different regression models as different predictor variables.

Growing degree-days are summed over three growing season lengths—early ($GDDear$), average ($GDDavg$), and maximum ($GDDmax$). Growing degree-days (GDD) are calculated for the growing season within each county (i) and year (t) using the rectangle method (Eq. 3.3):

$$GDD_{i,t} = \sum_{j=1}^{N} \frac{(T_{max}+T_{min})}{2} - T_{base} \qquad \text{(Eq. 3.3)}$$

where j represents each day in the consecutive growing season. For both crops, the daily average temperature is calculated without allowing the recorded maximum or minimum to exceed the ranges of temperatures for which plant growth occurs: assumed to be $T_{max} = 30^{\circ}$C and $T_{min} = 0^{\circ}$C. The minimum temperature at which plant growth will occur (T_{base}) is also set equal to 0°C for both crops. Because both barley and wheat have similar growing seasons, growing degree-days are summed over the same three theoretical growing season lengths, with the number of days listed:

(1) $GDDavg$ = Average growing season (N = 153): April 1st – August 31st
(2) $GDDear$ = Early growing season (N = 213): February 1st – August 31st
(3) $GDDmax$ = Maximum growing season (N = 274): February 1st – October 31st

We calculate cumulative growing degree-days for the first growing season if the daily temperature record is complete (no missing days). Because the second two growing seasons are longer, we calculate growing degree-days if the time series is missing up to 2 days of data on temperature. The three calculations of GDD are used in different regression models as different predictor variables.

Monthly climate statistics of historical precipitation [mm], minimum temperature [°C], maximum temperature [°C], and snow depth [cm] are collected in 43 Idaho counties. These climate statistics were calculated by US Climate Data, USCD, (http://usclimatedata.com) or the Western Regional Climate Center, WRCC, (http://www.wrcc.dri.edu/). Appendix A (Table A.3) lists the city used to represent each county-level climate normal along with the period of record used to compute a climate normal.

3.3 Physiographic Characteristics

Spatial variables are collected in 43 Idaho counties using ArcGIS Spatial Analyst toolbox from a digital elevation model (DEM), derived from a 3-arcsec (~80 m) National Elevation Dataset DEM into a 30-arcsec (~800 m) DEM (Daly *et al.* 2008). These include latitude at the SNOTEL station [°N], elevation at the SNOTEL station [m], county mean elevation [m], county standard deviation of elevation [m], elevation difference between the SNOTEL station and the county mean [m], and distance from the county to the SNOTEL station [m].

To calculate the distance between a county and a SNOTEL station, we either used the county centroid or the agricultural field centroid (Figure 3.2). All fields in Figure 3.1 are approximate locations of the non-irrigated agriculture occurring within a county. If it was difficult to visually distinguish non-irrigated agriculture from irrigated agriculture, the entire agricultural region was included.

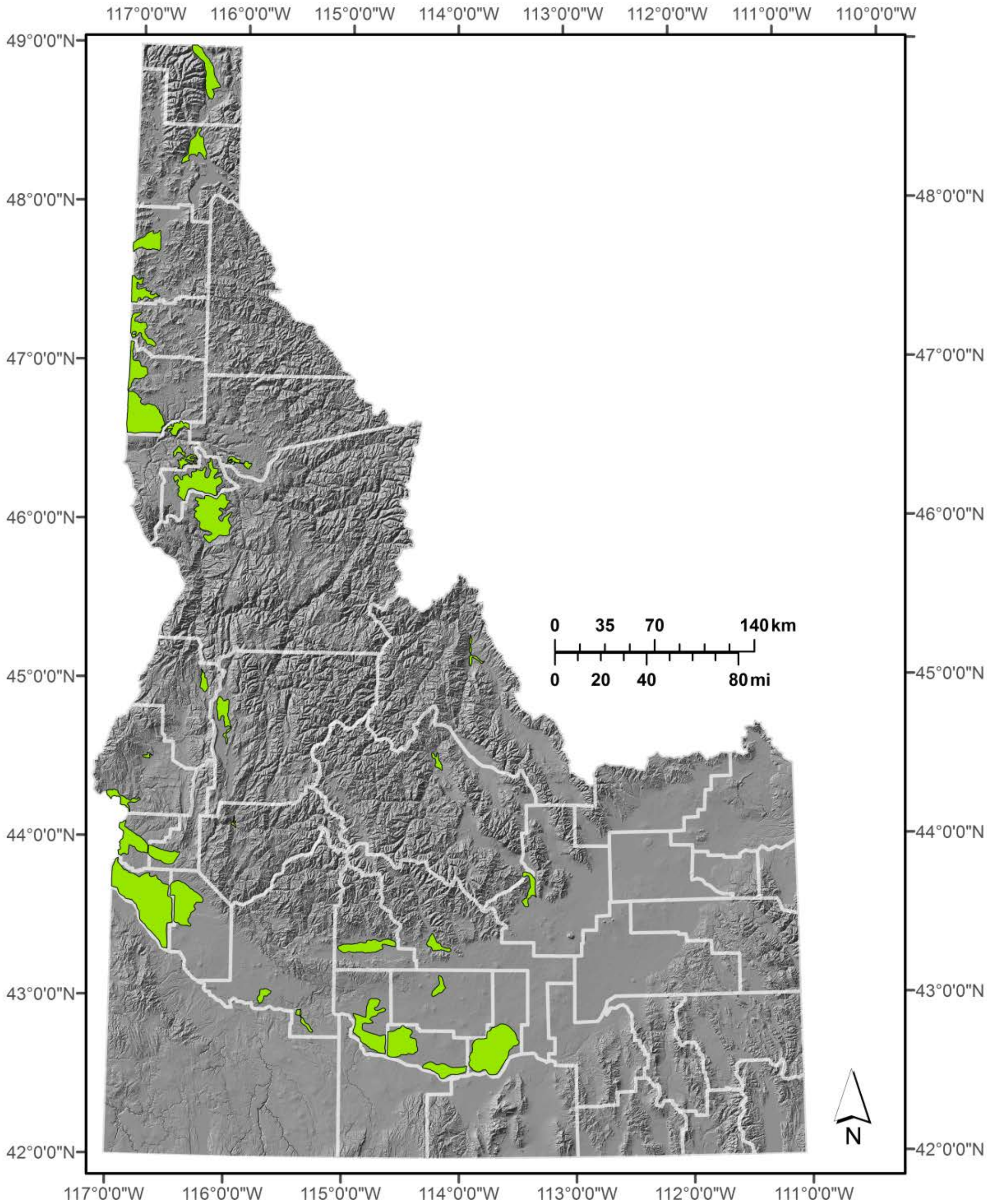


Figure 3.2. **Approximate non-irrigated field locations (green) are visually extracted in several Idaho counties.**

4 METHODS

Timing of snowmelt captures other climate characteristics (such as temperature) that also influence crop yield. We use the following methodology to control for these covariates and establish partial influence of snowmelt timing and yield. We additionally identify potential spatial controls on the varying direction of the relationship. We outline a comprehensive list of assumptions for our methodology in Appendix B.

To quantify the relationship between snowmelt timing and yield, we estimate a Pearson's linear correlation coefficient (rho) between final snowmelt date (x) at 16 SNOTEL stations and non-irrigated crop yield (y_c)—wheat yield N = 688; barley yield N = 688—in 43 Idaho counties using Equation 4.1.

$$rho_c = \frac{\sum xy_c}{\sqrt{\sum x^2 \sum {y_c}^2}} \qquad \text{(Eq. 4.1)}$$

where the subscript c denotes the specific crop: wheat (y_w) or barley (y_b).

The same 43 counties were used in the non-parametric analysis (Figure 4.1). A smaller subset of 24 counties was used in the parametric analysis due to their proximity to SNOTEL stations (Figure 4.1). Parametric and non-parametric methods are presented separately in detail below.

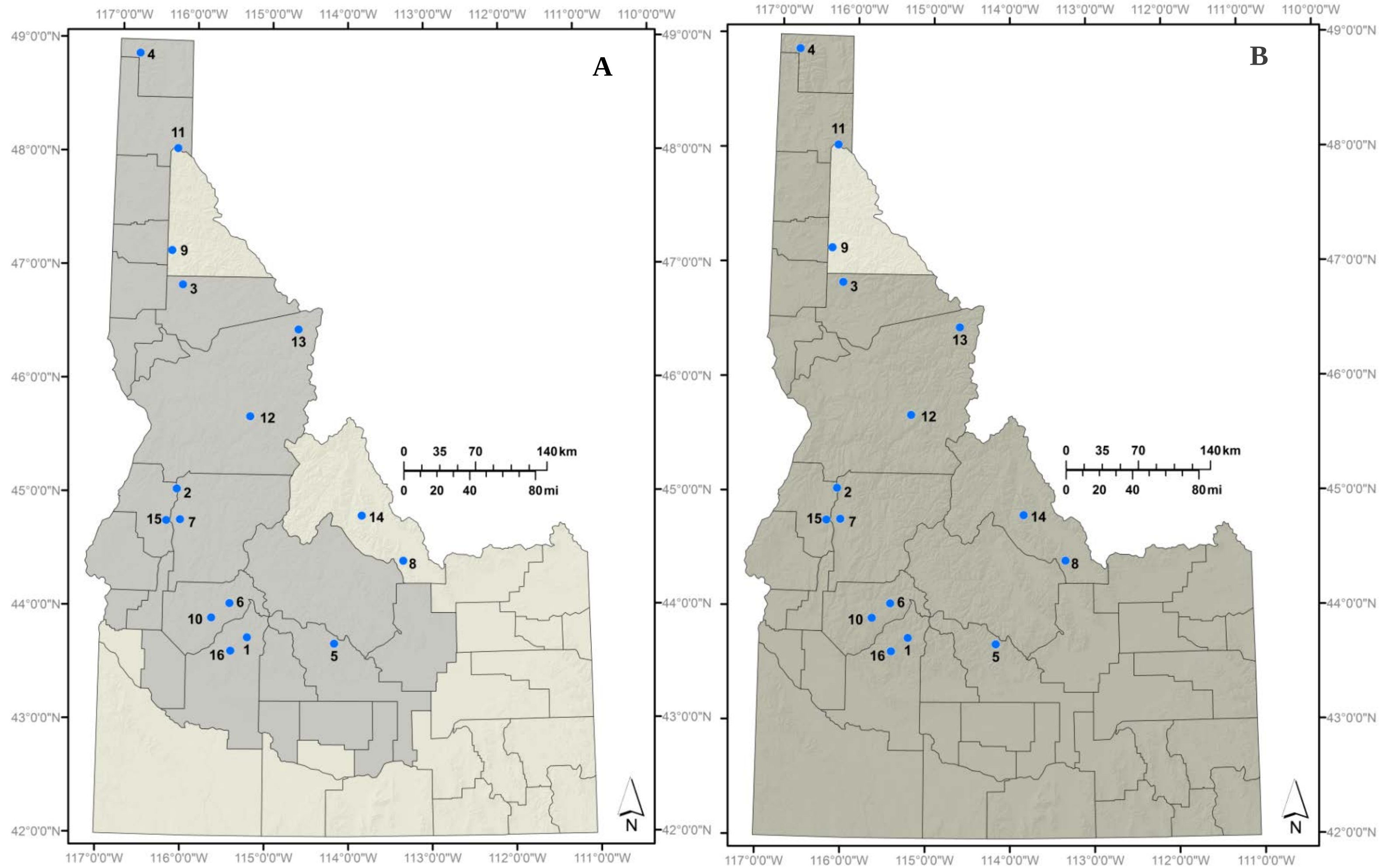


Figure 4.1. **Sample of counties used in the parametric and non-parametric analyses. Dark-shaded counties were used in (A) parametric analysis (*N* = 24) and (B) non-parametric analysis (*N* = 43). SNOTEL station locations are shown as blue dots, with station names listed in Table 4.1.**

Table 4.1. **SNOTEL stations corresponding to site ID from Figure 4.1 map.**

Site Number	Station Name	Site Number	Station Name
1	Atlanta Summit	9	Mica Creek
2	Brundage Reservoir	10	Mores Creek Summit
3	Elk Butte	11	Mosquito Ridge
4	Hidden Lake	12	Mountain Meadows
5	Hyndman	13	Savage Pass
6	Jackson Peak	14	Schwartz Lake
7	Long Valley	15	Squaw Flat
8	Meadow Lake	16	Trinity Mountain

4.1 Parametric Regression

In the parametric methodology, we quantify the partial impact of snowmelt timing on historical crop yield. Twenty-four counties are included in this regression analysis due to their proximal location to SNOTEL stations and robust historical record of non-irrigated crop yield (shaded counties, Figure 4.1). In this study, final snowmelt date at a SNOTEL station is assumed to correlate with an unmeasurable variable of county-level snowmelt date. To ensure the best representative station is chosen, the SNOTEL station is visually matched to the county based on distance and watershed boundaries. A detailed description of SNOTEL-County pairings is discussed in Appendix A. Table A.1 presents the specific pairing justification used for each county.

