USING MOUNTAIN SNOWPACK TO PREDICT SUMMER WATER AVAILABILITY IN SEMIARID MOUNTAIN WATERSHEDS

by

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DEDICATION

This work is dedicated to my family, especially my parents, Barb and Ken, my brother Robert, and my husband Nathanial. Thank you for always encouraging me to do my best - even when I get discouraged. I am incredibly blessed to have you all in my life.

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ABSTRACT

In the mountainous landscapes of the western United States, water resources are dominated by snowpack. As temperatures rise in spring and summer, the melting snow produces an increase in river flow levels. Reservoirs are used during this increase to retain surplus water, which is released to supplement growing season water supply once the peak flows decrease to below water demands. Once there is no longer surplus natural flow of water, the water accounting changes – referred to as the *day of allocation* (DOA), and water previously retained within the reservoir is used to supplement the lower flow levels. The amount of water stored in the reservoir on the day of this accounting shift determines the water allocated to water right holders for the remainder of the water year. Predicting the day that allocated water will be determined is of special interest to both regulators and those that retain water rights per the Prior Appropriation Law. A method to forecast this day is developed using daily snow water equivalent data for the Boise, Payette, and Upper Snake Rivers in a multiple linear regression model. The melt rates of snowpack are typically comparable to using the maximum accumulation of that snowpack as predictor variables for *day of allocation*. Therefore, water users can be confident in predictions based on snowpack to determine what crops can be grown. The primary controls on these variances are water demand and volume of water accumulated.

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LIST OF ABBREVIATIONS

BSU	Boise State University
GC	Graduate College
TDC	Thesis and Dissertation Coordinator
DOA	Day of Allocation
USGS	United States Geological Survey
USDA	United States Department of Agriculture
NRCS	National Resources Conservation Service
IDWR	Idaho Department of Water Resources
USBR	United States Bureau of Reclamation
SNOTEL	Snow Telemetry

CHAPTER ONE: INTRODUCTION

Snowmelt-driven streamflow from mountainous regions is an essential resource for one-sixth of the human population (Barnett, Adam, & Lettenmaier, 2005). In these regions, seasonal water availability can be estimated based on the amount of snow accumulation in winter. Approximately 50-70% of the total water supply in the mountainous western United States comes from snow (Bales et al., 2006). Snow accumulates in the mountains throughout the cold season, which is typically considered to be November 1 to March 31 (Bohr and Aguado, 2001) in North America. During this time, the snowpack functions as a reservoir of water. As the temperatures rise, the spring and summer melt from the snowpack produces a temporary, predictable increase in river discharge within respective basins. The annual increase in river discharge has the potential to cause flooding (Perkins, Pagano, & Garen, 2009), but it is also a major resource for water storage in the upcoming dry season, when there is less natural supply and high demand due to irrigation. This project explores relationships between mountain snow and critical streamflows to provide information and tools to assist water resource management.

The term “critical flow” refers to a streamflow rate that is significant to water resource management in a basin. Peak annual streamflow is a clear, definable flow of interest (**Figure *1***). Other relevant flows include low flow, surplus flow, and flood stage. For example, low flow would be associated with a river level that cannot sustain demand. There are also surplus flows, which indicates that there is more than enough water to meet agricultural needs. Flood stage refers to a flow that is dangerously high and may cause damage. In addition to flow rates, the volumes, timing, and duration of flows are important. For example, when a flow occurs, the duration above that flow can be quantified. The volume above a threshold flow value indicates the volume that may be stored or attributed to flooding, depending on the flow of interest. In Idaho and much of the western US, critical flows in major river basins are maintained using reservoirs. Surplus water can be retained in a reservoir until the drier periods of summer. Water managers desire more aid in managing reservoirs in snow-dominated regions, especially with the unpredictability of shifting climates (Berghuijs, Woods, & Hrachowitz, 2014; Mote et al., 2003; Viviroli et al., 2011).

In the Western United States, most water accounting is done by Prior Appropriation distribution. Most of the western US uses Prior Appropriation doctrine. Per prior appropriation doctrine, those that are first in time are first in right. Water claims that have been in existence longer are associated with higher priority than the more recent water claims. A water claim refers to the amount of space in a reservoir that a water user will receive during periods of restricted flow and high demand. While a reservoir is filling, water users can have their full right of water. Once the reservoir stops accruing water, those with water rights are assigned a given amount of water for the remainder of the growing season based on the total storage in the reservoir.

Idaho uses Prior Appropriation as described in Idaho code section §42-602. Per the water law of Prior Appropriation, those who have the water first in time are first in right. Water right holders in Idaho have their water delivered per contracts they have with the federal government (Idaho code section §42-801).

A key flow unique to Idaho water management is the *day of allocation* (DOA) flow. The *day of allocation* is an annual occurrence in three of Idaho's watersheds: Snake, Boise, and Payette. In these basins, spring snowmelt is captured and stored in reservoirs to be metered out for summer water rights. The *day of allocation* marks a date when changes occur in how water rights are managed, and is defined as when these three criteria are met: (1) natural flow is less than water demand at a point in the river downstream from most demand, (2) reservoir storage is at its maximum for the water year, and (3) water rights are at a maximum for an irrigation season. The natural water supply is the flow of a river that would occur without obstructions. Therefore, when reservoirs are upstream, the measured flow differs from the natural flow by an amount equal to the instantaneous rate of change in reservoir storage. The natural flow can be calculated by adding the change in storage to the measured flow downstream of a reservoir.

Prior to the DOA, irrigation water demand downstream of a reservoir is less than the natural streamflow from meltwater into a reservoir. All water users can have their full water rights prior to this date. After the DOA, the water demand cannot be met by natural streamflow, and each spaceholder has a finite volume of reservoir water for the remainder of the growing season. Because of this, an early DOA creates a lower rate at which farmers use their stored water than in years with a later *day of allocation.*

In the summer months, those with more recent water claims will have shorter availability of their full water right than those with older water claims. The water supply before *day of allocation* comes from the unregulated flow of the river. On the *day of allocation*, the amount of water that each spaceholder is allotted is determined for the remainder of the growing season. When the *day of allocation* is later than average, water users can be less restrictive on the rate at which they use their supply of water, allowing greater crop possibilities.

The *day of allocation* is important because it determines the restrictive time water users must use their water supply from the reservoir. Depending on the overall volume of water stored in the reservoir, the users may not obtain as much water during the melt season. In these cases, the growing season is not only restricted in time; the space of water allotted to water users is also limited. This reduces the amount of options that farmers have when planning out the growing season.

The *day of allocation* impacts downstream water users. For example, growers may make decisions about what crop to plant based if the *day of allocation* will be early or late. Another possibility with a later *day of allocation* would be the planting of a second crop mid-summer, after the first has been harvested. Farmers are known to check first with water supply specialists before deciding what crops to plant and checking to see if a second crop is feasible. Predictions of the *day of allocation* would greatly benefit agriculture. The premise of this study is that because natural flow into reservoirs is a dominant determinant on of the *day of allocation*, and that natural flow is strongly related to properties of the mountain snowpack (Barnhart et al., 2016), there is likely a historical relationship between properties of mountain snow and the *day of allocation*.

The freshwater resources that come from snowmelt are important for agriculture, human consumption, hydropower, and recreation. Restrictions are already placed on the water users every growing season (Idaho Department of Water Resources, “Analysis of the availability of water rights in the Stewart Decree”, unpublished report, 2015). As the growing season progresses, water rights are cut to some extent for all users. In water shortage years, the cuts occur earlier, which restricts the type of crops that should be planted. In years with limited water supply, major restrictions must be placed on water usage. When water is more plentiful, the restrictive period is smaller. Therefore, crops that consume high amounts of water, such as potatoes, should be planted when the water forecasts are average or above average. This would avoid failed crops due to inadequate water supply.

In the Western US, mountain snowpack water supply is monitored by the USDA NRCS SNOTEL network along with in situ snow surveys conducted by NRCS personnel. Streamflow is monitored by the USGS. Both databases provide consistent daily data. With long-term trends of snowpack and streamflow, relationships among snowpack, streamflow, and DOA are uncovered. Statistical relationships among snow magnitude, snow melting, flow levels, and important dates of water appropriation are assessed. Parameters of the snowpack – such as accumulation and melt patterns - are examined against respective flows and volumes to aid in predicting water supply in each water year, even before snow begins to melt.

The timing and volume of streamflow is related to water management decisions. A water manager’s action to retain or release water in a reservoir will depend on the amount and timing of streamflow anticipated. Effects of this decision influence water users later in the year. Predicting the DOA based on hydrologic behaviors can help water managers to have more confidence in their decisions of what/when to plant. We will investigate the snow to streamflow relationships with respect to critical flow thresholds in watersheds.

The parameters of snowpack should be related to the volume of water supply later in the growing season. The maximum SWE of a snowpack indicates a volume of water available once the snow melts, which flows into streams and can be used for irrigation. If there is a greater volume of snow in the mountains, there will be adequate water supply for a longer period of the growing season.

The three conditions required for the *day of allocation* to occur are monitored by the USBR (US Bureau of Reclamation) through the melt season. However, just using these parameters does not directly provide ways to predict the *day of allocation* earlier in the season. An earlier prediction would allow for water users and farmers to have more confidence in their early-season selection of crops. Of the three parameters that determine the *day of allocation*, two of them are dependent on the snowpack. Due to these relationships, we hypothesize that significant statistical relationships exist between mountain snow parameters and the *day of allocation*.

Few studies have investigated relationships between snow and water management dates. Specifically, relationships between *day of allocation* and snow parameters are of special interest in this study. The proposed parameters in this study are: maximum snowpack, relative April Melt, relative May melt, relative June melt, and the beginning date of snow melt, where relative melt is the cumulative daily melt in a month divided by the maximum amount of SWE at a station in a water year. Maximum snowpack is a volume parameter of the water available as mountain snowpack, and the melt parameters are investigated due to the melt dates and quantities' shifting of the melt curve, which has a strong possibility of also shifting the hydrograph. The shifting of the hydrograph would then create a later *day of allocation*.

The objectives of this project include: 1) describing the relationships between SWE and river flows, 2) identifying relevant predictor variables for the *day of allocation*, and 3) building a multiple linear regression model based on these relevant predictor variables. The model can then be used in future scenarios to estimate the occurrence of the *day of allocation*.

In this project, I assess the statistical relationships between mountain snow and properties of streamflow relevant to the *day of allocation* in three basins in Idaho. The goal of the project is to develop a predictive tool that uses snow data to estimate when the *day of allocation* will occur. I conduct a statistical analysis of snowpack and flow to determine the best parameters to predict the *day of allocation*. Following this, specific parameters are used to create a multiple linear regression model of snow accumulation and melt parameters to *day of allocation*. Finally, model verification will be performed to determine the amount of error associated with each model.

To discern importance of SWE volume and melt patterns, the historical data of flows, SWE, and *day of allocation* are modeled to make a prediction of the *day of allocation*. Natural flows on the *day of allocation* indicate the water demand for each basin. Multiple linear regression techniques can weight parameters derived from the SNOTEL datasets to determine the strongest controls on the *day of allocation* within each basin. These controls include site locations, maximum accumulations, and melt relative to maximum accumulation. These models will weight parameters based on their error to create a model that best represents the relationships between the snowpack and the *day of allocation*.

Specifically, the following questions are investigated:

1) How do patterns of snowpack affect natural flow levels?
2) What specific parameters of snowpack affect the *day of allocation?*
3) How does the accumulation and monthly melting of snowpacks affect the *day of allocation*?

CHAPTER TWO: BACKGROUND

2.1. SNOTEL Sites

SWE (snow water equivalent) is the depth of water that snowpack will yield upon melt. The Natural Resources Conservation Service's (NRCS) Snow Telemetry (SNOTEL) sites measure SWE, and the values are validated and recorded in an online database. SWE is calculated from values obtained with a snow pillow and pressure transducer. Values of SWE are logged daily and are publicly available through the NRCS. There are over 800 SNOTEL stations across the United States, primarily in the western regions at high elevations. The SNOTEL network has existed since the 1960s, and the number of sites continues to grow. Many key sites have a record of over 30 years.

2.2. Streamflow

There are multiple sources of streamflow data. The United States Geological Survey (USGS) has a network of over 27,000 operational sites throughout the United States recording daily values for surface water. The United States Bureau of Reclamation (USBR) also logs daily streamflow through their Hydromet network, which is focused on management of water in the Pacific Northwest. Both USGS and USBR streamflow data were used. All the streamflow data used in this analysis is unregulated flow, which is the flow that would occur naturally if there were no reservoirs in place. Therefore, the values used represent the amount of flow that would be going through a point if there were no reservoirs. The flows represent the natural hydrology of each watershed.

In addition to recording actual flow through a river, the USBR calculates and records the ‘unregulated’ flow in a river. The unregulated flow is calculated by adding the change in reservoir storage with the actual flow. This represents what the flow would be if there were no diversions or dams along the rivers.

2.3. Snow to Streamflow Relationships

The snowpack in the in mountainous regions functions as a temporary reservoir of water during the winter months. High elevation sites are the most useful SNOTEL stations for estimating summer streamflow. Even though lower elevation sites are more representative of basin area, they are associated with weaker relationships between precipitation to streamflow than the high elevation sites (Mote, 2006). This could be due to a multitude of reasons. When snow accumulates, low elevation sites are more susceptible to mid-winter melting due to temperature fluctuations (Nayak, Marks, Chandler, & Seyfried, 2010). The high-elevation sites are typically colder throughout the winter, which causes more precipitation to occur (Katzfey, 1995a, 1995b; Roe, 2005; Sinclair, 1994), and these sites typically retain their snowpack until late spring. Therefore, the snowpack at high-elevation sites better represents the winter precipitation in a basin than the snowpack of low-elevation SNOTEL sites.

Streamflow in the mountainous western United States predominantly occurs with the melting of the snowpack in the spring and summer months. Early season snowmelt is less rapid than late-season snowmelt due to increasing radiative forcing (Trujillo & Molotch, 2014) and increased vegetation activity (Jeton, Dettinger, & Smith, 1996) in the later period of melt. Another study found that earlier, slower snowmelt may result in decreased streamflow efficiency since more time allows for more evapotranspiration of the snowpack (Barnhart et al., 2016). Therefore, we are incorporating timing and amount of melt to predict discharge thresholds.

Models can be created using the snowpack and melt patterns to estimate streamflow (Leppi, DeLuca, Harrar, & Running, 2012; Luce & Holden, 2009; Stewart, 2009; Stewart, Cayan, & Dettinger, 2005). When creating the model inputs, the first variable available in the season is maximum SWE, or maximum value of snowpack in the water year. Maximum SWE has been shown to better represent water availability than April 1 SWE (Bohr & Aguado, 2001). While April 1 SWE may show trends in regression analysis, many basins continue to accumulate snowpack after April 1, making the maximum SWE a better representation of water availability for predicting streamflow.

The timing of melt in snow-dominated systems influence streamflow timing. Early season snowmelt is less rapid than late-season snowmelt due to increasing radiative forcing (Trujillo & Molotch, 2014) and increased vegetation activity (Jeton et al., 1996) in the later period of melt. Another study found that earlier, slower snowmelt may result in decreased streamflow efficiency since more time allows for more evapotranspiration of the snowpack (Barnhart et al., 2016). Therefore, we are evaluating how amount of SWE, melt progression, and start of melt can be used to predict discharge thresholds.

Some things not really described here… snow albedo, dust and surface energy balance; the relationship between vegetation and snow, sublimation.

2.4. Water Accounting

Understanding the basics of water accounting is critical to knowing the importance of this study. The water accounting in the Western United States varies by state and basin. While many basins in the West need reservoirs for a steady irrigation supply in growing season,

Water rights accounting is the set of computational tools used by a watermaster to quantify natural flow availability and use, to track storage of use on a daily, after-the fact basis. In water accounting, there are two main types of flow: *stored flow* and *natural flow*.

Stored flow is the water more than computed flow. This is water previously accrued in the reservoir that is released when the water demand is greater than the natural flow in the watershed.

Natural flow is the water that would be flowing in a river system without reservoir operations and diversions. Therefore, *natural flow* represents the hydrologic behaviors of the watershed. All flows used for this study are natural flows within a certain watershed.

Reach gain is another term commonly used by watermasters to describe natural flows. If a reach along a river is positive or negative, this indicates whether the specific section of the river is gaining or losing water. A gaining stream has a net inflow of water to the reach, and a losing stream as a net outflow of water to the reach. The method of calculating a *reach gain* is as follows:

$$Reach\ Gain = Outflow - Inflow + Diversions + Reservoir\ Change\ in\ Content + Reservoir\ Evaporation$$

Outflow is the river discharge at the end of the reach. *Inflow* is the river discharge at the beginning of the river reach. *Diversions* is the sum of canal and pump diversions from the river reach. *Reservoir Change in Content* is the daily increase (+) or decrease (-) in physical content of any reservoirs within the river reach. *Reservoir Evaporation* is the calculated evaporative losses from the reservoir. Methods used to calculate the evaporation term vary with climate and basin. The evaporative losses in reservoirs and streams do not affect the timing of *day of allocation* (Lyle Swank, personal communication, 2016).

Reservoir systems play a large role in regulating the variety of flows that can occur. Large amounts of excess water can be retained in reservoirs from snow ablation events. This excess water from the reservoir is available to supplement natural flow later in the growing season, when natural flow levels cannot sustain agriculture demand. Alternatively, during high flows, water can be retained to mitigate downstream flooding.

Natural flow into a reservoir is seldom equal to regulated flow out of the reservoir. The flow out of a reservoir is regulated to fluctuate with downstream demand and water rights. Water managers use streamflow prediction to help anticipate and control river flows to meet certain water demands. There is no standardized method for the prediction of the water supply for basins in the semiarid mountain regions. Underestimated discharge leads to an increased risk of flooding; however, overestimating flow can further decrease water in a shortage year. Accurately predicting critical flows and water supply from snow melt is crucial to sustaining flows for those who depend on the consistency of the river.

CHAPTER THREE: STUDY AREAS AND DATA SOURCES

3.1. Boise River Basin

The Boise River Basin has three reservoirs along the Boise River channel and a large amount of available data. The basin is in west-central Idaho, and it covers an area of 2,680 square miles. Boise River Basin is classified as a semiarid mountainous watershed. Figure 2 is a map of this basin with a specified section of the Boise River, SNOTEL sites, and stream gauges used in this analysis.

The three main dams in the Boise River Basin are Anderson Ranch, Arrowrock, and Lucky Peak. Anderson Ranch and Arrowrock are managed by the U.S. Bureau of Reclamation (USBR), and Lucky Peak is a U.S. Army Corps of Engineers facility. Arrowrock and Anderson Ranch are storage reservoirs, and Lucky Peak was built for flood control. The U.S. Army Corps and the USBR cooperate to regulate the flow of the Boise River during flooding. Once flooding ends, flows from Lucky Peak are controlled by the watermaster and depend on irrigation demand. These dams are upstream from the Treasure Valley and they can be used to control how the water supply will be distributed over time.

The SNOTEL sites used in the Boise River Basin are Atlanta Summit, Graham Guard, Jackson Peak, Mores Creek, Trinity Mountain, and Vienna Mine. Graham Guard is the lowest elevation site; snow melts sooner at this location than at the other SNOTEL sites in the basin. The names of the SNOTEL sites and stream gauges are listed with their respective elevation in Table 1. The maximum SWE values at these SNOTEL sites are a major part of the analysis, so the lowest, highest, and average maximum SWE at each site are recorded in Table 2.

Table 1 Boise River Basin sites in the analysis and the elevation of the gauges. The Lucky Peak streamflow gauge data is maintained by the USGS (site 13201500) and USBR, and the SNOTEL sites are maintained by the NRCS.

	Boise River Basin Sites	
	Name	Elevation [ft]
Stream Gauge	Lucky Peak	3,055
SNOTEL Sites	Atlanta Summit	7,580
	Vienna Mine	8,690
	Mores Creek	6,100
	Graham Guard	5,690
	Jackson Peak	7,070
	Trinity Mtn	7,770

Table 2 Summary statistics of historical maximum SWE values at each Boise River Basin SNOTEL site. The mean, maximum, and minimum of these maximum SWE values are in this table and represent the range of maximum SWE throughout the period of record for this study. Units are in inches.

N = 31 (years)	Graham Guard	Atlanta Summit	Jackson Peak	Mores Creek	Trinity Mtn.	Vienna Mine
Mean (μ)	13.2	30.1	28.2	30.8	38.2	34.2
Min	5.7	17.8	16.1	14.9	20.7	19.1
Max	19.9	46.8	43.5	47.2	71.5	58
St. Dev (σ)	4.1	8.5	7.9	9.2	12.3	10.1

While the actual flow coming from the reservoirs is regulated, there is data available for modeled unregulated flow through the USBR. Unregulated flow is the actual flow coming out of the reservoirs plus the change in storage of the upstream dams. This unregulated flow value shows what the flow would be if there were no dams or reservoirs upstream of Lucky Peak.

The water rights begin to be cut following the *day of allocation*. In the Boise River Basin, the *day of allocation* must meet three criteria: the remaining natural flow at Middleton must be zero, the paper fill stops accruing, and the total storage of the reservoir system stops accruing. Following this point, water rights start being cut, and flow is supplemented by water stored in the reservoirs

The flow at Middleton is used as a determining factor due to the agriculture demand and natural water supply to the river. Downstream from Middleton, the Boise River returns to net gains in flow. The agriculture demand downstream from Middleton is naturally sustainable, and the Bryan and Stewart decrees do not cover water claims downstream from Middleton.

In the Boise River basin, there are 29 years of *day of allocation* data that overlap with SNOTEL and streamflow data. The years in the analysis are from 1986 to 2015. The current *day of allocation* methods were incorporated in 1986. The *day of allocation* on the Boise River has ranged from May 10 to July 17 over the years of the current operation method with a standard deviation of 17.3 days. The average *day of allocation* is June 20 for the period of record (Figure 3).

3.2. Payette River Basin

The Payette River Basin is in southwestern Idaho. The river is 62 miles long, and the drainage area is 3,240 square miles. The two main reservoirs along the Payette River are the Cascade and Deadwood. The Cascade Reservoir has a high capacity relative to the region. The entire Payette Reservoir system can hold over 800,000 acre-feet of water.

The SNOTEL sites for the Payette River Basin include: Banner Summit, Big Creek Summit, Deadwood Summit, and Jackson Peak (Figure 4). Two of these stations have intermittent data until water year 1990. The names of the SNOTEL sites and stream gauges are listed with their respective elevation in Table 3. The maximum SWE values at these SNOTEL sites are a major part of the analysis, so the lowest, highest, and average maximum SWE at each site are recorded in Table 4.

The stream gauge for the Payette River Basin is located near Emmett, ID. Due to the upstream reservoirs from these sites on the Payette River, the USBR data must be used so that flows represent natural hydrology instead of regulated flows. The USBR data accounts for the change in storage within the reservoirs along the river, whereas the USGS gauge only records the actual flow level of the river.

Table 3 Payette River Basin sites in the analysis and the elevation of the gauges. The Emmett streamflow gauge data is maintained by the USGS (site 13249500) and USBR, and the SNOTEL sites are maintained by the NRCS.

Payette River Basin Sites		
	Name	Elevation [ft]
Stream Gauge	Emmett	2,626
SNOTEL Sites	Banner Summit	7,040
	Deadwood Summit	6,860
	Big Creek Summit	6,580
	Jackson Peak	7,070

Table 4 Summary statistics of historical maximum SWE values at each Payette River Basin SNOTEL site. The mean, maximum, and minimum of these maximum SWE values are in this table and represent the range of maximum SWE throughout the period of record for this study. Units are in inches.

N = 26 (years)	Banner Summit	Big Creek	Deadwood Summit	Jackson Peak
Mean (μ)	25.5	31.9	42.5	27.6
Min	13.2	18.1	19.4	17.3
Max	39.8	48.2	70.3	43.5
Std. Dev. (σ)	7.2	8.9	13.2	7.9

The *day of allocation* in the Payette river must meet the following criteria: 1) the natural flow minus diversions at Letha is zero, 2) total storage of the reservoir system stops accruing, and 3) paper fill stops accruing. The current method of determining the *day of allocation* is from 1993-2015. Therefore, there are 23 full water years of data for use in developing prediction methods of the *day of allocation*. The record of *day of allocation* in the Payette basin has varied from June 3 to July 31 with a standard deviation of 15.2 days using the current method of determination. The average date is July 10 over the entire record.