We isolate the partial impact of snowmelt timing by controlling for other climate and physiographic characteristics. We estimate coefficients in each model to attribute variation in the non-irrigated wheat and barley yield (Y_{it}) to variation in snowmelt date (SM_{it}), precipitation (P_{it}), and growing degree-days (GDD_{it}). We include county-level fixed effects to control for within-year effects that differ across counties. Including county-level fixed effects minimizes omitted variable bias in the regression model. Fixed effects allow the regression equation intercept to be different in each county, capturing all predictor variables that we are not measuring within a county (such as elevation, soil moisture, farmer decisions, etc.). In each model (Equations 4.2 and 4.3), the term $\varepsilon_{i,t}^{FE}$ is an idiosyncratic error term that explains random deviations from the predicted regression line and may include omitted variables, randomness, measurement error, and/or modeling choices. We assume that $\varepsilon_{i,t}^{FE} \sim NIID(0, \sigma^2)$ and test whether this assumption is appropriate using the diagnostics presented in Appendix B. All parameters are estimated using the method of ordinary least squares.

The first "Total" regression model (Equation 4.2) estimates non-irrigated wheat and barley yield ($Y_{i,t}$) separately as a function of snowmelt date ($SM_{i,t}$), precipitation ($P_{i,t}$), and growing degree-days ($GDD_{i,t}$).

$$Y(w;b)_{i,t}^{FE} = \beta_{SM} SM_{i,t}^{FE} + \beta_{GDD} GDD(avg;ear;max)_{i,t}^{FE} + \beta_P P(ann;sum;spr)_{i,t}^{FE} + \varepsilon_{i,t}^{FE} \quad \text{(Eq. 4.2)}$$

Wheat yield (Yw_{it}) and barley yield (Yb_{it}) are estimated separately according to nine combinations of explanatory variables (with the three above stated measures of growing degree-days and three measures of precipitation used in separate models).

Therefore, eighteen total regression models are estimated using the “Total” regression model (Equation 4.2)—9 for predicting wheat yield and 9 for predicting barley yield.

We estimate a second “Interaction” regression model (Equation 4.3) that uses the same predictor variables as above with the addition of an interaction dummy variable to identify the interaction between correlation direction and predictor variables.

$$Y(w;b)_{i,t}^{FE} = \beta_{SM} SM_{i,t}^{FE} + \beta_{GDD} GDD(avg;ear;max)_{i,t}^{FE} + \beta_P P(ann;sum;spr)_{i,t}^{FE}$$
$$+ \beta_{SM}(C_i\, SM_{i,t}^{FE}) + \beta_{GDD}(C_i\, GDD(avg;ear;max)_{i,t}^{FE})$$
$$+ \beta_P(C_i\, P(ann;sum;spr)_{i,t}^{FE} +) + \varepsilon_{i,t}^{FE}$$

(Eq. 4.3)

We hypothesize that different processes govern the impact of snowmelt timing on yield in positively and negatively correlated counties. We test this hypothesis using an interaction term, C_i , which allows the marginal effect of each predictor to differ between positively and negatively correlated counties. A negative correlation between snowmelt date and yield indicates that earlier snowmelt dates correspond with increased crop yield, on average. Conversely, a positive correlation between snowmelt date and yield indicates that earlier snowmelt date corresponds with decreased crop yield, on average. Some counties exhibit a different correlation direction for the two crops, wheat and barley. A summary of those correlation coefficients and significance between non-irrigated wheat or barley yield are included in Table A.2.

A dummy variable, C_i, is constructed as follows according to the direction of the correlation coefficient between final snowmelt date and yield. C_i is then multiplied by predictor variables (precipitation, snowmelt date, and growing degree-days) and each resulting interaction term is included in the model as a predictor variable.

$$C_i = \begin{cases} 1 \; if \; positive \; correlation \\ 0 \;\; ifnegative \; correlation \end{cases} \qquad \text{(Eq. 4.4)}$$

The positively (C_i = 1) and negatively (C_i = 0) correlated counties are presented below in Table 4.2 and Figure 4.2. These county-SNOTEL pairings were chosen according to the aforementioned methodology in Appendix A as to not bias the coefficient estimates by only including significant correlations. Table 4.3 contains a summary of all regression models—“Total” and “Interaction”—with the included variables and number of observations.

Table 4.2. **Pearson’s linear correlation coefficients—barley (rho_b) and wheat (rho_w)—between county-level crop yield and snowmelt timing at the indicated SNOTEL station. ‘*’ denotes significance at *P* ≤ 0.10, ‘**’ denotes significance at *P* ≤ 0.05, and ‘***’ denotes significance at *P* ≤ 0.01.**

County	SNOTEL station	rho_b	rho_w
Ada	Trinity	0.1387	0.1654
Adams	Brundage	0.1853	-0.1349
Benewah	Micah	0.0680	-0.1159
Blaine	Hyndman	0.0713	0.3005**
Boise	Jackson Peak	0.2624*	0.2061
Bonner	Hidden Lake	-0.2386*	-0.0014
Boundary	Hidden Lake	-0.195	-0.1783
Butte	Hyndman	0.2594	0.1114

Camas	Atlanta	0.3939**	0.4414***
Clearwater	Mountain Meadows	-0.0546	-0.0397
Custer	Schwartz	0.3628	-0.1086
Elmore	Trinity	0.4176***	0.3884**
Gem	Jackson Peak	0.0780	0.3798**
Gooding	Trinity	0.0602	0.1983
Idaho	Mountain Meadows	0.0432	0.0461
Kootenai	Mosquito Ridge	0.0076	-0.2019
Latah	Elk Butte	0.1952	0.0521
Lewis	Mountain Meadows	-0.0153	0.0457
Lincoln	Hyndman	0.0180	0.2157
Minidoka	Hyndman	0.3911**	0.2431*
Nez Perce	Mountain Meadows	0.0731	0.1733
Payette	Jackson Peak	0.1625	0.0971
Valley	Long Valley	-0.1174	-0.2292
Washington	Squaw Flat	0.0746	0.1053

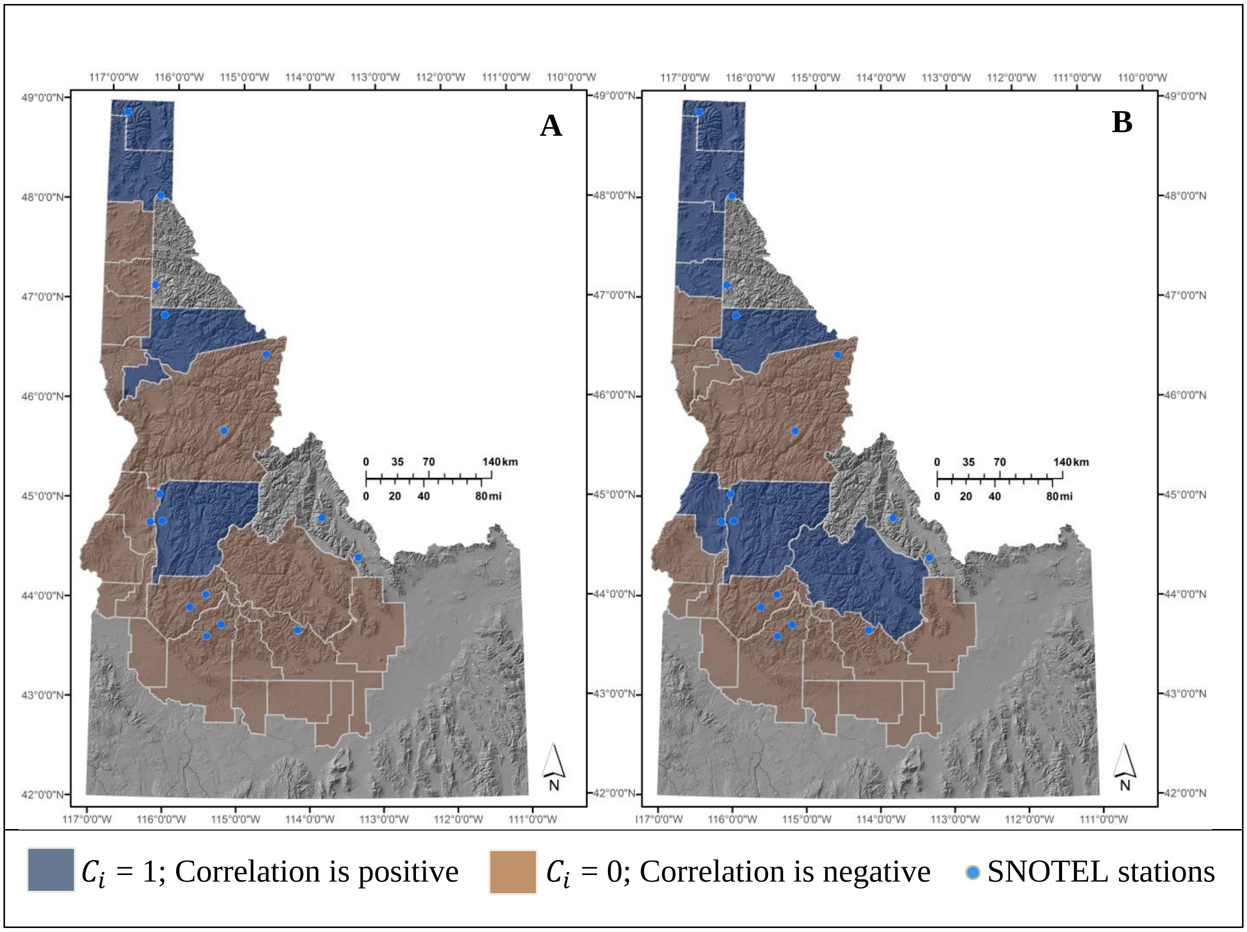


***Figure 4.2*. Dummy variable, C_i, in each county characterizes the correlation direction between yield and snowmelt date. Orange designates a positive correlation (C_i = 1) and blue designates a negative correlation (C_i = 0) between non-irrigated yield—(A) Barley, (B) Wheat—and final snowmelt date.**

Table 4.3. **Summary table of all regression models. Equations 4.2 "Total" and 4.3 "Interaction" were used to predict wheat yield and barley yield separately using every combination of precipitation and growing degree-day variable summation. Column one of this table abbreviates the model type for future reference in study results. The model type abbreviation in column one denotes the following information separated by a period: Type of regression model ("Total" uses Equation 4.2, "Interaction" uses Equation 4.3); specific crop; precipitation variable; growing degree-day variable. Each variable term is expanded in the subsequent columns. The same snowmelt timing variable is used as a predictor in every model type. Number of observations for each model type are denoted in the final column.**

Model Type	Y	P	GDD	N_{obs}
Total.Y_w.P_{ann}.GDD_{avg}	Wheat	Annual	Average	467
Total.Y_w.P_{ann}.GDD_{ear}	Wheat	Annual	Early	631
Total.Y_w.P_{ann}.GDD_{max}	Wheat	Annual	Maximum	575
Total.Y_w.P_{spr}.GDD_{avg}	Wheat	Spring	Average	467
Total.Y_w.P_{spr}.GDD_{ear}	Wheat	Spring	Early	631
Total.Y_w.P_{spr}.GDD_{max}	Wheat	Spring	Maximum	575
Total.Y_w.P_{sum}.GDD_{avg}	Wheat	Summer	Average	467
Total.Y_w.P_{sum}.GDD_{ear}	Wheat	Summer	Early	631
Total.Y_w.P_{sum}.GDD_{max}	Wheat	Summer	Maximum	575
Total.Y_b.P_{ann}.GDD_{avg}	Barley	Annual	Average	504
Total.Y_b.P_{ann}.GDD_{ear}	Barley	Annual	Early	676
Total.Y_b.P_{ann}.GDD_{max}	Barley	Annual	Maximum	621
Total.Y_b.P_{spr}.GDD_{avg}	Barley	Spring	Average	504
Total.Y_b.P_{spr}.GDD_{ear}	Barley	Spring	Early	676
Total.Y_b.P_{spr}.GDD_{max}	Barley	Spring	Maximum	621
Total.Y_b.P_{sum}.GDD_{avg}	Barley	Summer	Average	504

Total.$Y_b.P_{sum}.GDD_{ear}$	Barley	Summer	Early	676
Total.$Y_b.P_{sum}.GDD_{max}$	Barley	Summer	Maximum	621
Interaction.$Y_w.P_{ann}.GDD_{avg}$	Wheat	Annual	Average	467
Interaction.$Y_w.P_{ann}.GDD_{ear}$	Wheat	Annual	Early	631
Interaction.$Y_w.P_{ann}.GDD_{max}$	Wheat	Annual	Maximum	575
Interaction.$Y_w.P_{spr}.GDD_{avg}$	Wheat	Spring	Average	467
Interaction.$Y_w.P_{spr}.GDD_{ear}$	Wheat	Spring	Early	631
Interaction.$Y_w.P_{spr}.GDD_{max}$	Wheat	Spring	Maximum	575
Interaction.$Y_w.P_{sum}.GDD_{avg}$	Wheat	Summer	Average	467
Interaction.$Y_w.P_{sum}.GDD_{ear}$	Wheat	Summer	Early	631
Interaction.$Y_w.P_{sum}.GDD_{max}$	Wheat	Summer	Maximum	575
Interaction.$Y_b.P_{ann}.GDD_{avg}$	Barley	Annual	Average	504
Interaction.$Y_b.P_{ann}.GDD_{ear}$	Barley	Annual	Early	676
Interaction.$Y_b.P_{ann}.GDD_{max}$	Barley	Annual	Maximum	621
Interaction.$Y_b.P_{spr}.GDD_{avg}$	Barley	Spring	Average	504
Interaction.$Y_b.P_{spr}.GDD_{ear}$	Barley	Spring	Early	676
Interaction.$Y_b.P_{spr}.GDD_{max}$	Barley	Spring	Maximum	621
Interaction.$Y_b.P_{sum}.GDD_{avg}$	Barley	Summer	Average	504
Interaction.$Y_b.P_{sum}.GDD_{ear}$	Barley	Summer	Early	676
Interaction.$Y_b.P_{sum}.GDD_{max}$	Barley	Summer	Maximum	621

4.2 Non-parametric Regression

In the non-parametric methodology, we identify potential mechanisms responsible for the varied correlation direction. We do this using classification/regression trees to classify the direction/magnitude of the previously introduced Pearson's linear correlation coefficients rho_c (Equation 4.1). A classification tree predicts the correlation direction: rho_c = 1 if positive (meaning yield is historically lower in years with earlier snowmelt timing) and rho_c = 0 if negative (meaning yield is historically higher in years with earlier snowmelt timing). A regression tree predicts the correlation magnitude of rho_c by classifying the coefficient value.

The following criteria are considered when including a correlation coefficient in the analysis:

1) N_{yrs}: The length of the time series used to calculate the correlation coefficient is predicted using a time series $N_{yrs} \geq 30$ and $N_{yrs} \geq 20$.
2) P_{rho}: Trees predict significant correlation coefficients ($P_{rho} \leq 0.10$) and to predict all calculated coefficients ($P_{rho} \leq 1.0$).

Of the *N* = 688 total calculated coefficients, the sample size (N_{tree}) of correlation coefficient/direction used in each classification/regression tree is included in Table 4.4. More positive correlation coefficients—meaning yield is lower on average with an earlier snowmelt date—exist in all trees. The number of positive coefficients (N_{pos}) and percentage of total (% pos) are also summarized in Table 4.2. We use the entire dataset of calculated correlation coefficients (*N* = N_{tree}) as the dependent variable to grow each tree.

Four categories describe the predictor variables in all classification and regression trees: Physiographic characteristics (x1), precipitation (x2), snowfall (x3), and temperature (x4). Table 4.5 lists the variable abbreviations and descriptions, with sixty-five total variables used to grow each tree. Trees are terminated when all correlations are classified. In terminal trees, a single predictor variable occurs at each tree node, splitting the data until all data is classified. We then prune terminal trees to the best level, which has the least amount of nodes within one standard error of the minimum cost.

Second, we utilize a random forest algorithm to generate classification and regression trees that randomly choose a subset of predictor variables from our total pool of 65 variables. The model produces 1000 trees with each tree using 10 random predictor variables from Table 4.5 to classify the correlation coefficients. Rather than outputting the best fit tree, the random forest approach outputs variable importance across all randomly generated trees. The random forest analysis accounts for the possibility that variables in the “best fit instance,” or pruned tree, may be highly correlated with other variables. In this scenario, the variable responsible for the mechanism that explains correlation direction will not be apparent in the “best fit tree.” Rather than considering the single best fit from the 65 variables in a single classification or regression tree, this method allows us to choose the most influential variables when other variables are omitted, outputting the relative variable importance.

Predictor importance in the random forest analysis is calculated by dividing the summed changes in the mean squared error (MSE) after splits on every predictor by the number of branch nodes. Predictor importance ranges from $-\infty$ to 1, with a value of zero meaning that the variable has no importance in predicting the dependent variable. A predictor importance value greater than zero, therefore, indicates some importance.

Table 4.4. **Summary statistics for classification and regression trees.**

Tree #	Crop	N_{yrs}	P_{rho}	N_{tree}	N_{pos}	% pos
w.1	Wheat	≥30	≤0.10	106	93	87.7
w.2	Wheat	≥20	≤0.10	110	96	87.3
w.3	Wheat	≥30	≤1.0 (all)	576	376	65.3
w.4	Wheat	≥20	≤1.0 (all)	618	395	63.9
b.1	Barley	≥30	≤0.10	100	95	95.0
b.2	Barley	≥20	≤0.10	103	97	94.2
b.3	Barley	≥30	≤1.0 (all)	563	390	69.3
b.4	Barley	≥20	≤1.0 (all)	588	405	68.9

Table 4.5. **Predictor variables used in Classification/Regression trees to predict direction/magnitude of rho_b and rho_w.**

Abbreviation	Description of Predictor Variable
x1.Distance	Distance between field/county centroid and SNOTEL station [m]
x1.Zcounty	County mean elevation [m]
x1.Topo	County standard deviation of elevation [m] – proxy for topography
x1.Zsnotel	SNOTEL station elevation [m]
x1.LatSnotel	SNOTEL station latitude [°N]
x1.Zdiff	Elevation difference between SNOTEL station and county mean [m]
x1.County	County (numeric value 1-43)
x1.District	Crop District (numeric value 1-4)
x1.Snotel	SNOTEL station (numeric value 1-16)
x2.Precip1	Average Precipitation in January [mm]

x2.Precip2	Average Precipitation in February [mm]
x2.Precip3	Average Precipitation in March [mm]
x2.Precip4	Average Precipitation in April [mm]
x2.Precip5	Average Precipitation in May [mm]
x2.Precip6	Average Precipitation in June [mm]
x2.Precip7	Average Precipitation in July [mm]
x2.Precip8	Average Precipitation in August [mm]
x2.Precip9	Average Precipitation in September [mm]
x2.Precip10	Average Precipitation in October [mm]
x2.Precip11	Average Precipitation in November [mm]
x2.Precip12	Average Precipitation in December [mm]
x2.Psum	Average cumulative summer precipitation (May – July) [mm]
x2.Pspr	Average cumulative spring precipitation (April – May) [mm]
x2.Pann	Average cumulative annual precipitation [mm]
x3.Snow1	Cumulative snow depth in January [cm]
x3.Snow2	Cumulative snow depth in February [cm]
x3.Snow3	Cumulative snow depth in March [cm]
x3.Snow4	Cumulative snow depth in April [cm]
x3.Snow5	Cumulative snow depth in May [cm]
x3.Snow6	Cumulative snow depth in June [cm]
x3.Snow7	Cumulative snow depth in July [cm]
x3.Snow8	Cumulative snow depth in August [cm]
x3.Snow9	Cumulative snow depth in September [cm]
x3.Snow10	Cumulative snow depth in October [cm]
x3.Snow11	Cumulative snow depth in November [cm]
x3.Snow12	Cumulative snow depth in December [cm]
x3.SnowAvg	Cumulative average snow depth January – April [cm]
x4.Tmin1	Average Minimum Temperature in January [°C]
x4.Tmin2	Average Minimum Temperature in February [°C]
x4.Tmin3	Average Minimum Temperature in March [°C]
x4.Tmin4	Average Minimum Temperature in April [°C]

x4.Tmin5	Average Minimum Temperature in May [°C]
x4.Tmin6	Average Minimum Temperature in June [°C]
x4.Tmin7	Average Minimum Temperature in July [°C]
x4.Tmin8	Average Minimum Temperature in August [°C]
x4.Tmin9	Average Minimum Temperature in September [°C]
x4.Tmin10	Average Minimum Temperature in October [°C]
x4.Tmin11	Average Minimum Temperature in November [°C]
x4.Tmin12	Average Minimum Temperature in December [°C]
x4.Tmax1	Average Maximum Temperature in January [°C]
x4.Tmax2	Average Maximum Temperature in February [°C]
x4.Tmax3	Average Maximum Temperature in March [°C]
x4.Tmax4	Average Maximum Temperature in April [°C]
x4.Tmax5	Average Maximum Temperature in May [°C]
x4.Tmax6	Average Maximum Temperature in June [°C]
x4.Tmax7	Average Maximum Temperature in July [°C]
x4.Tmax8	Average Maximum Temperature in August [°C]
x4.Tmax9	Average Maximum Temperature in September [°C]
x4.Tmax10	Average Maximum Temperature in October [°C]
x4.Tmax11	Average Maximum Temperature in November [°C]
x4.Tmax12	Average Maximum Temperature in December [°C]
x4.GDDmax	Average growing degree-days for “maximum” growing season
x4.GDDavg	Average growing degree-days for “average” growing season
x4.GDDear	Average growing degree-days for “early” growing season
x4.Tstress	Number of months with Tmax > 30°C (heat stress proxy)

5 RESULTS

In this section, we first present the correlation between snowmelt timing and yield. Next, we present parametric and non-parametric results in separate sections. Parametric results establish the magnitude and direction of snowmelt timing impacts on yield. Non-parametric results determine select climatic/physiographic controls on this relationship. Written significance is established at $P \leq 0.10$.

The distribution of correlation coefficients is positively skewed, indicating that more counties exhibit a positive historical correlation between yield and snowmelt date (Figure 5.1). This positive skew means that on average, early snowmelt timing corresponds with lower non-irrigated crop yield in Idaho counties. The correlation analysis considered all SNOTEL-county pairings, regardless of distance from a SNOTEL station and watershed boundaries. Figure 5.2 shows the variation in this correlation coefficient within a single county dependent on which SNOTEL station is chosen to calculate the correlation coefficient.

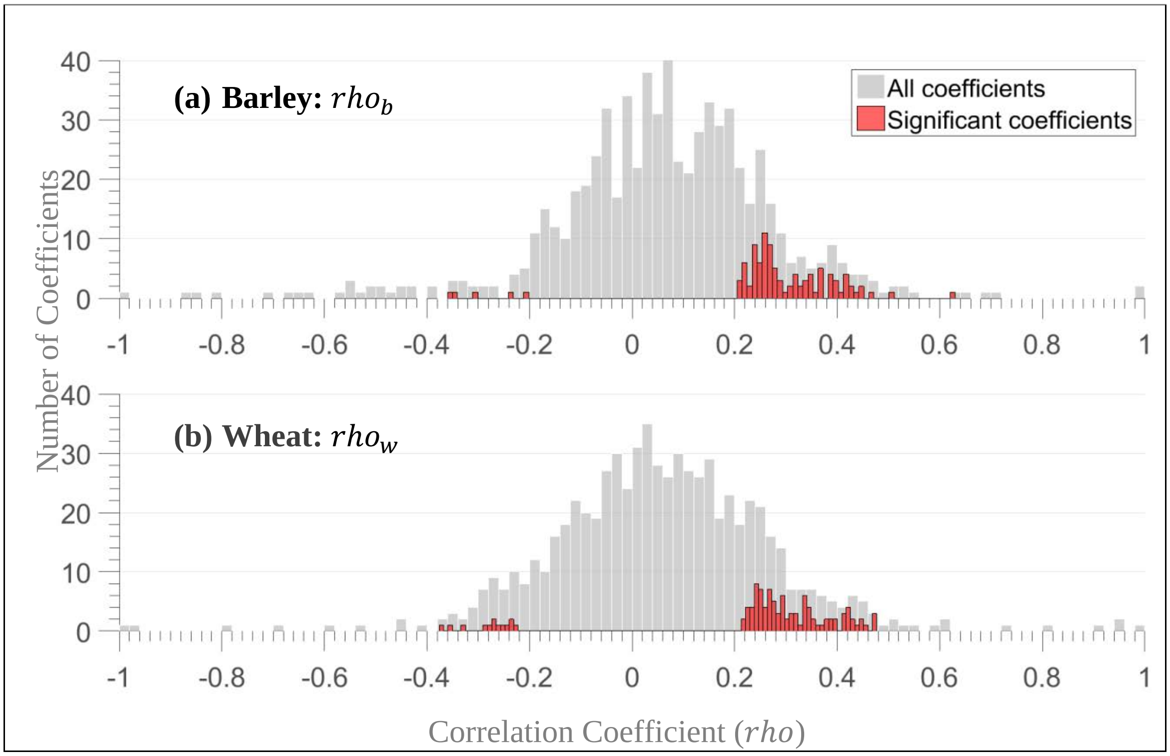


***Figure 5.1*.** **Distribution of correlation coefficients between county-level crop yield—(a) Barley (b) Wheat—and snowmelt date. All coefficients are represented by gray bars and significant coefficients (*N* ≥ 25 years; *P* ≤ 0.10) are shown in red. Both distributions skew positively, indicating early snowmelt date corresponds to lower yield, on average, in most SNOTEL-County pairings. Few significant pairings correlate negatively.**