3.3. Upper Snake River Basin

The Upper Snake River Basin is primarily located in eastern Idaho, but it also includes parts of Wyoming, Utah, and Nevada. The basin covers 28,821 square miles, and the altitude of the mountain peaks range between 7,000 and 12,000 feet (Parr et al., 1998). There are more than 30,000 stream miles. The region is semi-arid - like the Boise and Payette basins. The primary reservoir on the Snake River is American Falls, which is in Eastern Idaho. Other major reservoirs include Jackson Lake, Palisades, Grassy Lake, Island Park, and Lake Walcott. The total space available in the reservoir system is over 4,000,000 acre-feet.

The SNOTEL sites for the Upper Snake River Basin include: Grassy Lake, Lewis Lake Divide, Black Bear, Phillips Bench, and Two Ocean Plateau (Figure 5). These sites have a record that spans during the period of record for the current *day of allocation* criteria. The melt seasons are consistent for all SNOTEL sites. The names of the SNOTEL sites and stream gauges are listed with their respective elevation in Table 5.

The maximum SWE values at these SNOTEL sites are a major part of the analysis, so the lowest, highest, and average maximum SWE at each site are recorded in Table 6.

Table 5 Snake River Basin sites in the analysis and the elevation of the gauges. The Heise streamflow gauge data is maintained by the USGS (site 13037500) and USBR, and the SNOTEL sites are maintained by the NRCS.

Snake River Basin Sites		
	Name	Elevation [ft]
Stream Gauge	Heise	5,015
SNOTEL Sites	Grassy Lake	7,265
	Lewis Lake Divide	7,850
	Black Bear	8,170
	Phillips Bench	8,200
	Two Ocean Plateau	9,240

Table 6 Summary statistics of historical maximum SWE values at each Snake River Basin SNOTEL site. The mean, maximum, and minimum of these maximum SWE values are in this table and represent the range of maximum SWE throughout the period of record for this study. Units are in inches.

N = 36 (years)	Black Bear	Two Ocean Plateau	Phillips Bench	Lewis Lake Divide	Grassy Lake
Mean (μ)	42.8	34.3	29.7	35.1	34.7
Min	23.6	20.1	17.3	18.3	18.6
Max	73.9	55.1	50.4	61.4	57.6
Std. Dev. (σ)	14.7	12.0	11.1	13.5	11.7

The stream gauge used in the Upper Snake Analysis is the modeled discharge of the Snake River at Heise. Due to upstream diversions, the gauge must be corrected to represent the natural flow of the basin. The site is corrected by the USBR’s Hydromet network (https://www.usbr.gov/gp/hydromet/).

The *day of allocation* in the Upper Snake River Basin occurs when the following occur: 1) the natural flow at Milner Dam is zero, 2) total storage of the reservoir system stops accruing, and 3) paper fill stops accruing. There are 34 years where this operation has been in use; the record spans from 1982 to 2014, but years 1985 and 1989 are not valid for use with these criteria. The earliest *day of allocation* on record is April 25, and the latest is July 30. The average *day of allocation* on the Snake River is June 26, and the standard deviation is 21.1 days.

CHAPTER FOUR: METHODS

The overarching goal is to develop a statistical model that can be used to predict the *day of allocation* from information about the mountain snowpack. I use a multiple linear regression (MLR) approach to discover relationships between several explanatory variables and a response variable. To construct an MLR model it is necessary to identify statistically significant predictor variables. In the following sections I describe how I:

1. Confirm that there is a relationship between snow and streamflow
2. Identify predictor variables for the MLR to *day of allocation*
3. Construct the MLR
4. Cross-validate the MLR

Several analyses are performed to meet and verify the overarching goals.

1) To describe the relationships between SWE from SNOTEL and flow from USGS, linear regressions are used. These methods will bring out how patterns of SWE are related to the streamflows.
2) The next goal, identifying relevant predictor variables for the *day of allocation*, will be met by linear regressions of SWE variables and *day of allocation*.
3) Once predictor variables are identified, the third goal, building a multiple linear regression model, can be done. The multiple linear regression model is done for all three of the basins.
4) The verification for the models is done by checking the R^2 values and using a jackknife RMSE analysis.

4.1. Confirm Relationships Among Snow, Streamflow, and DOA

4.1.1. How can the *day of allocation* be described with flow?

Flow verification is done several different ways. Water managers may know certain flow levels, such as low flow and flood stage. In this case, we use the knowledge of the water managers as a place to begin analysis. Water regulators may know the approximate flows during the *day of allocation*, but verifying these approximations with historical data ensures the best flow threshold value is used. Verification is done by plotting the flow values on the historical *day of allocation*(s) and finding the mean of those flows. The mean represents the flow demand over the reach. Flow verifications are performed on each of the basins, as water demand is different in the three areas.

The flow values are further inspected by creating regressions with the date of indicative flow value to the actual *day of allocation*. The relationship and respective error between the *day of allocation* representative flow occurrence and the actual *day of allocation* are determined. With the average streamflow value, we find when the indicative *day of allocation* flow value occurred on each year. Using the dataset of flow value occurrences and actual *day of allocation*, a regression is created to determine how well the indicative flow value corresponds to the *day of allocation*. These regressions should be related due to the consistent yearly demand throughout the growing season. Given a strong relationship, the flow demand is verified as a constant from year to year, and *day of allocation* is easy to estimate when the streamflow recession is close to the mean demand.

4.2. Identify Predictor Variables for the *Day of Allocation*

In project design, I hypothesized that the *day of allocation* is related to:

1. The amount of snow in the basin draining to a river
2. The date that net melting of snow begins
3. The rate that snow melts, or the duration of the ablation period

The SNOTEL sites used in this study were selected for several reasons. Many the SNOTEL sites in this study are located at high elevations. When a SNOTEL site is located at a high elevation, the snow will be less likely to melt out mid-winter due to the colder average temperatures in high sites. High elevations are less influenced by climate variations and are more reliable for estimating water availability based on the snowpack (Nayak et al., 2010). According to another study, strong relationships with precipitation are found in areas of high elevation (Mote, 2006).

4.2.1. How does the maximum SWE affect the *day of allocation*?

The amount of snow in a basin is indicated by the maximum value of SWE that accumulated at SNOTEL stations (Figure 1). Historically, the USDA SNOTEL program identifies April 1 SWE as the indicator of summer water supply. However, maximum SWE has been shown to better represent water availability than April 1 SWE (Bohr & Aguado, 2001), and verification was done for the sites in this study. While April 1 SWE may show relationships, many basins continue to accumulate snowpack after April 1, making the maximum SWE a better representation of water availability from melt.

4.2.2. How does the start of melt affect the *day of allocation*?

Because the DOA is a date, it should be related with the date at which significant increases in water supply begins. In this study, we should be that date at which significant melt begins. The beginning of melt can be described as the date of 10% melt. Ten percent melt is used, rather than the day of maximum SWE, because melt combined with more periods of accumulation typically occur until the snowpack has melted approximately ten percent (Ferguson, McNamara, Flores, & Marshall, 2017). Once ten percent melt occurs, the snow will melt rapidly until the site has no remaining snow.

The start of melt is evaluated with respect to *day of allocation* due to the relation of ten percent melt to maximum discharge in the river in a basin. If the start of melt is related to this flow parameter, the possibility of the start of melt being related to the *day of allocation* is worth investigation.

4.2.3. How do melt rates affect the *day of allocation*?

The next potential variables in the *day of allocation* are the degree of melt of the snowpack. An earlier melt will lead to an earlier *day of allocation*, and a slower melt will extend the natural water supply to last later into the summer. The melting process is evaluated relative to the total amount of snowpack for the water year. The value calculated indicates snowpack melted and snowpack remaining during the melt season. The amount of melt that occurs over a certain time (a month in this study) is divided by the total amount of SWE in the season, forming a melt ratio for each SNOTEL site in each month.

$$Melt\ Ratio = \frac{Amount\ of\ SWE\ melted\ in\ a\ time\ period}{Maximum\ SWE\ in\ water\ year}$$

The melt ratio is the amount of SWE melted in each time frame divided by the maximum SWE accumulated for the year. In this study, the amount of SWE melted is calculated by using the SWE time derivative on a daily time step and adding the negative changes, or snow melt, over each month that relates to melt. Using the melt ratios on multiple sites and evaluating these values to the *day of allocation* with multiple linear regressions represents ablation in basins.

4.3. Construct Multiple Linear Regression Models

4.3.1. Using a multiple linear regression model

A model can be built using the SWE parameters that are related to the *day of allocation*. Multiple linear regression models are used to discover relationships between several explanatory variables and a response variable. Figure 6 shows how a multiple linear regression model uses multiple variables to obtain a prediction.

To weight the terms going into the model, multiple linear regression with known explanatory variables are used. The number of inputs for each basin varies depending on each basin's availability of SNOTEL sites with consistent, long-term datasets that match with the availability of *day of allocation* data. Terms that are not revealing useful information (such as months with no melt occurring or remaining) may be removed, and the model can be evaluated with the most useful terms possible. In some months, presence or absence of snow can be a better way to evaluate the term, so some are made into dummy variables with a 0 or 1 value (absence or presence, respectively).

The models are created using the 'fitlm' function in Matlab (MATLAB Release 2015a, The MathWorks, Inc., Natick, Massachusetts, United States.**).** Predictions can be generated by using the model from 'fitlm' with new inputs in the function 'predict'. When using the 'fitlm' function, the variables for all years will be considered with the respective *day of allocation* dataset for those years. The output of the 'fitlm' function is a model where future SWE parameters can be used to predict another *day of allocation* when they are multiplied by the constants and added to the intercepts from the 'fitlm' model. The model created by a 'fitlm' function can be saved, and the 'predict' function can use the model and new parameters to generate predictions with Matlab. 'Fitlm' outputs weights and error for each variable in the equation. The option in ‘predict’ must be ‘observation’ for parameter ‘Prediction’ due to the model using a new set of data to estimate the *day of allocation*.

4.4. Verification of the Models

To determine the error within the model, the datasets for each model can be validated by pulling five randomized years of data out of each basin’s dataset for model validation and using the remaining years of data to create a model. The five verification years of *day of allocation* are compared against the model’s predictive performance for the *day of allocation*. The RMSE for the model’s performance versus the actual *day of allocation* is recorded, and this process is repeated 1000 times for each of the 12 models. A histogram is created for the collection of RMSE values for every model. The mean, 10th percentile, and 90th percentile of each model’s RMSE distribution is calculated. The verification models show the robustness of the original models calculated from the full datasets (***Figure 7***).

CHAPTER FIVE: RESULTS

Basic relationships of SWE to streamflow values are investigated, and several of the regressions revealed strong relationships (Appendix). Maximum SWE is related to runoff volumes and days above threshold flow levels for respective basins. Regressions between snow and streamflow seem to be stronger in higher elevation sites versus lower elevation sites, likely due to less fluctuation in SWE until spring at the higher elevations from cooler temperatures.

Volume of SWE can be directly related to the runoff volumes in a year. The strong relationships of up to an R^2 of 0.91 (adj = 0.88) can be attained by performing regressions between maximum SWE at SNOTEL sites to the volume of water through a point downstream in a river (Figure 8). Because of this, the maximum SWE can be used to predict the water supply volume.

Maximum SWE also relates highly to the number of days above threshold flow values ($R^2 = 0.88$, adj $R^2 = 0.85$) (Figure 9). The threshold flow values are critical flows that a river may or may not exceed depending on how the snowpack melts. Based on these findings, the remainder of the study considers how *day of allocation* in three different watersheds can be predicted using maximum SWE and cumulative melt percentages of April, May, and June.

5.1. Flow and Day of Allocation Relationships

5.1.1. Boise River Flows on the Day of Allocation

When investigating critical flows in other basins for the *day of allocation*, using the flow values on the date helps approximate flow values indicative of the *day of allocation* for water managers. In the Boise River basin, the *day of allocation* is near the final occurrence of 4,000 cfs of unregulated flow at Lucky Peak (Figure 10). The indicative flow of 4,000 cfs follows the annual streamflow peak from snowpack in the years of 1986-2014 (29 years). This flow value represents the total amount of diversions of water rights between Lucky Peak and Middleton. There is a strong relationship between *day of allocation* and date of flow value for Boise River basin. For the Lucky Peak station, using the day when the flow goes below 4,000 cfs and plotting regressions with that date to the *day of allocation* shows a strong trend. The R^2 value is 0.96. Therefore, the natural flow value of 4,000 cfs and the *day of allocation* are very closely related.

5.1.2. Payette River flows on the *Day of Allocation*

In the Payette River, the first instance below 2,000 cfs following the streamflow peak closely matched the occurrence of the *day of allocation*. This is different from the Boise River, where the closest instance was the final measurement of the indicative flow level. The relationship between the first occurrence of the indicative flow level and the *day of allocation* is the highest in the Payette Basin at R^2 being 0.99 (Figure 11). This indicates that the relationship between streamflow magnitude and the *day of allocation* is strongest in the Payette.

5.1.3. Upper Snake River flows on the *Day of Allocation*

The indicative flow for the Snake River is obtained by using the average flow that occurs on the *day of allocation* at Heise from 1982-2014 (33 years). The indicative flow on the *day of allocation* for the Snake River is 14,000 cfs of natural flow through Heise. Heise is approximately 150 miles from Milner Dam, where the flow must be zero when accounting for diversions between the two gauges. Therefore, this indicates that 14,000 cfs of natural flow is typically used in diversions between Heise and Milner Dam. The relationship between the *day of allocation* and the days on which the indicative flow occurs is an adjusted R^2 of 0.90 (Figure 12). Therefore, 90% of the variation in the *day of allocation* can be explained by the flow value of 14,000 cfs.

5.2. *Day of Allocation* Predictor Variables

The parameters of maximum SWE and monthly melt ratios were found to relate to the *day of allocation* (Correlations of SWE Parameters to Day of Allocation - Appendix A). The variables that had significant relationships with *day of allocation* were placed into the multiple linear regression models in order of data availability in the water year. However, the relationship between date of 10 percent melt and *day of allocation* is extremely weak (R^2 of 0.02). This observation indicates that the timing of melt initiation and the *day of allocation* are not related. This may be attributed to the fact that the parameter of 10% melt date does not indicate the total volume of snow to be melted. Another factor could be that the *day of allocation* is more closely tied to how the streamflow decreases in mid-summer.

5.2.1. Progression through the melt season increases data availability

As the melt season goes from maximum accumulation to the final melting period, predictions for the *day of allocation* can be made using the MLR model. Each basin has four models in this study. The first model only incorporates the maximum accumulation of SWE at each of the SNOTEL sites. Therefore, if a basin uses 5 SNOTEL sites, five variables will be used for the first model's inputs.

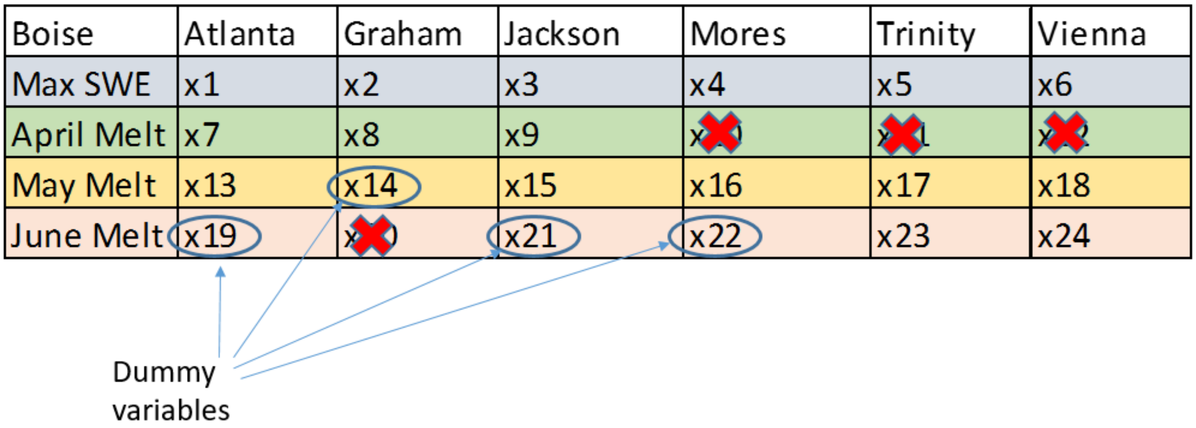
For Models 2-4 in each basin, the melt ratios are also inputs. Model 2 incorporates the melt ratios from April for each of the SNOTEL sites in addition to the maximum accumulation of SWE. Model 3 uses maximum accumulation, April melt ratios, and May melt ratios. Model 4 requires inputs from maximum accumulation, April melt ratios, May melt ratios, and June melt ratios. Therefore, using the example of 5 SNOTEL sites in a basin, Models 2, 3, and 4 will have a maximum of 10, 15, and 20 variables, respectively.

5.2.2. Model exceptions and alterations

Certain sites are not useful during specific time frames in regards to melt. Some sites are removed from the April melt ratio criteria because there is frequently still accumulation of SWE occurring in many high elevation sites, and the melt at the sites during April is not significant or close to a normal distribution. In addition, some sites always melt out by May, and the June melt ratios are always zero for the period of record. These terms are removed as well.

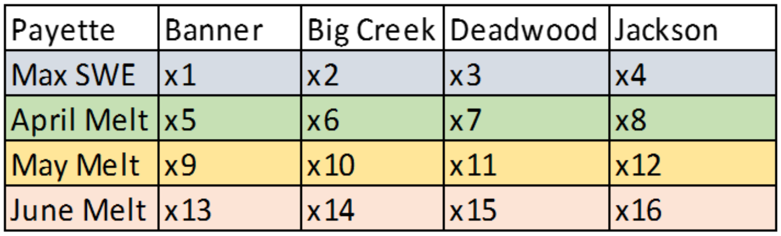
Some parameters must be modified to be more useful. Some site/month combinations have nothing left to melt in approximately half of the years on record. Therefore, the presence or absence of melting is more important in determining the *day of allocation* than the actual quantity of melt. These parameters are made binary, with a zero representing no melt and a one representing the occurrence of melt at a given site. Table 7, Table 8, and Table 9 show which variables remain and which are changed for the MLR models.

Table 7 In the Boise River Basin, four of the original terms are not included in the final MLR model, and four other terms are switched to dummy variables, which reveal either a presence or absence of melting of snow at the sites.



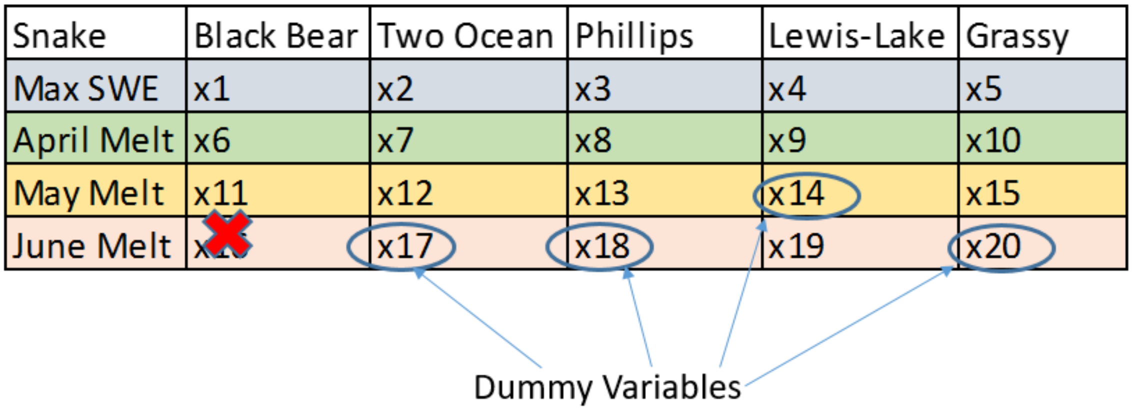
Boise	Atlanta	Graham	Jackson	Mores	Trinity	Vienna
Max SWE	x1	x2	x3	x4	x5	x6
April Melt	x7	x8	x9	~~x10~~	~~x11~~	~~x12~~
May Melt	x13	x14	x15	x16	x17	x18
June Melt	x19	~~x20~~	x21	x22	x23	x24

Table 8 In the Payette, all the original terms are used. This is the only basin where no terms were deleted or made into dummy variables for the final MLR model.



Payette	Banner	Big Creek	Deadwood	Jackson
Max SWE	x1	x2	x3	x4
April Melt	x5	x6	x7	x8
May Melt	x9	x10	x11	x12
June Melt	x13	x14	x15	x16

Table 9 In the Snake, one variable was removed due to no snow presence in the period of record. Four variables are switched to dummy variables since the presence or absence of melting is more indicative than the actual melt ratios.



Snake	Black Bear	Two Ocean	Phillips	Lewis-Lake	Grassy
Max SWE	x1	x2	x3	x4	x5
April Melt	x6	x7	x8	x9	x10
May Melt	x11	x12	x13	x14	x15
June Melt	~~x16~~	x17	x18	x19	x20

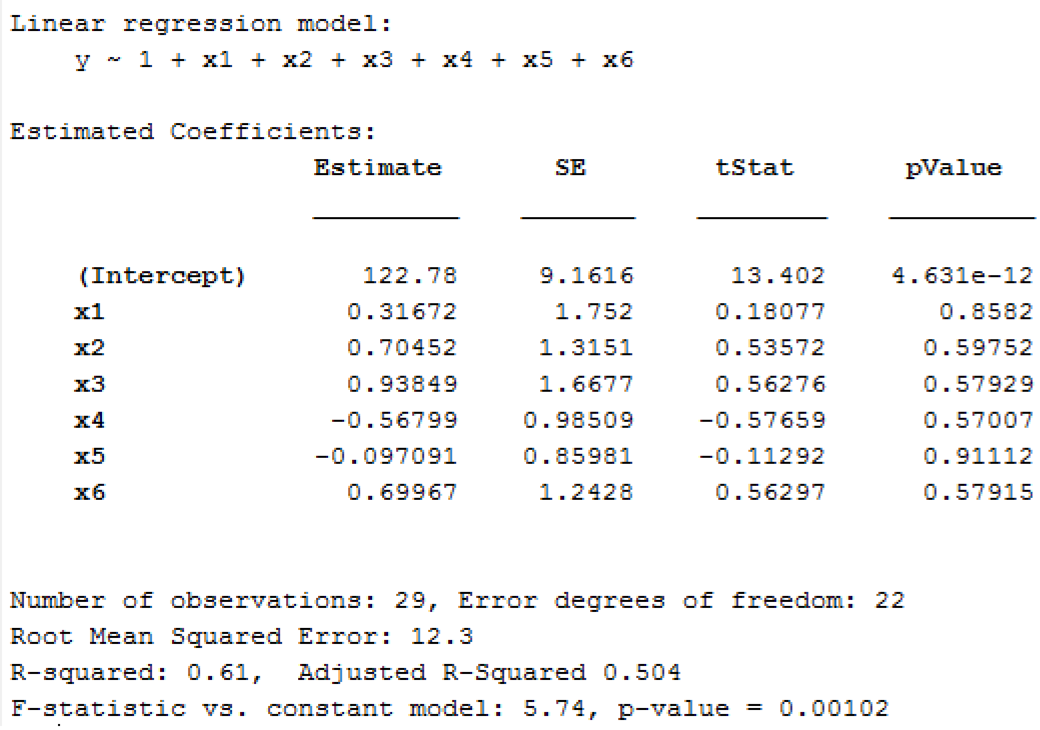
5.3. Results of the Multiple Linear Regression Models

The model results are in the format of an equation with error components. The tables for each model are presented in the following format in Statistics for Final Models (Appendix A):

Table 10 The values in this table are multiplied by the respective maximum SWE values and added with the y-intercept to obtain a prediction for DOA.