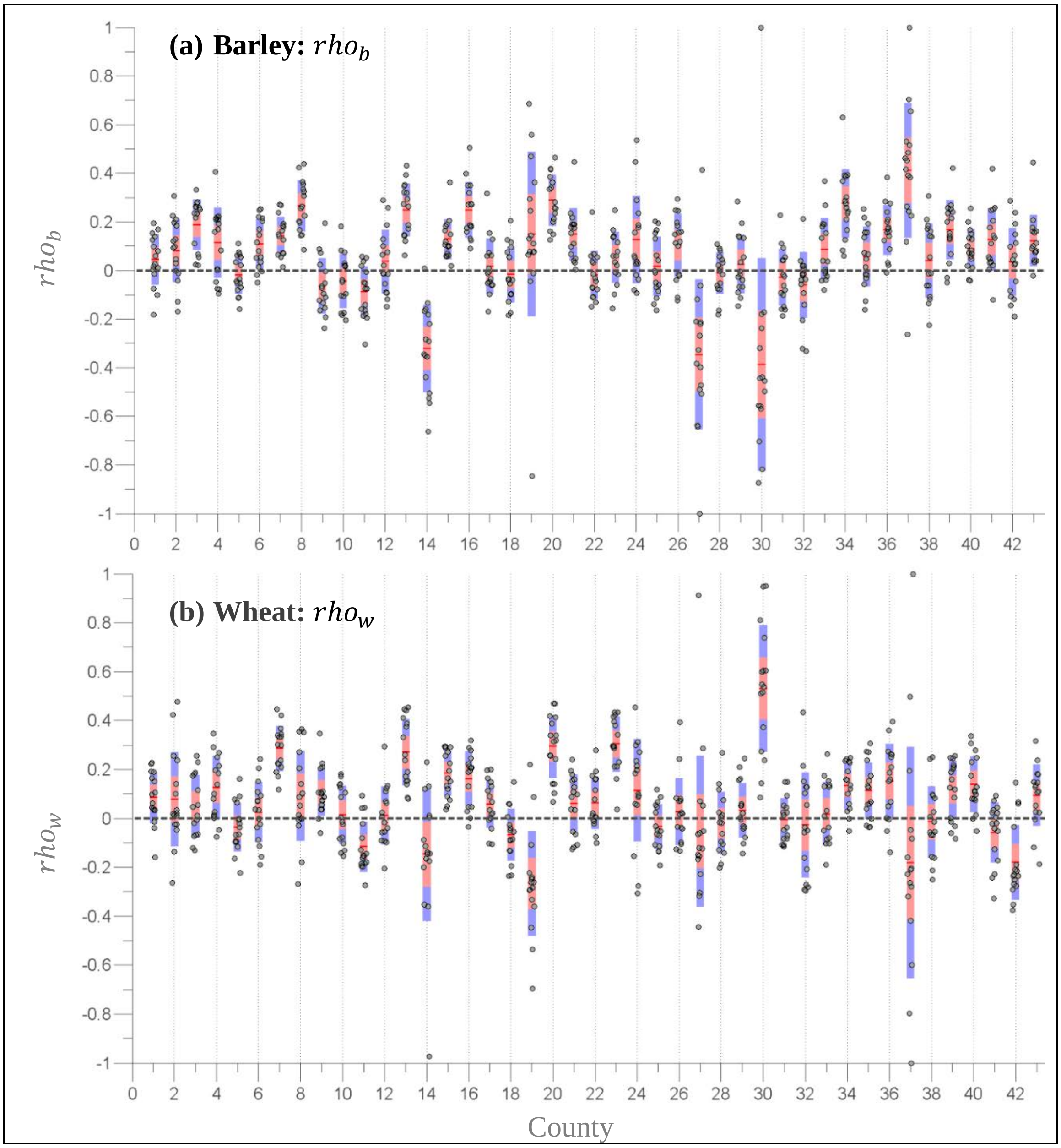
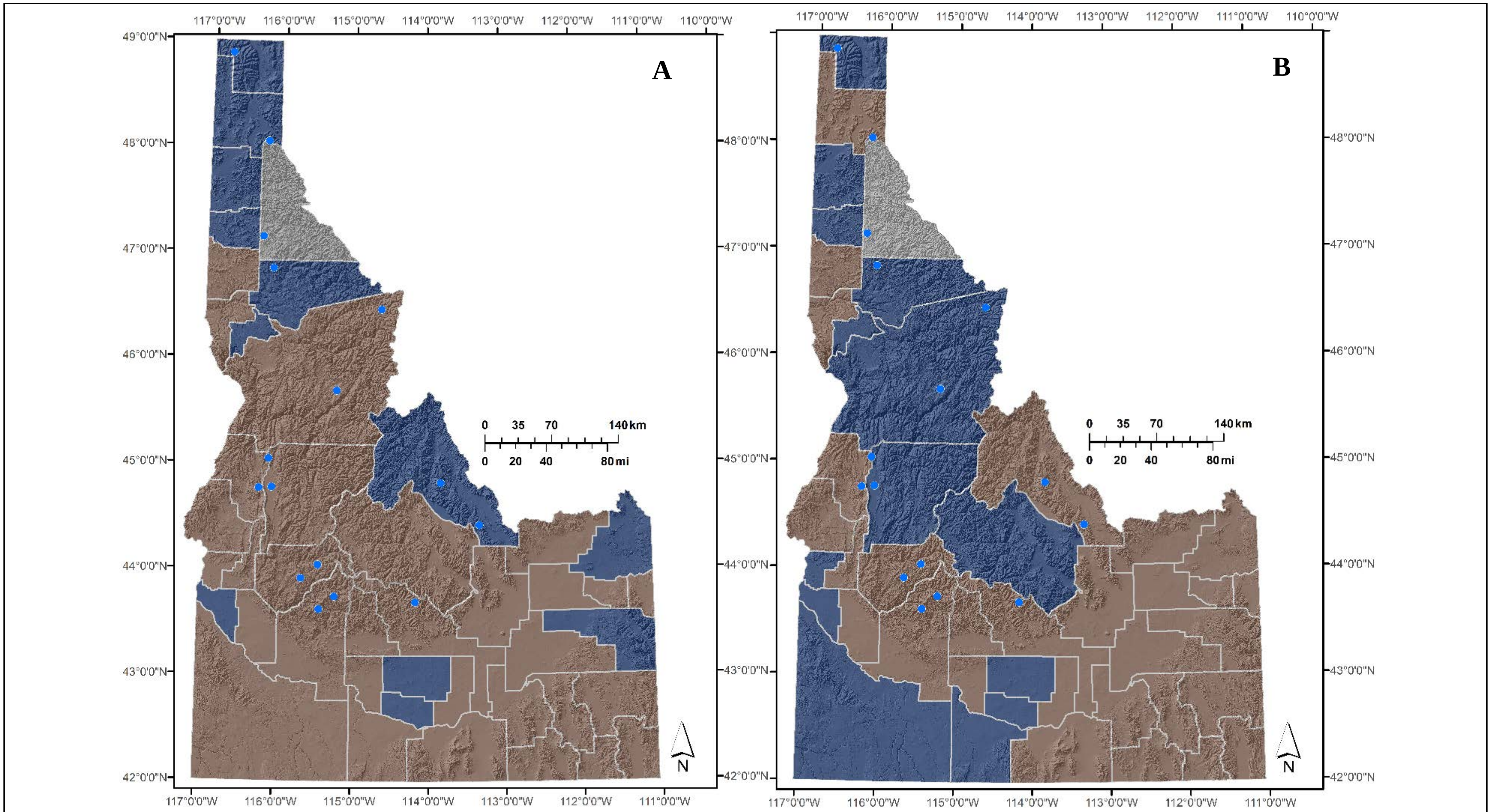


***Figure 5.2*. Variation in the observed correlation between county-level yield—(a) Barley (b) Wheat—and snowmelt date at all stations. This figure demonstrates the standard deviation of rho_c when using different SNOTEL stations to calculate the coefficient. Data points represent a single correlation coefficient between snowmelt timing at a SNOTEL station (*N* = 16) and yield in a county (*N* = 43). See Table 3.1 for county names (1:43).**



C_i = 0; Correlation is negative C_i = 1; Correlation is positive SNOTEL stations

Figure 5.3. **Average of all correlation coefficients between non-irrigated yield—(A) Barley, (B) Wheat—in each county and snowmelt date at 16 SNOTEL stations. Orange designates a positive correlation and blue designates a negative correlation.**

5.1 Estimation Results from the Parametric Model

Regression model results are summarized in Tables 5.1 - 5.4. Each table presents the coefficient and significance of predictor variables and interaction terms for all estimated regression models.

First, we present "Total" regression model results using Equation 4.2 without an interaction term for correlation direction. The partial impact of snowmelt timing did not significantly predict wheat or barley yield in any model. Spring and summer precipitation significantly predict barley yield, and more precipitation over these time periods corresponds with higher average historical yield (Table 5.1). All estimates for growing degree-days significantly predict barley yield, and a longer/warmer growing season corresponds with lower historical barley yield, on average. All estimates for precipitation (annual, spring, and summer) significantly predict wheat yield with historical yield being higher in years with more precipitation (Table 5.2). Growing degree-days did not significantly predict wheat yield in any model.

Second, we present "Interaction" regression model results using Equation 4.3 with an interaction term for correlation direction. In all regression models, snowmelt timing significantly predicts barley yield (Table 5.3). This significance is true in both directions of impact according to the interaction term (shown in Figure 4.2). In most counties, barley yield is lower on average in years with earlier snowmelt timing. Snowmelt timing significantly predicts wheat yield in models using summer precipitation as a predictor variable (Table 5.4).

In models where precipitation significantly predicts barley/wheat yield, more precipitation corresponds with higher historical yield on average. Precipitation significantly predicts yield only when using spring and summer variables. Growing degree days significantly predict barley yield only, in models using “Average” and “Early” growing season months (Table 5.3).

Table 5.1*.** **Coefficient estimates for residual barley yield predicted using “Total” regression models that do not use an interaction term (Equation 4.2). We present the coefficients on each predictor variable in units of bushels per acre. ‘*’ denotes significance at $P \leq 0.10$ ‘**’ denotes significance at $P \leq 0.05$, and ‘’ denotes significance at $P \leq 0.01$.**

Model Type	Snowmelt	Precipitation	Growing Degree-Days
Total.Y_b.P_{ann}.GDD_{avg}	-0.0126	0.0055	-0.0074**
Total.Y_b.P_{ann}.GDD_{ear}	-0.0012	0.0049	-0.0066***
Total.Y_b.P_{ann}.GDD_{max}	0.0231	0.0027	-0.0045**
Total.Y_b.P_{spr}.GDD_{avg}	-0.0089	0.0260**	-0.0071**
Total.Y_b.P_{spr}.GDD_{ear}	0.0055	0.0156*	-0.0064***
Total.Y_b.P_{spr}.GDD_{max}	0.0185	0.0170*	-0.0047**
Total.Y_b.P_{sum}.GDD_{avg}	-0.0198	0.0511***	-0.0055*
Total.Y_b.P_{sum}.GDD_{ear}	-0.0127	0.0521***	-0.0055***
Total.Y_b.P_{sum}.GDD_{max}	0.0043	0.0548***	-0.0033*

Table 5.2. **Coefficient estimates for residual wheat yield predicted using "Total" regression models that do not use an interaction term (Equation 4.2). We present the coefficients on each predictor variable in units of bushels per acre. '*' denotes significance at $P \leq 0.10$, '**' denotes significance at $P \leq 0.05$, and '***' denotes significance at $P \leq 0.01$.**

Model Type	Snowmelt	Precipitation	Growing Degree-Days
Total.$Y_b.P_{ann}.GDD_{avg}$	-0.0083	0.01319**	-0.0044
Total.$Y_b.P_{ann}.GDD_{ear}$	0.0269	0.0086**	-0.0014
Total.$Y_b.P_{ann}.GDD_{max}$	0.0304	0.0069*	-0.0020
Total.$Y_b.P_{spr}.GDD_{avg}$	0.0164	0.0218**	-0.0044
Total.$Y_b.P_{spr}.GDD_{ear}$	0.0353	0.0235**	-0.0012
Total.$Y_b.P_{spr}.GDD_{max}$	0.0303	0.0243**	-0.0025
Total.$Y_b.P_{sum}.GDD_{avg}$	0.0044	0.0500***	-0.0028
Total.$Y_b.P_{sum}.GDD_{ear}$	0.0233	0.0446***	-0.0008
Total.$Y_b.P_{sum}.GDD_{max}$	0.0187	0.0487***	-0.0016