	Atlanta	Graham	Jackson	Mores	Trinity	Vienna
Max SWE multiplier	.32	.70	.94	-.57	-.1	.70

Table 11 This table shows the output of the model from Matlab. In addition to the constants and y-intercept, the standard error, t-statistics, and p-values are also included for the input parameters.



```
Linear regression model:
    y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6

Estimated Coefficients:
                   Estimate       SE        tStat       pValue  
                   _________    _______    ________    _________

    (Intercept)       122.78     9.1616      13.402    4.631e-12
    x1               0.31672      1.752     0.18077       0.8582
    x2               0.70452     1.3151     0.53572      0.59752
    x3               0.93849     1.6677     0.56276      0.57929
    x4              -0.56799    0.98509    -0.57659      0.57007
    x5             -0.097091    0.85981    -0.11292      0.91112
    x6               0.69967     1.2428     0.56297      0.57915


Number of observations: 29, Error degrees of freedom: 22
Root Mean Squared Error: 12.3
R-squared: 0.61,  Adjusted R-Squared 0.504
F-statistic vs. constant model: 5.74, p-value = 0.00102
```

For the models (this one is Model 1 of Boise River), the *day of allocation* is calculated by multiplying the variables and the multipliers and adding the separate components together with the y-intercept. The output of each equation is the day of the calendar year. To calculate the prediction of DOA using this model, the equation used is below. Therefore, the six variables are all necessary for the calculation. A prediction cannot be made with this model if any one of the variables is not available.

$$\begin{aligned}
&Boise\ Day\ of\ Allocation \\
&\qquad = 122.8 + \left(.32 * (Atlanta\ Summit\ Max\ SWE)\right) \\
&\qquad + \left(.70 * (Graham\ Guard\ Max\ SWE)\right) \\
&\qquad + \left(.94 * (Jackson\ Peak\ Max\ SWE)\right) \\
&\qquad + \left(-.57 * (Mores\ Creek\ Max\ SWE)\right) \\
&\qquad + \left(-.1 * (Trinity\ Mtn\ Max\ SWE)\right) + (.70 \\
&\qquad * (Vienna\ Mine\ Max\ SWE))
\end{aligned}$$

While all the individual parameters are positively correlated with the DOA, two of the multipliers in this equation have negative values. Most of the regression models have negative constants for positive correlations. When variables are interacting, positive correlations can have negative constants. The negative constants can balance out some of the positive constants, and the balance can shift the prediction forward or backward depending on SWE distribution in the basins.

Using this equation with historical maximum SWE for DOA predictions and plotting them next to actual DOA values is shown in Figure 13. Using Model 1 for the Boise River Basin DOA has an average deviation of 8.67 days from actual to prediction. Figure 14 shows box and whisker plots of how the prediction and actual DOA compare among the 4 models for the Boise River.

5.3.1. Boise River Basin MLR

When relating SWE to *day of allocation*, maximum SWE is the first available input for the model. Using the 6 SNOTEL sites selected, the maximum SWE accounts for 0.50 of the variability in the *day of allocation (cite table).*

Table 12 Summary statistics of the 12 models presented in this study. There are 4 models for each basin. Years of data vary based on availability of data at certain sites.

Basin	Model #	Variables	R^2	Adjusted R^2	N (years)	RMSE (days)
Boise	1	6	.61	.504	29	12.3
Boise	2	9	.765	.647	28	10.6
Boise	3	15	.948	.877	27	6.37
Boise	4	20	.982	.921	27	5.1
Payette	1	4	.684	.614	23	9.45
Payette	2	8	.719	.558	23	10.1
Payette	3	12	.931	.848	23	5.93
Payette	4	16	.966	.874	23	5.41
Snake	1	5	.719	.663	31	12.3
Snake	2	10	.778	.667	31	12.2
Snake	3	15	.891	.782	31	9.86
Snake	4	19	.922	.787	31	9.74

After the month of April, the April melt ratios can be calculated for the SNOTEL sites. Because half of the SNOTEL sites are still frequently accumulating SWE during the month of April, only three sites are fit for incorporating the April melt ratio into model 2 of Boise, increasing the inputs to the model from six to nine – six maximum SWE values and three melt ratios for April. The adjusted R^2 increases from 0.50 to 0.65 The addition of the April melt increases the predictive power of the model's R^2 by 0.15 for the *day of allocation*.

Incorporating the May melt ratios into the model brings the model inputs from nine to thirteen. May melt is valid at all SNOTEL sites, but Graham Guard is frequently melted out by May. Due to this trend, May melt for Graham Guard was made into a dummy variable, where the melt of any snow was 1 and the melt of no snow was 0. These additional six inputs increase the adjusted R^2 of the model from 0.65 to 0.88.

Graham Guard has no snow to melt in June, so the June melt for Graham Guard is removed. Atlanta Summit, Jackson Peak, and Mores Creek are far from a normal distribution in June, so they are made into binary variables. Trinity Mountain and Vienna Mine have standard melt ratio values. The melt ratios in June bring the model inputs to 19, and the adjusted R^2 for the model after June is 0.92.

5.3.2. Payette River Basin MLR

In the years of 1993-2015 (23 years), the Payette River has had its *day of allocation* between June 3 to July 31. When investigating the indicative flow of the *day of allocation*, the flows at Emmett are, on average, 2000 cfs. Of the natural flows considered in this study, the natural flow at Emmett had the lowest variance from the mean flow on the *day of allocation* and is therefore the most consistent.

In the Payette River Basin, the maximum SWE has a 0.61 adjusted R^2 with the *day of allocation*. This indicates the predictive power of the model is 0.61. All four of the SNOTEL sites are used for the maximum SWE values.

The inclusion of April melt decreases the predictive power (adjusted R^2 from 0.61 to 0.56) among the variables, which contrasts from the Boise River, where the inclusion of April melt provides a significant increase in *day of allocation* explanation. This can be attributed to the higher elevation of the Payette Basin, where snow is still commonly accruing during the month of April. However, the normality of the distribution of April melt ratios are not affected. Because of the normality of the data, the parameters remain in the model. Also, if the maximum SWE occurs during the months of April in the sites, the *day of allocation* prediction can be recalculated with just maximum SWE variables in Payette.

The May melt in the Payette River basin increases the prediction ability of the *day of allocation*, moving the adjusted R^2 from 0.56 to 0.85 (+0.29). There are twelve inputs into the equation for this relationship between snowpack and *day of allocation*.

The June melt in the Payette River basin improves the model slightly. The adjusted R^2 goes from 0.85 to 0.87 (+0.02). Though the addition of June melt may increase the confidence slightly, this slight increase requires 16 inputs into the model.

Some of the streamflow data from the Emmett Gauge are incorrect. However, due to the questionable streamflow values being distant from the *day of allocation*, the analysis for the model is not affected.

When predicting the *day of allocation* from max SWE and melt rates, the predictions are more refined than they would with just maximum SWE. While the R^2 is 0.97, the adjusted R^2 of 0.87 is a more accurate representation of the prediction power of this model. Deadwood Summit and Big Creek are the most important in this model. When running statistics on melt as the season goes on, the May melt ratio provides the most information for when the *day of allocation* will occur.

5.3.3. Upper Snake River Basin MLR

When determining the *day of allocation* on the Snake river from SWE, the maximum SWE of the five SNOTEL sites are used. Using multiple linear regression of maximum SWE values to *day of allocation*, an adjusted R^2 of 0.66 is obtained, which is the strongest relationship among the three basins with using only maximum SWE (+0.16 from Boise and +0.06 from Payette).

Using the melt ratio from the month of April adds 5 inputs to the multiple linear regression model, bringing the total number of inputs to 10. The April melt ratios bring a slight increase in the adjusted R^2 of the trend - from 0.66 to 0.67. There is commonly SWE accumulation occurring during the month of April, so the melt of April is less indicative of how the snowpack melts in a season. However, the April melt ratios are normally distributed and remain as their ratios in the model as opposed to binary.

The melt ratios for the month of May and the maximum SWE create an adjusted R^2 of 0.78 with multiple linear regression. Lewis Lake Divide May Melt ratio is made binary, since the presence or absence of snow is more important than the melting of snow. There are 15 inputs for this model, and the adjusted R^2 from the maximum SWE to *day of allocation* increases by 0.11 when the May melt ratios are incorporated into the model.

June melt ratios bring the inputs of the model to 19. Black Bear's June melt ratio is removed from the model due to the frequent absence of snow at this site during the month of June. Three sites are made to only consider presence/absence of snow, and one site utilizes the actual melt ratios. The adjusted R^2 for the model is 0.79 The June melt ratios provide an overall increase in adjusted R^2 of 0.01. Of the three basins, this is the lowest adjusted R^2 with all the SWE data.

5.4. *Day of Allocation* Model Verification

5.4.1. Boise verification

See Figure 15 for the Boise River models' RMSE distributions. The RMSE in the verification for Model 1 averages 13.2 days, with 6 and 20 days as the 10th and 90th percentiles. Model 2's RMSE verification averages 11.8 days, with 10th and 90th percentiles of 4 and 19 days. There is a slight decrease in error between Model 1 and Model 2 for the Boise River Basin.

The RMSE of the Model 3 verification averaged 10.7 with a 10th and 90th percentiles of 5 and 17 days, respectively. Factoring in Maximum SWE, April melt, and May melt gives the lowest RMSE distribution among the four Boise River basin models.

The addition of the June melt ratios increases the predictive power of the model's R^2 by 0.04. The RMSE of the Model 4 verification averages 13.5 days, with 10th and 90th percentiles of 5 and 22 days. The final model in the Boise River basin gives the highest distribution of RMSE in the testing models. Therefore, the use of June melt ratios in predicting the *day of allocation* is not practical. June is also frequently when the *day of allocation* occurs, so other hydrograph indications such as streamflow recession may be more useful than June melt ratios.

5.4.2. Payette verification

See Figure 16 for the Payette models' distributions. The verification of Model 1 of the Payette River using RMSE provides a mean of 11.6 days and 10th and 90th percentiles of 5 and 21 days. Model 2 adds the relative melt during the month of April. This model's RMSE distribution has a mean of 12.6 days and 10th and 90th percentile values of 4 and 23 days. The inclusion of the April melt increases the absolute error of the model. Model 3 adds the May melt ratios to the list of inputs. The RMSE distribution from this model's verification has a mean of 12.9 and 10th and 90th percentile of 7 and 31 days. The error continues to increase with added terms in the Payette River regression models. Model 4 includes the June melt ratios in addition to the variables in Model 3. The mean RMSE of the verification models is 13.4 with 10th and 90th percentiles of 6 and 36. The error in Model 4 is the highest among all twelve of the models in this study. The predictive capability decreases with melt data in the Payette River basin model.

5.4.3. Upper Snake verification

See Figure 17 for the RMSE distribution of models for the Upper Snake River. The RMSE distribution from Model 1 verification has a mean of 11.7 days and 10th and 90th percentiles of 5 and 19. The mean of Model 2's RMSE verification distribution is 12.6 days with 10th and 90th percentile values of 6 and 21 days. The distribution of RMSE for Model 3 verification averages 12.7 days with 10th and 90th percentiles of 6 and 20 days. The distribution of Model 4's RMSE has a mean of 12.9 days with 10th and 90th percentiles of 5 and 21 days. The distributions for all four of the models in the Upper Snake verification are comparable. Therefore, the addition of SNOTEL data past the peak amount of SWE does not add much predictive capability for the *day of allocation*.

Table 13 Results from the RMSE distribution analysis for verification of the 12 separate models. This table shows how many years of consistent data are available for each basin, how many of those years are put into the model creation, and 5 years of data are used for verification for each model. This table also shows how many variables that potentially influence day of allocation are in each model. The average root mean square error values are shown for the verification of 1000 model/verification scenarios with the 10^th^ and 90^th^ percentiles.