Table 5.3. **Coefficient estimates for residual barley yield predicted using "Interaction" regression models that use an interaction term (Equation 4.3). We present the coefficients on each predictor variable in units of bushels per acre. '*' denotes significance at $P \leq 0.10$, '**' denotes significance at $P \leq 0.05$, and '***' denotes significance at $P \leq 0.01$.**

Model Type	Snowmelt	Precipitation	Growing Degree-Days	$Ci * SM$	$Ci * P$	$Ci * GDD$
Interaction.Y_b.P_{ann}.GDD_{avg}	-0.2315***	-0.0011	-0.0227***	0.2726***	0.0099	0.0180**
Interaction.Y_b.P_{ann}.GDD_{ear}	-0.1614**	-0.0030	-0.0129**	0.2068***	0.0130*	0.0074
Interaction.Y_b.P_{ann}.GDD_{max}	-0.1113*	-0.0066	-0.0074	0.1735**	0.0153*	0.0036
Interaction.Y_b.P_{spr}.GDD_{avg}	-0.2559***	0.0352**	-0.0211***	0.3141***	-0.0141	0.0167**
Interaction.Y_b.P_{spr}.GDD_{ear}	-0.1859***	0.0218	-0.0120**	0.2498***	-0.0071	0.0069
Interaction.Y_b.P_{spr}.GDD_{max}	-0.1447**	0.0252	-0.0059	0.2176***	-0.0104	0.0018
Interaction.Y_b.P_{sum}.GDD_{avg}	-0.2205***	0.0478***	-0.0131*	0.2576***	0.0026	0.0090
Interaction.Y_b.P_{sum}.GDD_{ear}	-0.1722***	0.0435***	-0.0090*	0.2074***	0.0149	0.0041
Interaction.Y_b.P_{sum}.GDD_{max}	-0.1234**	0.0493***	-0.0017	0.1696**	0.0111	-0.0020

Table 5.4. **Coefficient estimates for residual wheat yield predicted using "Interaction" regression models that use an interaction term (Equation 4.3). We present the coefficients on each predictor variable in units of bushels per acre. '*' denotes significance at $P \leq 0.10$, '**' denotes significance at $P \leq 0.05$, and '***' denotes significance at $P \leq 0.01$.**

Model Type	Snowmelt	Precipitation	Growing Degree-Days	$Ci * SM$	$Ci * P$	$Ci * GDD$
Interaction.Y_w.P_{ann}.GDD_{avg}	-0.0826	0.0115*	-0.0027	0.1070	0.0028	-0.0029
Interaction.Y_w.P_{ann}.GDD_{ear}	-0.0738	0.0077	-0.0003	0.1443**	0.0016	-0.0016
Interaction.Y_w.P_{ann}.GDD_{max}	-0.0774	0.0074	-0.0010	0.1586**	-0.0007	-0.0013
Interaction.Y_w.P_{spr}.GDD_{avg}	-0.0696	0.0373**	-0.0018	0.1264*	-0.0279	-0.0043
Interaction.Y_w.P_{spr}.GDD_{ear}	-0.0749	0.0423***	0.0006	0.1591***	-0.0323*	-0.0029
Interaction.Y_w.P_{spr}.GDD_{max}	-0.0820	0.0405***	0.0030	0.1666***	-0.275	-0.0023
Interaction.Y_w.P_{sum}.GDD_{avg}	-0.0900*	0.0554***	-0.0019	0.1408**	-0.0098	-0.0013
Interaction.Y_w.P_{sum}.GDD_{ear}	-0.0874*	0.0519***	-0.0003	0.1601***	-0.0124	-0.0009
Interaction.Y_w.P_{sum}.GDD_{max}	-0.0938*	0.0548***	-0.0006	0.1659***	-0.0105	-0.0015

5.2 Estimation Results from the Non-parametric Model

Most significant correlation coefficients ($N \geq 25$ years; $P \leq 0.10$) are in the positive direction, and earlier final spring snowmelt date corresponds with a decrease in yield for both crops on average. Of the N = 110 significant correlation coefficients between snowmelt timing and wheat yield ($N \geq 20$, $P < 0.10$), only 14 observations are negative—meaning yield is historically higher in years with early spring snowmelt. Likewise, of the N = 103 significant correlation coefficients between snowmelt timing and barley yield ($N \geq 20$, $P < 0.10$), only 5 observations are negative. Despite having few significant negative correlation coefficients, several specific controls predict the direction of correlation, presented below.

Instead of presenting each pruned classification/regression tree from Table 4.4, we present the variable responsible for the first node of each classification/regression tree. This first node (or "split") represents the most important predictor variable for initially classifying the correlation coefficient direction/magnitude (Table 5.5). In addition to the first tree node, we present the five most influential variables in the random forest analysis for predicting rho_b (Figure 5.4) and rho_w (Figure 5.5).

In both the classification/regression trees, latitude significantly predicts correlation direction/magnitude between snowmelt date and wheat yield (Figure 5), and earlier snowmelt date occurring at higher latitudes (above 47) corresponds with increased wheat yield (negative correlation). In the random forest analysis, important variables for wheat were *x1.LatSnotel, x1.Distance, x1.Zdiff, x1.Topo, x1.Zsnotel, x2.Precip3, x2.Precip4,* and *x3.Snow12.*

In the classification/regression tree analysis, county mean and standard deviation of elevation significantly predict the correlation direction/magnitude between snowmelt timing and barley yield. County elevation significantly predicts correlation direction between snowmelt date and barley yield, and crops grown in counties with low mean elevations (less than 770 meters) see increased yield with earlier snowmelt timing (correlation is negative). Standard deviation of county elevation significantly predicts correlation magnitude between snowmelt date and barley yield, and crops grown in counties with less topography (standard deviation less than 52 meters) see increased yield with earlier snowmelt timing (correlation is negative). In the random forest analysis, important predictor variables for barley yield were *x1.Zcounty, x1.Distance, x1.Zdiff, x1.Zsnotel, x2.Precip1, x2.Precip5, x2.Precip6,* and *x2.Precip11*.

Table 5.5. **Most important predictor (first split) in each classification/regression tree.**

Tree #	Crop	N_{yrs}	P_{rho}	Classification	Regression
w.1	Wheat	≥30	≤0.10	*x1.LatSnotel*	*x1.LatSnotel*
w.2	Wheat	≥20	≤0.10	*x1.LatSnotel*	*x1.LatSnotel*
w.3	Wheat	≥30	≤1.0 (all)	*x1.LatSnotel*	*x1.Zsnotel*
w.4	Wheat	≥20	≤1.0 (all)	*x1.LatSnotel*	*x1.Zsnotel*
b.1	Barley	≥30	≤0.10	--	*x1.Zcounty*
b.2	Barley	≥20	≤0.10	*x1.Zcounty*	*x1.Topo*
b.3	Barley	≥30	≤1.0 (all)	*x2.Precip6*	*x1.Zsnotel*
b.4	Barley	≥20	≤1.0 (all)	*x2.Precip6*	*x1.Zcounty*

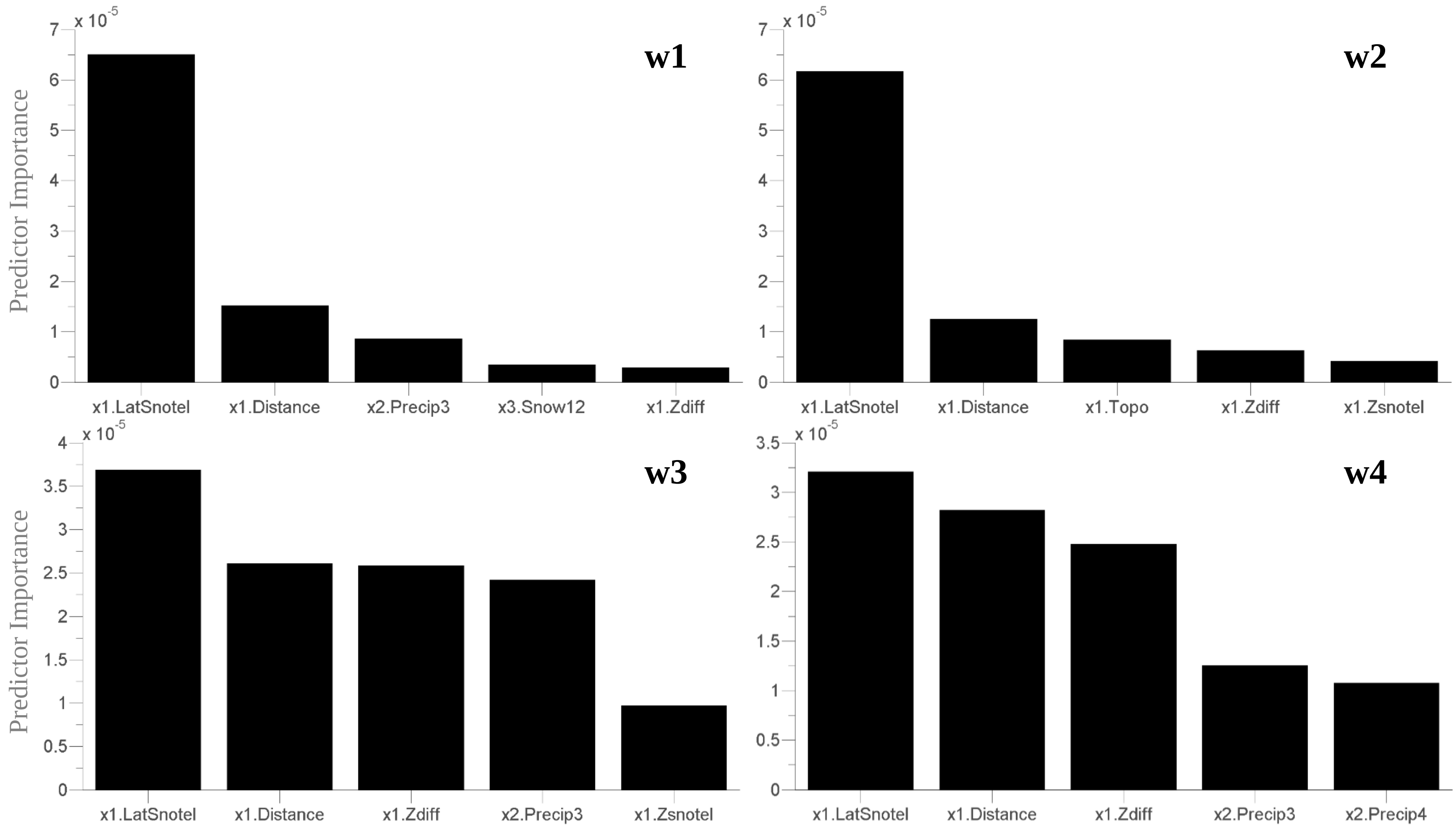


Figure 5.4. **Wheat predictor importance for the different tree combinations using random forest (see Table 4.4 for tree descriptions).**

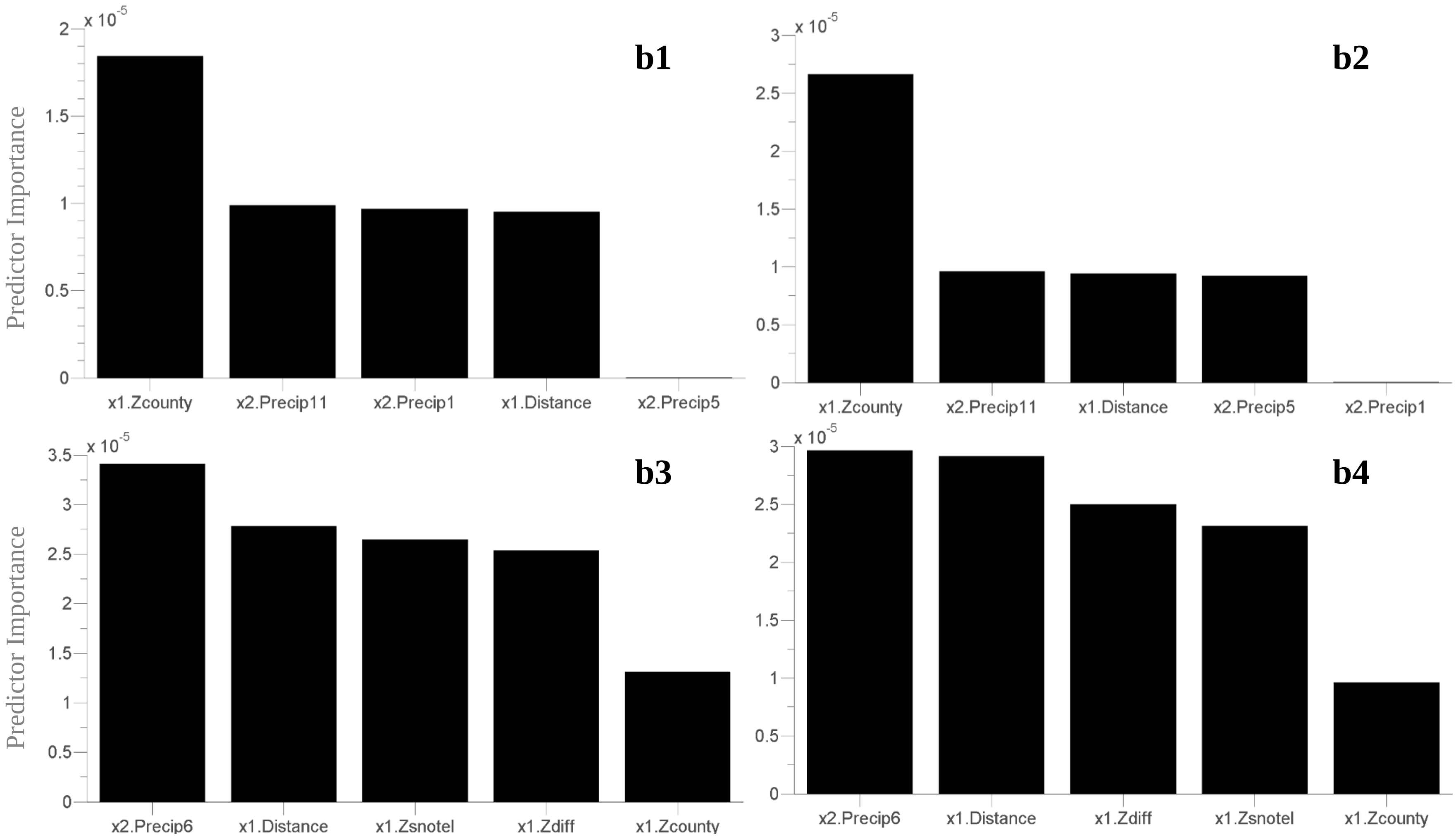


Figure 5.5. **Barley predictor importance for the different tree combinations using random forest (see Table 4.4 for tree descriptions).**

6 DISCUSSION

Most results support an average decrease in non-irrigated wheat and barley yield in Idaho during years with early snowmelt timing—an impact that is significant independently of climatic and physiographic characteristics. Hence, when snow melts early historically while everything else necessary to grow a non-irrigated crop is held constant (*i.e.*, precipitation, growing degree-days); wheat and barley yield is lower, on average. The established significant impact of snowmelt timing on historical crop yield varies in direction for different counties in Idaho. Despite the majority trend toward lower historical yield, there are counties in which crop yield is higher on average with earlier snowmelt. This study identifies important variables (notably spring and summer precipitation) that may buffer the largely negative impact of snowmelt timing on yield and begin to explain why some regions benefit. As crop yield continually responds to a changing climate, it is increasingly important that we consider the role of all climate interactions in yield fluctuations—and the timing of spring snowmelt appears an important player.

Snowmelt timing only acted as a significant predictor of yield in parametric regression models that included an interaction term for direction of impact. This is not surprising, as the varied positive and negative directions would sum to zero in the "Total" regression models without an interaction term. This is an important distinction, because the influence of snowmelt timing on yield will likely be drowned out in regions with varying directions of impact if proper methodologies are not employed.

Spring and summer precipitation were notably important in both parametric and non-parametric results. These variables significantly predicted both wheat and barley yield in the majority of multiple linear regression models. For these two dryland crops, higher precipitation results in higher crop yield, on average. However, when including the interaction term, precipitation's impact was only significant in models where early snowmelt timing predicted decreased yield. Although snowmelt timing significantly impacts barley yield in all interaction term models, it is only significant in predicting wheat yield when summer precipitation was used as the precipitation predictor variable. Likewise, in the non-parametric results, spring and summer precipitation both predict the varying direction of relationship between snowmelt timing and yield. We propose the mechanism that precipitation during this critical portion of the growing season may buffer the negative impact of early snowmelt timing's reduced soil moisture at the beginning of the growing season.

Other variables important to classifying the location of these positively versus negatively correlated counties were physiographic characteristics of the county or SNOTEL station. Wheat yield has historically benefitted from earlier snowmelt at higher latitudes, and Northern Idaho has higher historical non-irrigated wheat yield during years with early snowmelt timing. Higher latitudes generally correspond with higher summer precipitation in Idaho—and this may affirm our mechanism that non-irrigated producers located in counties with adequate moisture throughout the growing season may benefit from earlier snowmelt timing. The strong relationship between wheat yield and precipitation observed in our parametric results supports this interpretation that higher latitudes may supply adequate precipitation for non-irrigated wheat production. Higher latitudes also experience less insolation, and the parametric regression results suggest that a shorter, cooler growing season benefits non-irrigated barley yield. Latitude may therefore be capturing the combined impact of changing temperature and precipitation.

In predicting barley yield, the length of the growing season was a significant predictor, and more growing degree-days—meaning a warmer, longer growing season—resulted in less barley yield. Barley grown in counties with low elevation and low topography (standard deviation of elevation) may also benefit from earlier spring snowmelt. This result suggests that earlier snowmelt located on or near the elevation of the agricultural fields may benefit barley yield. Earlier snowmelt at lower elevations allows growers to plant earlier in the season—and also suggests that snow higher in the watershed (*i.e.,* at higher elevations) is still being stored as snowpack at the time of field-melt out. Therefore, early planting would allow capture of this stored snowpack by barley in years with earlier snowmelt timing. Many counties with low topographic relief exist in Northern (humid) Idaho, and this result of higher yield with early snowmelt may again be capturing our proposed precipitation mechanism.

In the non-parametric results, physiographic characteristics of the SNOTEL stations and counties were consistently chosen as the most important variables in predicting the correlation direction and magnitude between snowmelt timing and yield The same county-level yield may exhibit a positive or negative correlation with snowmelt timing depending on the SNOTEL station that is used to calculate the correlation coefficient. This suggests that SNOTEL station characteristics (*i.e.,* Is melt occurring early at high vs. low elevations? Promixal or distal to fields?) may additionally drive some of the observed relationship in our data. However, in the random forest analysis precipitation—specifically spring and summer—recurrently demonstrated itself as an important predictor variable.

The snowmelt timing impacts on non-irrigated yield have important implications for water supply to irrigated crops. This non-irrigated yield serves as a proxy for baseline yield—natural yield that occurs without supplemental water application beyond what is provided by the local climate. Crops may consequently require additional water in years with early spring snowmelt timing when baseline yield is lower. This has the potential to place the following demands on water supply in the future during years with early snowmelt timing:

(1) Demand for irrigation of currently non-irrigated crops.

(2) Demand for more water to be applied to irrigated crops during years with early spring snowmelt timing.

However, the application of irrigation water in the spring/summer may buffer the negative impact of early snowmelt timing on yield much like natural spring/summer precipitation appear to do. This result may give irrigated growers more certainty in their yield response to changing climate.

Although we are not physically modeling the processes controlling the relationship between snowmelt timing and yield, we are still able to draw important conclusions regarding the potential nature of the relationship itself. In most of our observations, baseline yield has been lower in the past during years with early snowmelt timing. This trend may hold true in the future if the processes governing this relationship remain the same. Because we have determined that the partial impact of snowmelt timing on yield is significant, future research may focus on the processes responsible for this relationship.

This study did not consider how growers may be changing the agricultural landscape. We did not include grower decision-making variables in our parametric or non-parametric methodology. Because there were few negative coefficients to use in the non-parametric analysis (in which early snowmelt timing correlated with higher crop yield), classification and regression tree models were limited in their ability to classify observations. Additionally, the non-parametric analysis was not exhaustive, and there are many variables—including grower decisions—that are likely important to the different observed directions of impact.

There is an additional need to refine the climate data used in the classification and regression trees in order to understand if these county and SNOTEL characteristics are arising from autocorrelation with climate variables. Expanding the non-parametric analysis will give us more insight into the processes governing the relationship between snowmelt timing and yield. Future work is necessary to determine if the spring/summer buffering hypothesis is upheld when a more rigorous set of predictor variables are considered.

7 CONCLUSIONS

This study advances our understanding of the relationship between snowmelt timing and non-irrigated crop yield in two substantial ways. First, we ascertain that historical final snowmelt date significantly influences non-irrigated crop yield independently of climatic and physiographic characteristics previously presumed to drive yield changes. The relationship direction varies for different Idaho counties, but baseline yield has been lower than average in the past during years with earlier snowmelt timing in most regions of Idaho. Second, we identify that some counties have seen increased historical yield in years with early snowmelt timing—reminding us of the complexities inherent in climate interactions. Spring and summer precipitation may buffer the negative impact of early snowmelt on yield in these benefitting regions. Semi-arid production regions of Idaho that do not receive adequate precipitation during the growing season will therefore be most vulnerable to continuing climate change.

Current considerations of the future impact of climate change on crop yield should be updated to consider early snowmelt timing when estimating future baseline yield in snowmelt-driven, semi-arid landscapes. Decreased summer precipitation is projected in the traditionally ‘summer dry’ Pacific Northwest climate zone (Mote and Salathé 2010), and early snowmelt timing will likely intensify the corresponding decrease in crop yield. Non-irrigated crops and unmanaged ecosystems will be most sensitive to the combined impacts of early snowmelt and decreased summer precipitation—especially in regions that already receive very little summer precipitation.

In addition to agricultural producers, these results pertain to water managers in arid, snowmelt-dominated regions—as a decrease in baseline yield will almost certainly increase demand for irrigation water. Land managers of unmanaged ecosystems may expect lower yield for grazing cattle in years with early snowmelt, and potentially less total biomass for ecosystem support. Land managers may also expect an earlier "die-off" of unmanaged vegetation with decreased summer precipitation, compounded in years with early snowmelt date. On landscapes prone to wildfires, such as the Western United States, early die-off will both increase the length of the fire season and predispose the landscape to easy ignition.

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APPENDIX A

Detailed Data Sources and Summary Statistics

Section A.1 presents detailed data sources for all variables. This section includes a description of SNOTEL–County pairings chosen for the parametric analysis, as well as weather stations chosen to represent county-level weather. Section A.2 presents county-level and SNOTEL station-level summary statistics for the variables used in the parametric analysis.

A.1 Data Sources

SNOTEL-County pairings

In choosing a SNOTEL-County pairing, we assume that final snowmelt date at the SNOTEL station level represents some broader variable of snowmelt in the county. We do not assume that the SNOTEL station snowmelt date exactly equals snowmelt date in the county. SNOTEL stations often experience a later final snowmelt date than the county due to the higher average elevation. Despite this, we assume that snowmelt date at the SNOTEL station correlates with an unmeasurable average snowmelt date occurring at the county scale.

A SNOTEL station was chosen to represent the county snowmelt date in the parametric analysis based on distance first and watershed boundaries second. The specific SNOTEL-County pairing is documented in Table A.1. In 16 counties, the nearest SNOTEL station to the county centroid was used to represent final snowmelt date in the county (labeled “Nearest” in Table A.1). The next-closest SNOTEL station was chosen if the nearest station did not fall within the watershed boundaries corresponding the county area. Table A.1 provides justification for each SNOTEL-County pairing.