	Boise (27 - 29 years)	Payette (23 years)	Snake (31 years)
Model 1 (Max SWE) Mean RMSE (10th/90th percentiles)	24 years -> model 6 variables 13.2 (6/20) days	18 years -> model 4 variables 11.6 (5/21) days	26 years -> model 5 variables 11.7 (5/19) days
Model 2 (Max SWE, April Melt) Mean RMSE (10th/90th percentiles)	22 years -> model 9 variables 11.8 (4/19) days	18 years -> model 8 variables 12.6 (4/23) days	26 years -> model 10 variables 12.6 (6/21) days
Model 3 (Max SWE, April and May Melt) Mean RMSE (10th/90th percentiles)	22 years -> model 13 variables 10.7 (5/17) days	18 years -> model 12 variables 12.9 (7/31) days	26 years -> model 15 variables 12.7 (6/20) days
Model 4 (Max SWE, April May and June Melt) Mean RMSE (10th/90th percentiles)	24 years -> model 18 variables 13.5 (5/22) days	18 years -> model 16 variables 13.4 (6/36) days	26 years -> model 19 variables 12.9 (5/21) days

CHAPTER SIX: DISCUSSION

6.1. Max SWE Controls *Day of Allocation*

In all three of the basins, using just maximum SWE values from SNOTEL sites can obtain confidence comparable to or better than the model using the additional melt ratios. While melt ratios may be useful in some years, they cannot be heavily relied on. Maximum SWE is a strong indicator of the volume and threshold values, which are key factors in the *day of allocation*.

The relationship between maximum SWE and *day of allocation* can be particularly useful for agriculture. The maximum SWE occurs at many SNOTEL sites near the time when farmers must make decisions on their crops for the rest of the growing season. If predictions made in March are comparable to those in mid-summer for *day of allocation*, decisions can be made with more confidence.

The maximum SWE is strongly related to total volume of water through a channel in a water year, especially in the basins with higher elevations. The *day of allocation* considers more than the total volume; it also considers the rate at which the snowpack melts. Therefore, incorporating the rate at which the snowpack is melting increases the R^2 for all basins analyzed. However, the RMSE verification shows that the addition of the melt ratios increases the amount of error within the models. This indicates that the models may have high R^2 values, but they may, in most cases, be overfit and less useful than the models that just use maximum SWE values.

6.2. *Day of Allocation* can be Predicted by Natural Flow Levels

For all three basins, there are flow levels indicative of the *day of allocation* (adjusted R^2 above 0.90). The weakest relationship was in the Snake River, with an adjusted R^2 of 0.90. This may be attributed to the vast size of the Snake River, and the Heise gauge used is approximately 150 miles upstream from Milner Dam, the gauge at which the *day of allocation* has specific criteria. The Boise and Payette indicative flows to *day of allocation* have adjusted R^2 values of 0.96 and 0.99, respectively. On the Boise River, the distance from Lucky Peak to Middleton is approximately 40 miles; on the Payette River, the distance from Emmett to Letha is close to 10 miles. These relationships could be attributed to the distance between the 2 measured sites – from gauge to gauge, where losses or gains can occur through evaporation or groundwater movement. The river with the largest amount of distance between the two gauges also has the highest error in indicative flow to *day of allocation*. Though the definition of the *day of allocation* does not explicitly define an upstream flow, the upstream flows are directly related to the criteria of the *day of allocation*.

6.3. Melt Rates Can Aid in Predictions

The *day of allocation* in water accounting has many factors. While the volume of SWE accumulated is important, the timing of melt can also be an important indicator of when the *day of allocation* will occur. However, the melt ratios of each site can be dependent on the maximum accumulation of SWE, since a deeper snowpack may be melting for a longer period than a shallower covering of snow.

The month on which the melt is most critical to the *day of allocation* varies depending on of the basin. The Boise River is primarily affected during the month of

April. The SNOTEL sites in the Boise River basin are lower than the SNOTEL sites in the Payette and the Upper Snake. In the Payette and Snake River basins, the April melt lowers the R^2 of the model. Therefore, removing the melt ratios for the month of April is necessary for several SNOTEL sites. Some sites of April melt are not highly related to streamflow because of the frequent accumulation of snow into the month of April (Ron Abramovich, personal communication, 2016), and melt is limited until the month of May.

The Snake River basin has a more gradual increase in adjusted R^2 in MLR Models 1-4 than the Boise and the Payette. While the Snake River has strong relationships in regards to maximum SWE to *day of allocation*, May and June melt only increase the R^2 by small increments (0.01, 0.11, and 0.01 as opposed to 0.25 for April in Boise and 0.29 for May in Payette). In this way, there is not a ‘key month’ of melt; rather, much of the variation that can be accounted for in the Snake River’s *day of allocation* is in the maximum accumulation of SWE.

Even though the addition of melt ratios increases the R^2 of the basin’s models, the RMSE verification does not always agree with conclusions made solely on adjusted R^2 values. The RMSE values are absolute, while the adjusted R^2 values are relative, and the verification statistics are stronger than the models’ statistics.

Due to the dependence of melt on total SWE accumulation, melt does not create a more robust model when terms are added with maximum SWE for a multiple linear regression model. However, maximum SWE is strongly related to total water supply volume, which is a significant contributor of the *day of allocation* and overall water supply for the growing season. *Day of allocation* is more of a function of the volume of water in the snowpack than how the snowpack melts, unlike the peak streamflow

(Ferguson et al., 2017). More seasonal data does not necessarily indicate a better prediction, which is good news for water users. Many water users are deciding on their seasonal crops in the month of March. March SWE is a good indicator of maximum SWE. Therefore, water users can have high confidence using March SWE to decide on which crops to grow.

6.4. Long term Trends for the Day of Allocation

Long-term climate shifting is evident in some of the data. The Boise analysis verifies the findings of the studies indicating that lower elevation sites have lower relationships to precipitation and are more susceptible to shifting of climate (Mote, 2006; Nayak et al., 2010). The use of this method in watersheds with low-elevation SNOTEL data may not yield relationships as strong as an analysis on a higher-elevation watershed. Graham Guard is the lowest elevation site in the Boise River Basin. There is a decrease in snowpack with time at this station with a p-value of .14. Therefore, there is moderate confidence in the trend of decreasing snowpack at Graham Guard. The p-values for other snowpack trends of sites in this study are much higher than that, and therefore have weaker trends for climate shift verification within the dataset.

In addition to trends of SWE to *day of allocation*, *day of allocation* also has trends over time. While the amount of error is high ($p > 0.4$ for all basins), two of the three of the watersheds indicate a *day of allocation* shift by three days earlier per decade. The Boise basin was the only watershed that did not have this trend; it indicated a slight positive (toward a later date) trend. This rate may also change over time, but the trend implies an average shift of a *day of allocation* 10 days earlier over a record of ~ 30 years. Further analysis may be done on the *day of allocation* dataset, where the years are separated by low and high water supply. SWE and water shortages were briefly investigated. Figure 18 show how annual water supply is tied to maximum SWE values and *day of allocation*. The trend of increasing dryness in dry years (Luce & Holden, 2009) may also have an impact on the *day of allocation*. In addition, Figure 19 shows how the first 10 and last 10 years of the *day of allocations* in each basin vary. The Boise River shows little change, but the Payette and Snake Rivers show and earlier shift in the *day of allocation*.

6.5. Start of Melt Not Related to *Day of Allocation*

The start of melt, which is defined in this study as when 10% of the snowpack is melted, was found to not be an indicator of the *day of allocation*. The result was initially surprising, since the peak flows were found to be strongly related to 10% melt. However, because the *day of allocation* is dependent on total amount of water available in a water year, the start of melt may be negligible. The *day of allocation* in the basins occurs when the streamflow is in its summer recession, which occurs after the bulk of volume of the melted snowpack has passed through. The years with more snowpack see later meltout dates, and therefore, later *day of allocation*s. This is because deep snow will take a longer time to melt than shallow depths of snow. Deeper snow also provides a larger amount of total water, which also contributes to a later *day of allocation*. The depth of snowpack is also related to the duration of natural flow being above a specific threshold. A deeper snowpack will provide more days above a threshold (such as water demand), regardless of when 10% of the snowpack was melted.

6.6. Model Assumptions and Weaknesses

The analysis contains multiple assumptions for its use. First, the model assumes that the SNOTEL sites being used will not see a major snowpack decline soon. The only SNOTEL site with a significant decline in its snow accumulation is Graham Guard (Boise River Basin), which is the lowest site in the analyses.

Several of the drainage areas have burned during the analysis period. In these cases, we will assume the changes in ablation will show up in the results of the analysis of a faster melting period. The faster melt of burned areas can be attributed to an increase in inception due to less tree cover (Anderson, McNamara, Marshall, & Flores, 2013).

The use of the daily data available also has limitations. Some of the daily data is estimated or provisional, meaning that there is a possibility for error in the readings. To minimize any errors within the data, checking for obvious erroneous values is necessary. Any years with extensive missing data between peak SWE and *day of allocation* will be removed.

The inputs necessary for current year predictions are daily SWE values. While there are many factors that contribute to streamflow, creating a model that uses only SNOTEL data to make predictions is simplistic. The models' limitations do not factor in rain, temperature, or prior soil moisture.

Rain creates complications for watersheds that have a larger rain to snow ratio. If a watershed relies mostly on snowpack for its water supply, the prediction methods used in this study will have more power. The Boise watershed, due to its lower elevation, has weaker regressions than the Snake and Payette River basins.

Temperature is a factor that influences snow, so while temperature is not directly factored into the equations used, the melting of snow accounts for temperature changes. This is important in the *day of allocation* predictions with melt ratios. Rain-on-snow events tend to produce higher peak discharges, but the error in simply using snow data is factored into the statistical analyses.

Demand is assumed constant in the model. While demand can change over time, and it is likely to increase, a major change in demand would require new parameters of allocating water. However, the current systems of calculating the *day of allocation* have remained constant for over 20 years.

6.7. The Improvement Problem

While the models presented are an improvement to current methods being used, they have their limitations. The methods used in the past were approximations based on streamflow values. While a streamflow is in recession, the watermasters have a good approximation of what the flows at a particular stream gauge have been near the DOA. With the ability to use SWE to determine a reasonable range of DOA, farmers can make informed decisions much earlier in the season. In a year with surplus water, a farmer may confidently plant crops that need more water to grow. In years with shortages, farmers can opt to plant crops that don't need much water to grow. In addition, if there is enough surplus water, some farmers may decide to plant both early and mid-summer, giving them as much as twice the amount. Knowing the DOA earlier can help farmers make these decisions, and farmers can let their buyers know what to expect.

However, the models presented are based on statistics, and a lot of variation still exists among the predictions. For example, many of the predictions generated have 50%

confidence intervals of about 20 days, or almost month. The primary concern with this is that there may not be enough precision and accuracy. However, with a range of 20 days, potential outliers of DOA can be detected early in the season. Early DOA is the primary concern since an early DOA will result in water shortages throughout the summer, especially in the later summer during the lowest natural flows. This can potentially lead to crop failures for the farmers. With predictions that detect the current range, these problems can be mitigated.

In addition, the degrees of freedom decrease as more variables are introduced. This may be the reason that the confidence intervals do not decrease by much, if at all, when going from Model 1 to Model 4. The wide confidence intervals, especially in the Payette models, may be due to the degrees of freedom rather than the actual predictive power of the model. In this case, the addition of more years of data to the models may be necessary. The parameters with the highest amount of predictive capability can also be considered, leaving some of the other parameters out in order to increase the degrees of freedom and therefore potentially decrease the width of confidence intervals.

The metrics selected as predictor variables were limited to information about SWE. The focused parameters were maximum accumulation, start of melt (10% of maximum SWE melted out), and monthly melt of April, May, and June. Most of these factors were found to influence DOA, apart from the start of melt (Correlations of SWE Parameters to Day of Allocation - Appendix A).

Further investigation of soil moisture and spring precipitation as rain may bring more precise and accurate predictions. The main component of summer water availability is the SWE accumulation, but future studies may find that parameters other than SWE create more robust predictions.

CHAPTER SEVEN: CONCLUSIONS

Despite its seemingly complicated nature, the *day of allocation* can be related to flows and SWE parameters. Important flows can be attributed to timing in relation to water accounting and allocation. The flows indicative of the *day of allocation* will differ depending on the size and water demand of a watershed.

The *day of allocation* is controlled by the water demand (which can be treated as a constant from year to year) and maximum SWE. While melt may seem important, the timing of melt does not improve the predictive capability of the model, based on the RMSE verification. A basin with more snowpack will melt out later than a basin with lower amounts of SWE, so the melt rates are dependent on the maximum SWE at the SNOTEL sites. SWE indicates a volume of water available, which is strongly related to the amount of water available from snowpack. Therefore, estimating the *day of allocation* based on SWE values prior to melt provides just as much confidence as the SWE values during melt. This is beneficial for farmers, who typically make decisions on which crops to plant when the snowpack is close to maximum values for the season.

The trend present in two of the three basins is the shift of the average *day of allocation* by one day earlier every three years. Because of the variability in the *day of allocation* dates, the R^2 values are small, and the p-values are greater than 0.4 for the basins. With more years of data, trends may be investigated further. Also, *day of allocation* trends in the Boise River Basin may become more apparent with a longer period of record.

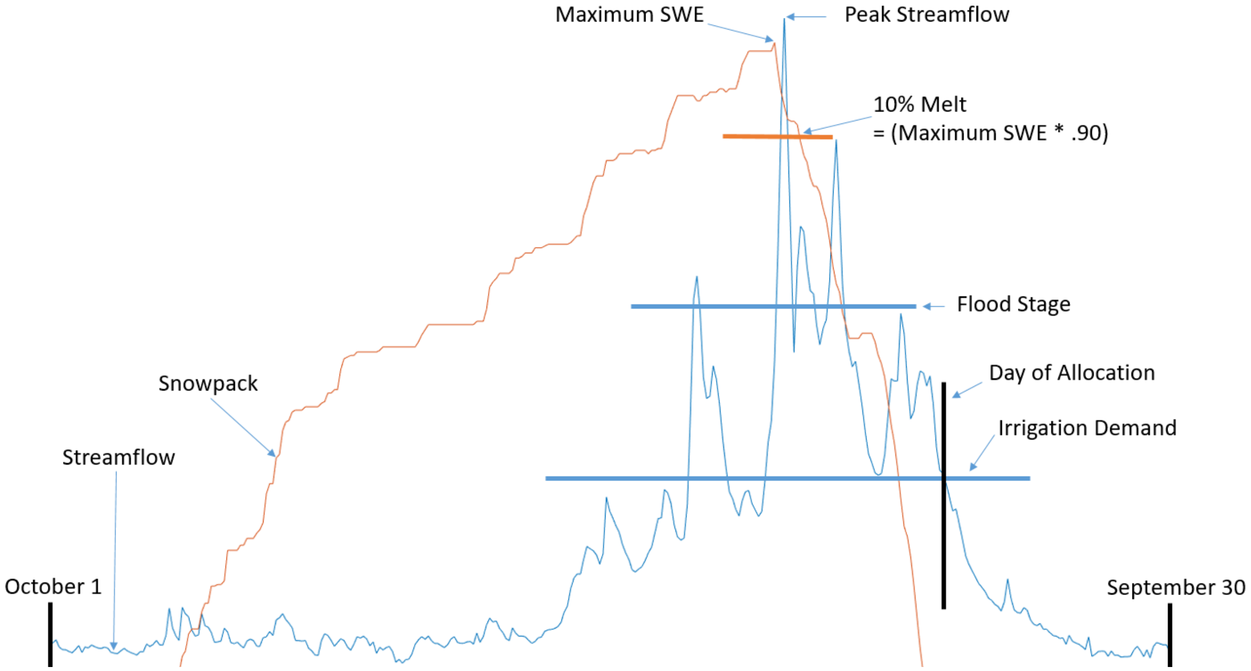


Figure 1 Variables considered in this study. The orange lines represent the snowpack, and the blue lines represent the streamflow.

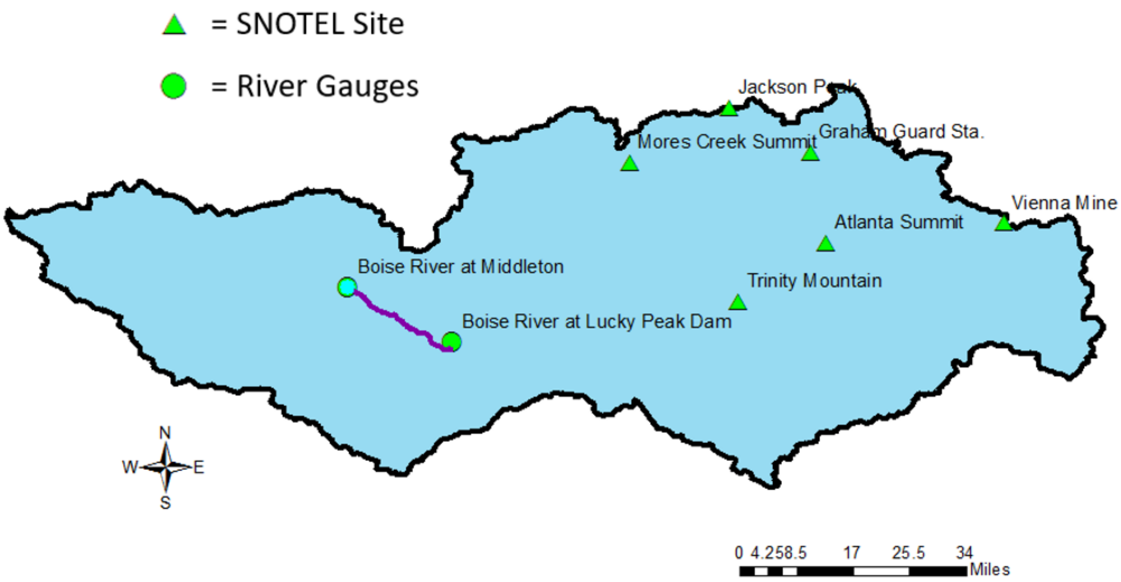


Figure 2 Map of the Boise River Basin with specified river reach, gauges, and SNOTEL sites used in this study

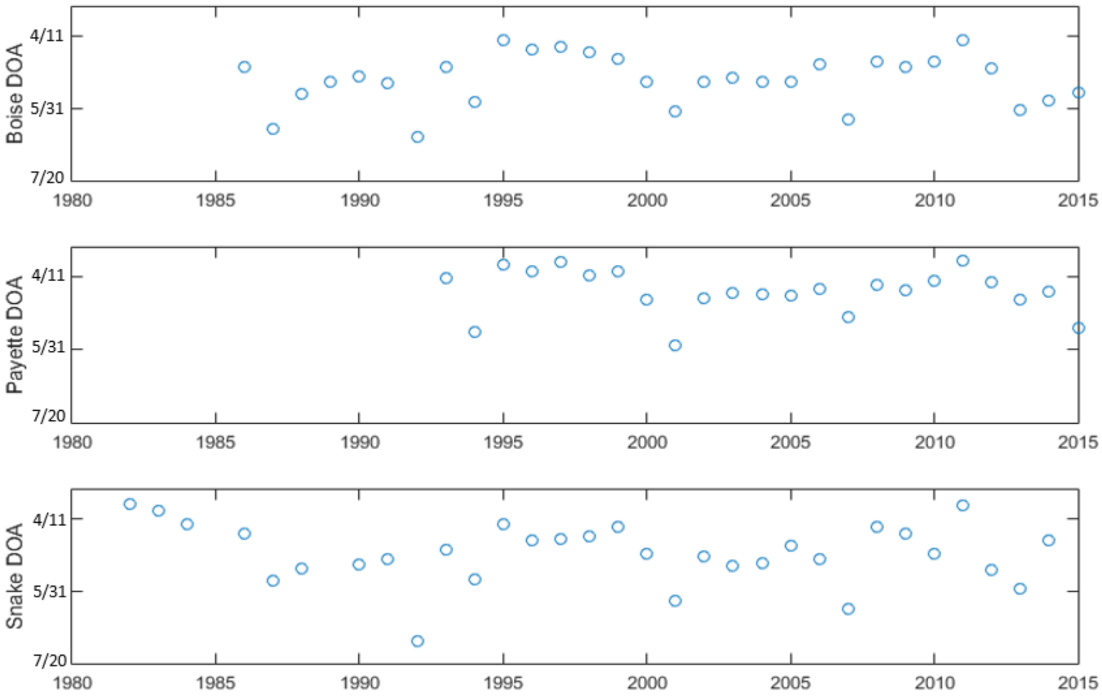


Figure 3 Historical day of allocation for the basins. The implementation of the use of this system was started in the 1980s, but the Payette River did not begin using the day of allocation system until the 1990s. While the range of historical day of allocation varies for each basin, relative timing to average values are similar across the three basins, which are located relatively close to each other.

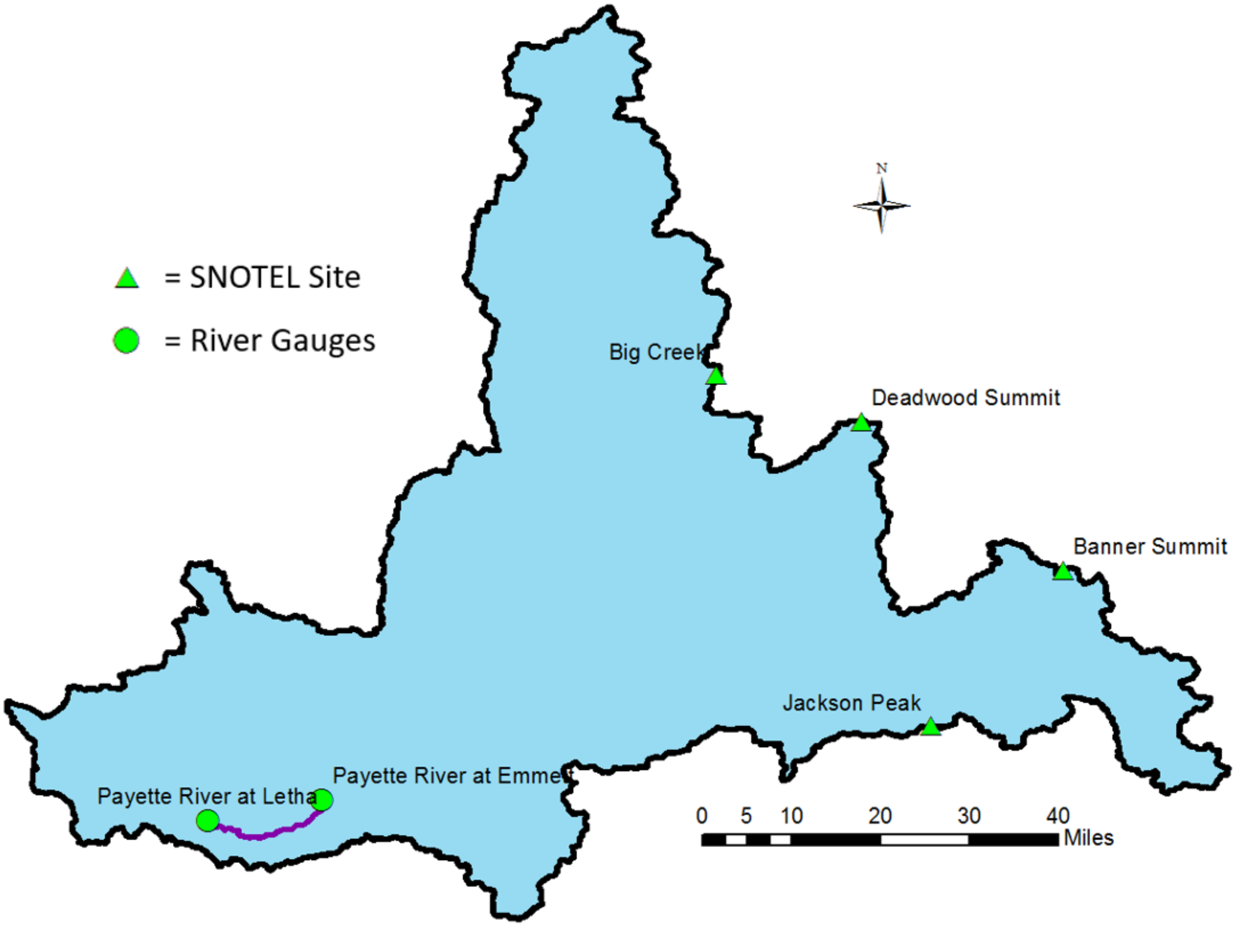


Figure 4 Map of the Payette River Basin with specified river reach, gauges, and SNOTEL sites used in this study.