Table A.1. **Data Source: SNOTEL station used to represent county-level snowmelt. The SNOTEL justification—Nearest or Watershed Boundaries—is included in the SNOTEL-County Justification column.**

County	SNOTEL station	SNOTEL-County Justification
Ada	Trinity	Watershed Boundaries
Adams	Brundage	Nearest
Benewah	Micah	Nearest
Blaine	Hyndman	Nearest
Boise	Jackson Peak	Watershed Boundaries
Bonner	Hidden Lake	Watershed Boundaries
Boundary	Hidden Lake	Nearest
Butte	Hyndman	Nearest
Camas	Atlanta	Nearest
Clearwater	Mountain Meadows	Watershed Boundaries
Custer	Schwartz	Nearest
Elmore	Trinity	Nearest
Gem	Jackson Peak	Watershed Boundaries
Gooding	Trinity	Nearest
Idaho	Mountain Meadows	Nearest
Kootenai	Mosquito Ridge	Watershed Boundaries
Latah	Elk Butte	Nearest
Lewis	Mountain Meadows	Watershed Boundaries
Lincoln	Hyndman	Nearest
Minidoka	Hyndman	Nearest

Nez Perce	Mountain Meadows	Nearest
Payette	Jackson Peak	Watershed Boundaries
Valley	Long Valley	Nearest
Washington	Squaw Flat	Nearest

Parametric Variables

Table A.2. **Data Source: Global Historical Climate Network (GHCN) data site used to calculate county-level precipitation and growing degree days.**

County	Precipitation GHCN	Temperature GHCN
Ada	Caldwell, ID	Caldwell, ID
Adams	New Meadows, ID	New Meadows, ID
Benewah	Moscow, ID	Saint Marie's, ID
Blaine	Richfield, ID (t < 1958) Picabo, ID (t > 1958)	Hailey, ID (t < 1958) Picabo, ID (t > 1958)
Boise	Garden Valley, ID	Garden Valley, ID
Bonner	Sandpoint, ID	Sandpoint, ID
Boundary	Bonner's Ferry, ID	Bonner's Ferry, ID
Butte	Arco, ID	Arco, ID
Camas	Fairfield, ID	Hill City, ID
Clearwater	Grangeville, ID	Grangeville, ID
Custer	Mackay, ID	Mackay, ID
Elmore	Glenn's Ferry, ID	Glenn's Ferry, ID
Gem	Emmett, ID	Emmett, ID
Gooding	Hazleton, ID:	Hazleton, ID

Idaho	Grangeville, ID	Grangeville, ID
Kootenai	Spokane, WA	Spokane, WA
Latah	Moscow, ID	Moscow, ID
Lewis	Grangeville, ID	Grangeville, ID
Lincoln	Hazleton, ID	Hazleton, ID
Minidoka	Hazleton, ID	Hazleton, ID
Nez Perce	Lewiston, ID	Orofino, ID ($t < 1953$) Lewiston, ID ($t > 1953$)
Payette	Payette, ID	Payette, ID
Valley	McCall, ID	McCall, ID
Washington	Weiser, ID	Weiser, ID

<u>Non-parametric Variables</u>

Table A.3. **Data Source: City used to estimate monthly climate normals at the county level. Monthly climate statistics are weather normal sums of historical precipitation (P), minimum temperature (Tmin), maximum temperature (Tmax), and snow depth (Snow). These climate statistics were calculated by US Climate Data, USCD, (usclimatedata.com) or the Western Regional Climate Center, WRCC, (http://www.wrcc.dri.edu/). The table below lists the data source (USCD or WRCC), site (city name), variables (Tmax, Tmin, P, Snow), and length of record (N years) used to calculate the climate normal. All site cities are in Idaho unless otherwise noted.**

County	Data Source	Site	Variable	N years
Ada	USCD	Boise	P, Tmax, Tmin, Snow	29
Adams	USCD	New Meadows	P, Tmax, Tmin	29
	WRCC	New Meadows	Snow	110
Bannock	USCD	Fort Hall	P, Tmax, Tmin, Snow	29
Bear Lake	USCD	Montpelier	P, Tmax, Tmin	29
	WRCC	Montpelier	Snow	60
Benewah	USCD	St. Maries	P, Tmax, Tmin, Snow	29
Bingham	USCD	Fort Hall	P, Tmax, Tmin, Snow	29
Blaine	USCD	Picabo	P, Tmax, Tmin, Snow	29
Boise	USCD	Garden Valley	P, Tmax, Tmin, Snow	29
Bonner	USCD	Sandpoint	P, Tmax, Tmin, Snow	29
Bonneville	USCD	Idaho Falls	P, Tmax, Tmin	29
	WRCC	Idaho Falls	Snow	57
Boundary	USCD	Bonner’s Ferry	P, Tmax, Tmin, Snow	29
Butte	USCD	Arco	P, Tmax, Tmin	29
	WRCC	Arco	Snow	100

Camas	USCD	Fairfield	P, Tmax, Tmin	29
	WRCC	Fairfield	Snow	57
Canyon	USCD	Parma	P, Tmax, Tmin	29
	WRCC	Parma	Snow	84
Caribou	USCD	Grace	P, Tmax, Tmin	29
	WRCC	Grace	Snow	98
Cassia	USCD	Burley	P, Tmax, Tmin, Snow	29
Clark	USCD	Dubois	P, Tmax, Tmin, Snow	29
Clearwater	USCD	Orofino	P, Tmax, Tmin	29
	WRCC	Orofino	Snow	78
Custer	USCD	Mackay	P, Tmax, Tmin	29
	WRCC	Mackay	Snow	107
Elmore	USCD	Glenns Ferry	P, Tmax, Tmin	
	WRCC	Glenns Ferry	Snow	57
Franklin	USCD	Preston	P, Tmax, Tmin, Snow	29
Fremont	USCD	Ashton	P, Tmax, Tmin, Snow	29
Gem	USCD	Emmett	P, Tmax, Tmin	29
	WRCC	Emmett	Snow	109
Gooding	USCD	Bliss	P, Tmax, Tmin	29
	WRCC	Bliss	Snow	106
Idaho	USCD	Grangeville	P, Tmax, Tmin, Snow	29
Jefferson	USCD	Hamer	P, Tmax, Tmin, Snow	29
Jerome	USCD	Hazleton	P, Tmax, Tmin, Snow	29

Kootenai	USCD	Spokane, WA	P, Tmax, Tmin, Snow	29
Latah	USCD	Moscow	P, Tmax, Tmin, Snow	29
Lemhi	USCD	Salmon	P, Tmax, Tmin, Snow	29
Lewis	USCD	Orofino	P, Tmax, Tmin	29
	WRCC	Orofino	Snow	78
Lincoln	USCD	Richfield	P, Tmax, Tmin	29
	WRCC	Richfield	Snow	58
Madison	USCD	Rexburg	P, Tmax, Tmin, Snow	29
Minidoka	USCD	Rupert	P, Tmax, Tmin	29
	WRCC	Rupert	Snow	29
Nez Perce	USCD	Orofino	P, Tmax, Tmin	29
	WRCC	Orofino	Snow	78
Oneida	USCD	Malad City	P, Tmax, Tmin, Snow	29
Owyhee	USCD	Grandview	P, Tmax, Tmin	29
	WRCC	Grandview	Snow	101
Payette	USCD	Payette	P, Tmax, Tmin, Snow	29
Power	USCD	American Falls	P, Tmax, Tmin	29
	WRCC	American Falls	Snow	57
Teton	USCD	Driggs	P, Tmax, Tmin	29
	WRCC	Driggs	Snow	111
Twin Falls	USCD	Twin Falls	P, Tmax, Tmin	29
	WRCC	Twin Falls	Snow	49
Valley	USCD	McCall	P, Tmax, Tmin, Snow	29

Washington	USCD	Weiser	P, Tmax, Tmin	29
	WRCC	Weiser	Snow	57

A.2 Summary Statistics

<u>Summary Statistics by County</u>

Table A.4. **Summary Statistics: Wheat Yield (bpa)**

County	*N* years	Mean (μ)	StDev (σ)	Min	Max
Ada	50	19.8	5.2	10.0	31.7
Adams	44	24.8	7.0	11.6	43.0
Bannock	63	26.4	6.5	16.0	43.1
Bear Lake	61	21.5	5.6	13.8	38.6
Benewah	58	48.6	14.1	20.6	78.6
Bingham	61	22.4	6.5	10.0	39.6
Blaine	52	19.7	5.6	9.2	34.0
Boise	39	23.9	6.8	11.0	40.0
Bonner	45	32.6	12.6	15.0	60.0
Bonneville	63	27.0	7.4	16.1	43.2
Boundary	61	55.0	15.6	27.4	87.9
Butte	45	18.4	8.1	4.0	49.0
Camas	55	19.0	5.9	3.6	32.3
Canyon	22	20.5	4.8	13.5	31.7
Caribou	63	30.7	8.5	18.2	50.8
Cassia	63	24.4	7.0	10.5	42.5

Clark	57	22.2	7.4	8.9	45.8
Clearwater	63	46.9	13.2	20.6	77.4
Custer	21	18.5	8.5	10.0	50.0
Elmore	60	20.5	5.9	4.7	36.6
Franklin	63	28.2	6.1	15.4	46.2
Fremont	62	30.6	9.2	17.5	55.4
Gem	43	24.3	7.7	9.7	50.0
Gooding	23	19.3	3.2	13.5	27.0
Idaho	63	51.7	15.7	19.8	85.1
Jefferson	38	22.6	7.4	9.7	37.5
Jerome	19	14.9	4.7	5.8	24.0
Kootenai	58	42.8	14.6	16.4	76.8
Latah	63	56.2	16.1	24.0	84.9
Lemhi	6	17.7	2.3	15.0	20.0
Lewis	61	54.0	14.1	22.6	85.1
Lincoln	36	16.3	7.7	4.0	42.0
Madison	63	27.6	6.7	16.6	44.3
Minidoka	59	22.8	10.0	5.6	48.8
Nez Perce	63	56.4	15.7	28.1	85.0
Oneida	63	24.2	5.5	12.6	38.9
Owyhee	6	24.3	8.6	16.0	38.1
Payette	53	26.4	10.1	12.0	53.8
Power	63	24.3	5.9	14.9	42.3

Teton	62	28.2	8.1	14.2	50.8
Twin Falls	55	22.6	7.9	9.7	40.8
Valley	40	21.3	8.1	9.0	53.1
Washington	63	28.1	7.5	13.6	48.8
All Counties (μ)	**50**	**28.5**	**8.5**	**13.5**	**49.6**

Table A.5. **Summary Statistics: Barley Yield (bpa)**

County	*N* years	Mean (μ)	StDev (σ)	Min	Max
Ada	60	23.0	7.5	7.0	50.0
Adams	55	30.2	8.3	15.8	57.0
Bannock	71	28.9	7.2	10.8	42.6
Bear Lake	70	27.4	7.0	10.8	48.1
Benewah	71	42.6	14.7	20.0	73.6
Bingham	64	25.0	6.8	12.0	45.5
Blaine	69	27.0	10.6	11.0	68.2
Boise	47	25.5	7.6	10.0	43.0
Bonner	62	36.0	12.4	13.0	65.0
Bonneville	71	33.3	8.4	12.6	55.0
Boundary	69	55.9	18.4	25.0	95.6
Butte	38	22.4	5.6	13.0	40.0
Camas	68	23.2	7.5	5.4	40.3
Canyon	32	21.3	6.9	11.0	40.0

Caribou	71	37.9	10.4	17.3	69.9
Cassia	68	24.5	7.5	10.0	39.2
Clark	59	24.8	8.0	10.0	48.0
Clearwater	70	40.2	11.6	20.0	66.0
Custer	14	21.9	6.0	12.0	32.0
Elmore	66	25.6	10.7	10.0	63.3
Franklin	70	31.5	7.1	12.0	45.1
Fremont	71	36.1	11.2	15.0	59.6
Gem	65	25.8	6.2	15.0	40.0
Gooding	20	21.8	8.8	12.0	45.0
Idaho	71	42.4	12.8	20.5	75.0
Jefferson	51	27.8	10.0	10.0	70.0
Jerome	13	20.4	4.0	15.0	27.0
Kootenai	68	39.2	13.2	15.0	65.0
Latah	71	47.8	14.4	21.9	80.3
Lemhi	9	20.2	5.6	12.0	30.0
Lewis	71	44.3	13.4	21.2	79.2
Lincoln	17	26.3	10.2	15.0	50.0
Madison	71	30.8	9.0	11.3	50.5
Minidoka	44	24.9	11.4	7.5	70.0
Nez Perce	70	48.1	15.0	22.0	76.0
Oneida	71	27.4	8.0	10.6	46.7
Owyhee	10	23.1	6.4	14.0	38.0

Payette	38	22.2	5.0	15.0	35.0
Power	66	23.7	6.6	10.2	42.1
Teton	71	30.9	8.7	11.1	49.3
Twin Falls	51	23.3	6.2	12.0	38.0
Valley	50	25.8	9.0	10.0	56.0
Washington	70	33.2	9.7	14.0	57.5
All Counties (μ)	**56**	**30.1**	**9.2**	**13.5**	**53.7**

Table A.6. **Summary Statistics: Annual Precipitation – used in MLR [mm]**

County	*N* years	Mean (μ)	StDev (σ)	Min	Max
Ada	50	63	277.2	70.1	130.4
Adams	44	41	592.5	113.0	333.4
Benewah	63	58	741.4	136.9	395.2
Blaine	61	71	306.4	86.5	155.2
Boise	58	42	649.8	157.2	366.2
Bonner	61	62	838.0	129.4	486.3
Boundary	52	55	565.1	123.3	278.8
Butte	39	33	236.6	66.3	150.9
Camas	45	38	422.7	97.5	241.6
Clearwater	63	60	593.5	104.3	383.5
Custer	61	55	243.8	69.8	132.8
Elmore	45	27	254.1	71.7	105.2

Gem	55	67	334.3	74.0	159.6
Gooding	22	68	257.6	70.7	109.7
Idaho	63	60	593.5	104.3	383.5
Kootenai	63	81	416.4	84.7	267.8
Latah	57	77	627.7	132.0	354.2
Lewis	63	60	593.5	104.3	383.5
Lincoln	21	68	257.6	70.7	109.7
Minidoka	60	68	257.6	70.7	109.7
Nez Perce	63	63	320.1	59.8	196.9
Payette	62	53	279.2	73.4	132.0
Valley	43	61	681.7	120.3	463.5
Washington	23	50	294.2	79.7	125.9
All Counties (μ)	**50**	**58**	**443.1**	**94.6**	**248.1**

Table A.7. **Summary Statistics: Spring Precipitation – used in MLR [mm]**

County	*N* years	Mean (μ)	StDev (σ)	Min	Max
Ada	63	51.6	27.1	4.6	128.3
Adams	41	88.1	34.9	19.6	193.0
Benewah	58	106.3	37.8	32.1	221.2
Blaine	71	51.2	26.7	10.2	128.2
Boise	42	87.7	44.8	19.2	196.6
Bonner	62	119.2	49.1	30.9	244.8

Boundary	55	75.7	34.1	17.0	176.1
Butte	33	53.0	27.5	9.2	134.5
Camas	38	62.7	34.3	3.5	150.1
Clearwater	60	154.0	44.4	67.4	245.8
Custer	54	44.6	22.6	2.3	104.7
Elmore	27	39.1	19.9	8.8	80.2
Gem	67	62.9	31.8	11.2	152.0
Gooding	68	50.7	28.1	6.3	166.7
Idaho	60	154.0	44.4	67.4	245.8
Kootenai	81	65.7	34.0	15.0	223.4
Latah	77	109.4	47.7	28.6	262.8
Lewis	60	154.0	44.4	67.4	245.8
Lincoln	68	50.7	28.1	6.3	166.7
Minidoka	68	50.7	28.1	6.3	166.7
Nez Perce	63	71.7	30.2	18.5	164.1
Payette	53	47.7	28.0	4.9	163.9
Valley	61	109.4	41.9	46.1	229.7
Washington	50	45.7	29.4	6.4	163.2
All Counties (μ)	**58**	**79.4**	**34.1**	**21.2**	**181.4**

Table A.8. **Summary Statistics: Summer Precipitation – Used in MLR [mm]**

County	*N* years	Mean (μ)	StDev (σ)	Min	Max
Ada	63	50.8	26.8	6.2	119.8
Adams	41	107.3	38.2	44.1	182.1
Benewah	58	124.7	43.4	38.9	240.2
Blaine	71	53.4	35.0	0.3	219.6
Boise	42	94.3	49.8	10.0	239.6
Bonner	62	149.6	57.5	57.0	308.5
Boundary	55	108.1	47.1	37.9	242.6
Butte	33	74.0	36.6	17.1	145.9
Camas	38	76.2	37.7	10.3	154.2
Clearwater	60	192.7	60.0	75.7	335.7
Custer	55	83.8	40.2	8.9	194.7
Elmore	27	44.5	31.4	5.6	142.2
Gem	67	63.3	32.9	10.7	163.3
Gooding	68	53.9	25.5	6.4	124.7
Idaho	60	192.7	60.0	75.7	335.7
Kootenai	81	82.2	36.2	27.9	232.8
Latah	77	118.0	47.5	33.7	285.8
Lewis	60	192.7	60.0	75.7	335.7
Lincoln	68	53.9	25.5	6.4	124.7
Minidoka	68	53.9	25.5	6.4	124.7
Nez Perce	63	89.6	35.1	35.0	204.5

Payette	53	54.5	27.4	5.6	168.7
Valley	61	132.9	50.6	44.0	329.6
Washington	50	53.2	30.4	6.2	166.9
All Counties (μ)	58	95.9	40.0	26.9	213.4

Table A.9. **Summary Statistics: Growing Degree-Days (average) – Used in MLR**

County	*N* years	Mean (μ)	StDev (σ)	Min	Max
Ada	31	2799.5	154.1	2460.6	3043.2
Adams	36	2208.9	344.8	1752.5	2933.6
Benewah	45	2302.0	140.9	2029.0	2585.4
Blaine	50	2182.6	136.7	1898.4	2474.4
Boise	13	2430.8	119.6	2190.4	2633.4
Bonner	43	2195.4	94.8	2025.8	2444.2
Boundary	19	2335.1	93.1	2219.6	2541.9
Butte	22	2222.0	127.3	1984.3	2483.7
Camas	40	2072.9	100.3	1833.5	2236.3
Clearwater	39	2165.2	134.7	1957.6	2520.7
Custer	23	2096.6	130.4	1869.1	2360.9
Elmore	17	2843.7	151.1	2594.1	3191.7
Gem	26	2755.0	134.2	2504.2	3064.0
Gooding	31	2583.3	127.5	2299.1	2854.7
Idaho	39	2165.2	134.7	1957.6	2520.7

Kootenai	78	2438.3	144.1	2186.8	2815.9
Latah	45	2302.0	140.9	2029.0	2585.4
Lewis	39	2165.2	134.7	1957.6	2520.7
Lincoln	31	2583.3	127.5	2299.1	2854.7
Minidoka	31	2583.3	127.5	2299.1	2854.7
Nez Perce	66	2780.5	132.8	2516.4	3107.3
Payette	24	2827.4	134.5	2548.7	3120.4
Valley	33	1809.0	113.2	1600.4	2101.6
Washington	26	2838.2	158.0	2547.4	3189.8
All Counties (μ)	**35**	**2403.6**	**139.0**	**2148.3**	**2710.0**

Table A.10. **Summary Statistics: Growing Degree-Days (early) – Used in MLR**

County	*N* years	Mean (μ)	StDev (σ)	Min	Max
Ada	47	3153.9	199.6	2761.2	3568.8
Adams	44	2401.5	388.3	1875.1	3234.8
Benewah	66	2503.2	169.7	2193.8	2940.9
Blaine	65	2341.7	175.1	1977.8	2843.8
Boise	22	2678.8	114.8	2485.1	2896.6
Bonner	56	2377.1	122.1	2161.9	2686.5
Boundary	24	2544.4	119.8	2370.1	2864.7
Butte	21	2351.6	146.4	2077.4	2632.8
Camas	60	2166.1	144.4	1876.4	2520.4

Clearwater	55	2426.6	157.2	2102.7	2906.1
Custer	29	2188.6	156.8	1920.3	2570.4
Elmore	25	3202.2	175.3	2872.8	3586.3
Gem	37	3082.2	155.8	2612.3	3404.4
Gooding	51	2852.3	182.3	2516.0	3461.3
Idaho	55	2426.6	157.2	2102.7	2906.1
Kootenai	79	2662.4	175.4	2289.1	3215.3
Latah	66	2503.2	169.7	2193.8	2940.9
Lewis	55	2426.6	157.2	2102.7	2906.1
Lincoln	51	2852.3	182.3	2516.0	3461.3
Minidoka	51	2852.3	182.3	2516.0	3461.3
Nez Perce	70	3130.9	169.6	2726.3	3662.6
Payette	37	3147.9	180.9	2865.4	3624.6
Valley	42	1940.4	135.2	1629.2	2197.2
Washington	42	3151.9	167.1	2797.6	3697.4
All Counties (μ)	**48**	**2640.2**	**170.2**	**2314.2**	**3091.3**

Table A.11. **Summary Statistics: Growing Degree-Days (maximum) – Used in MLR**

County	*N* years	Mean (μ)	StDev (σ)	Min	Max
Ada	43	4001.5	216.9	3556.6	4412.9
Adams	35	3048.2	430.5	2535.3	3934.6
Benewah	62	3260.2	183.9	2893.9	3700.6

Blaine	58	3031.7	195.9	2628.3	3557.5
Boise	14	3469.2	102.3	3291.3	3612.7
Bonner	51	3035.8	152.0	2735.0	3440.4
Boundary	17	3260.5	127.4	3069.9	3580.7
Butte	17	2990.1	158.9	2744.7	3333.9
Camas	53	2830.9	168.4	2538.2	3183.7
Clearwater	46	3123.3	183.8	2761.8	3610.7
Custer	18	2852.6	195.6	2588.2	3225.1
Elmore	19	4067.2	220.3	3713.8	4492.3
Gem	30	3948.6	161.9	3470.9	4222.3
Gooding	43	3632.0	170.7	3301.7	4011.3
Idaho	46	3123.3	183.8	2761.8	3610.7
Kootenai	79	3411.4	205.2	3009.8	3996.0
Latah	62	3260.2	183.9	2893.9	3700.6
Lewis	46	3123.3	183.8	2761.8	3610.7
Lincoln	43	3632.0	170.7	3301.7	4011.3
Minidoka	43	3632.0	170.7	3301.7	4011.3
Nez Perce	68	4010.5	191.3	3566.1	4515.3
Payette	34	4006.5	195.7	3720.6	4463.5
Valley	39	2517.0	152.5	2179.3	2886.9
Washington	36	4014.4	203.0	3644.2	4585.0
All Counties (μ)	**42**	**3386.8**	**187.9**	**3040.4**	**3821.3**

Summary Statistics by SNOTEL station

Table A.12. **Summary Statistics: Final spring snowmelt date (Julian day)**

SNOTEL station	*N* years	Mean (μ)	StDev (σ)	Min	Max
Atlanta Summit	62	165	14	129	195
Brundage Reservoir	55	152	10	129	175
Elk Butte	42	161	14	135	181
Hidden Lake	79	151	11	113	178
Hyndman	64	135	11	110	154
Jackson Peak	66	161	11	133	181
Long Valley	63	110	18	72	147
Meadow Lake	49	160	13	130	181
Mica Creek	89	140	12	96	164
Mores Creek Summit	57	155	11	130	181
Mosquito Ridge	57	159	10	135	178
Mountain Meadows	79	156	11	114	180
Savage Pass	80	159	10	127	178
Schwartz Lake	92	150	10	123	164
Squaw Flat	63	142	12	112	165
Trinity Mountain	97	179	15	134	212
All Stations (μ)	**68**	**152**	**12**	**120**	**176**

APPENDIX B

Model Assumptions and Diagnostics

B.1 Model Assumptions

This study uses two statistical methods to explore the historical relationship between snowmelt timing and non-irrigated crop yield. Inherent to any empirical analysis are a list of benefits, limitations, and assumptions. We outline these separately for the parametric and non-parametric approaches.

The parametric methodology is more statistically powerful than the non-parametric methodology for establishing the relationship between snowmelt timing and yield as we can control for covariates. In doing so, we rely on assumptions about the shape of the distribution in the underlying population and about the parameters of the assumed distribution. In assuming a linear relationship, we impose the following assumptions of the classical linear regression model (CLRM). Estimating a fixed effects regression model further assumes that these assumptions hold under fixed effects.

a) The model parameters are linear.

b) There is random variation in our observations.

c) We are randomly sampling from the population to ensure that every response has an equal chance of being observed.

d) The random errors are normally distributed with a mean of zero and a constant standard deviation. Error in the explanatory variables can introduce a non-zero mean in three ways: A drift in the process, a drift in the measurement system, or a miscalibrated measuring system.

e) There is no multicollinearity, meaning no independent variable can be expressed as a perfect linear function of any other independent variable.

f) There is no autocorrelation, meaning the error term does not exhibit a systematic relationship over time.

g) There is no homoskedasticity, meaning the error variance is equal regardless of the value of the independent variable.

The non-parametric methodology makes less assumptions about the distribution of measurements. Some limitations include: (1) It is less statistically powerful than the parametric methodology, meaning there is less of a chance that a non-parametric technique will indicate two variables are associated with each other, (2) A larger sample size is required to have the same power as a parametric test, and (3) The results are often less easy to interpret than the results of parametric tests. A benefit over the parametric methodology is that we will capture any non-linear interactions that the parametric approach misses.

B.2 Model Diagnostics

Diagnostics allow us to identify violations of the classical linear regression model. Of the aforementioned assumptions, we are able to test for (1) Heteroskedasticity, (2) Multicollinearity, (3) Autocorrelation, and (4) Fixed effects appropriateness. Diagnostics are performed on initial model configurations that did not use an interaction term.

(1) To assess heteroskedasticity we estimate an auxiliary regression to predict the squared residual from each primary regression. There is no significant evidence for the presence of heteroskedasticity in any model. (2) To test for multicollinearity, we first identified the correlation magnitude between all predictor variables used in the primary regression model. Additionally, we estimated separate auxiliary regressions using annual precipitation, spring precipitation, growing degree-days, and snowmelt timing as the

dependent variables. No correlations between any two independent variables exceed 0.784, indicating that no two independent variables exhibit near-perfect multi-collinearity. Additionally, correlation directions are in the expected direction. All auxiliary regressions that exclude county dummy variables and interaction terms indicate varying evidence of multi-collinearity. When county dummy variables are included, all auxiliary regressions indicate high evidence of multi-collinearity. (3) To assess autocorrelation we visually inspect a plot of the residual against the lagged residual for each primary regression and found no evidence of autocorrelation. (4) We used the Hausmann test to decide appropriateness of a fixed effects regression model vs. random effects. The Hausmann test recommends use of fixed effects.

The coefficient estimates are assumed to be BLUE (the best unbiased linear estimator) according to ordinary least squares.