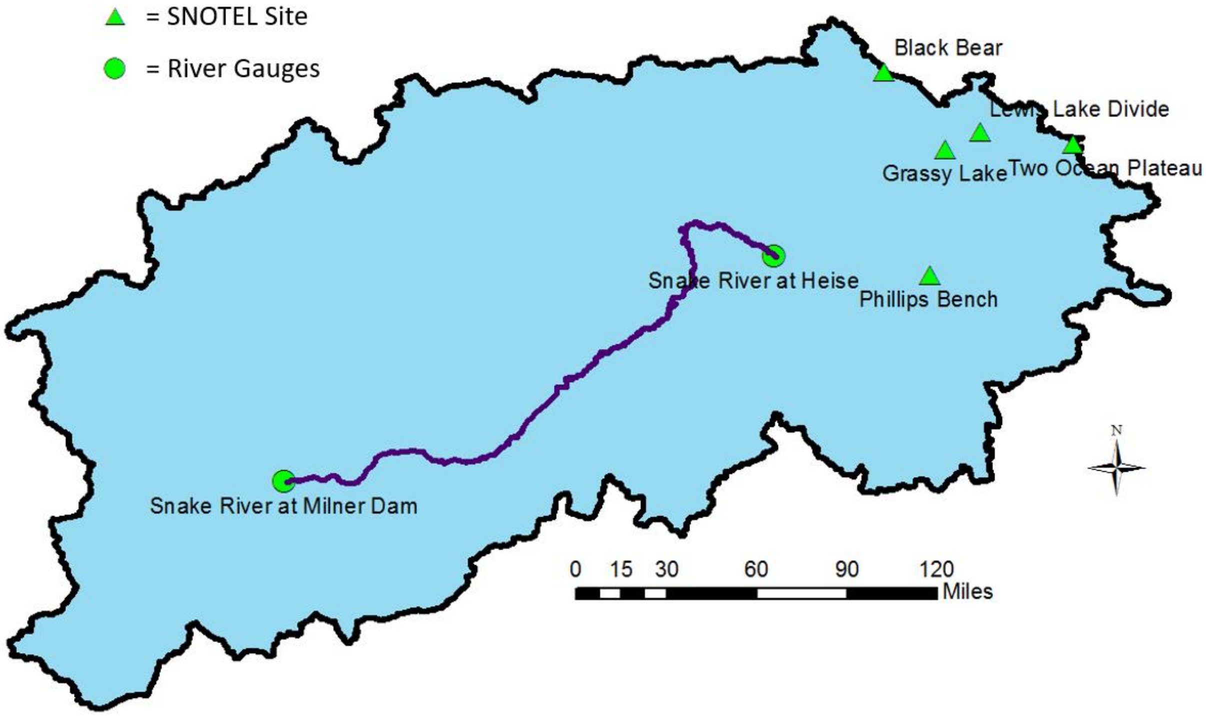


Figure 5 Map of the Snake River Basin with specified river reach, gauges, and SNOTEL sites used in this study

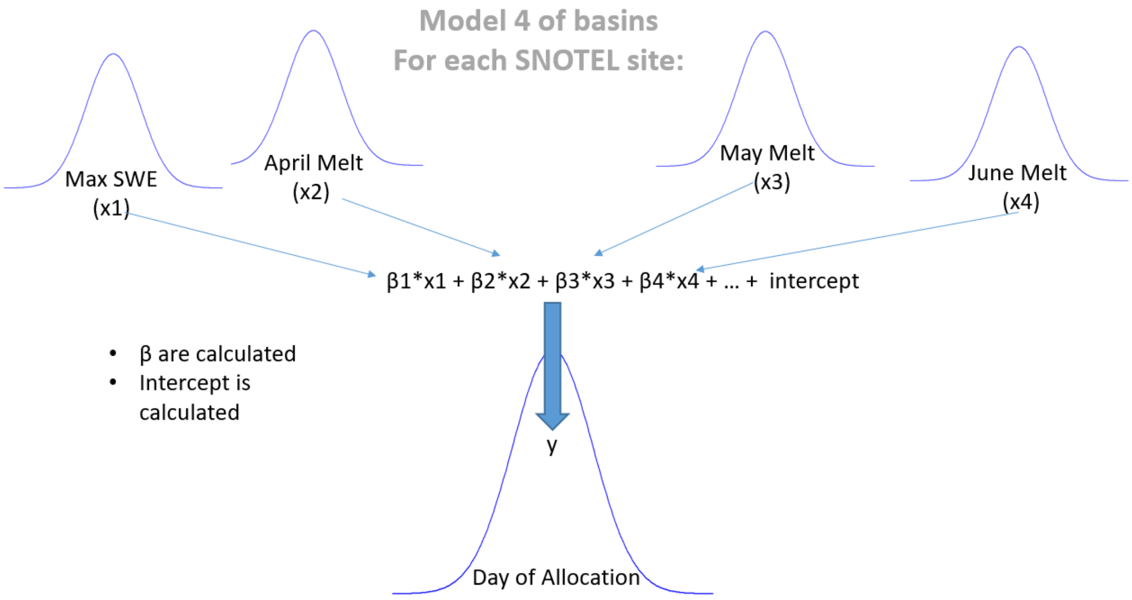
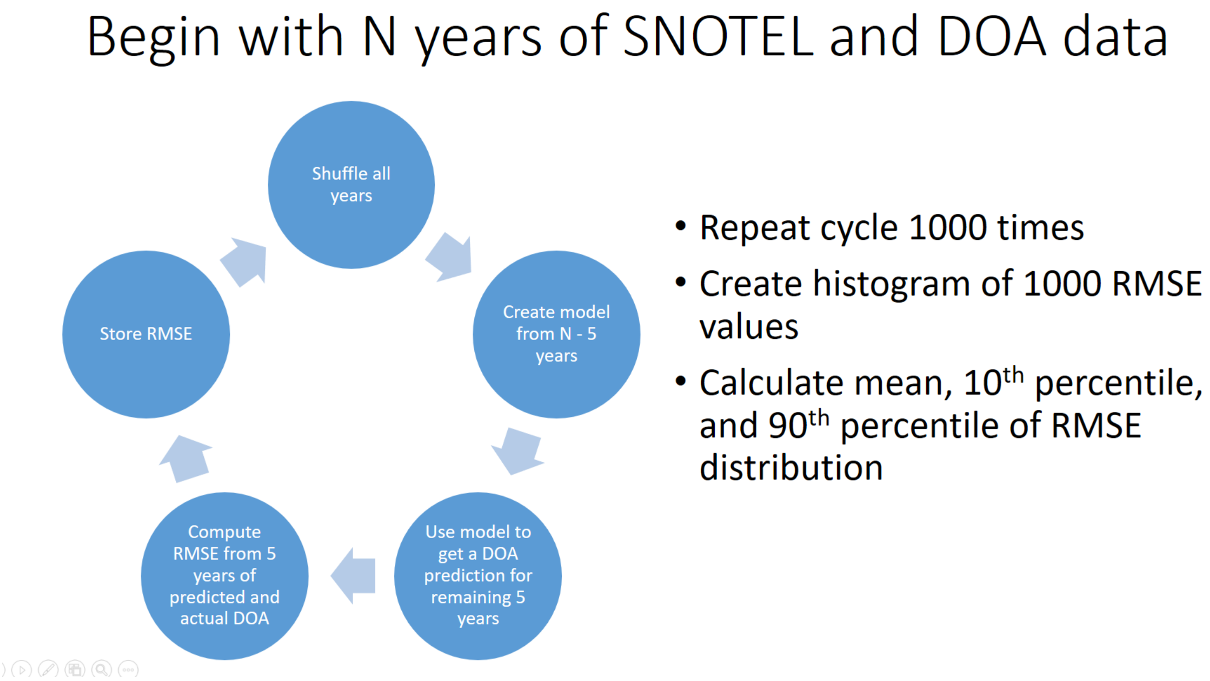


Figure 6 Multiple linear regression takes several variables into account, weights them by calculating beta values for future y predictions.



Begin with N years of SNOTEL and DOA data

Shuffle all years

Create model from N - 5 years

Use model to get a DOA prediction for remaining 5 years

Compute RMSE from 5 years of predicted and actual DOA

Store RMSE

- Repeat cycle 1000 times
- Create histogram of 1000 RMSE values
- Calculate mean, 10th percentile, and 90th percentile of RMSE distribution

Figure 7 The process of validating the models is done by using a bootstrap method of withholding 5 years from each dataset for verification. Using this method, there is no overlap in error calculation and model building.

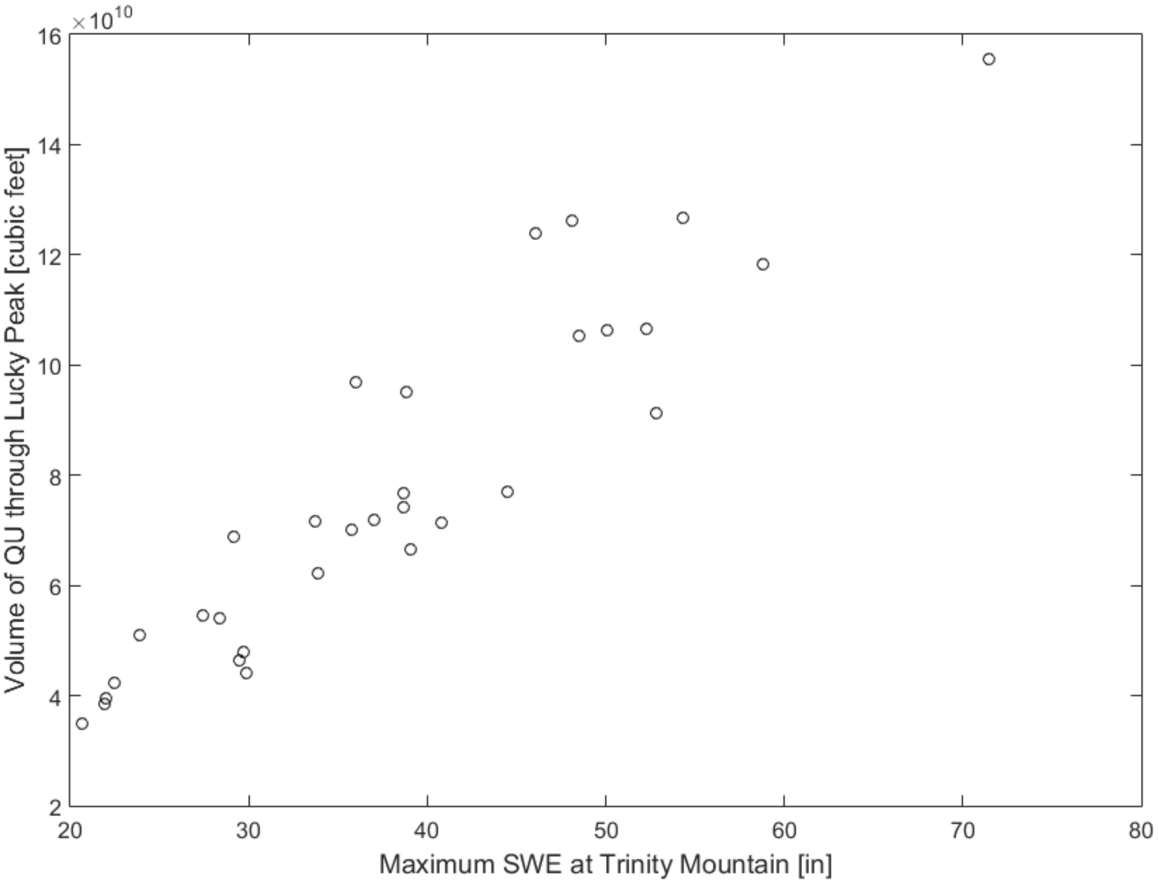


Figure 8 Maximum SWE values correspond to the volume of natural flow through the Boise River. This reveals that the values of maximum SWE can help estimate the volume of runoff and therefore the summer water availability for water users and regulators.

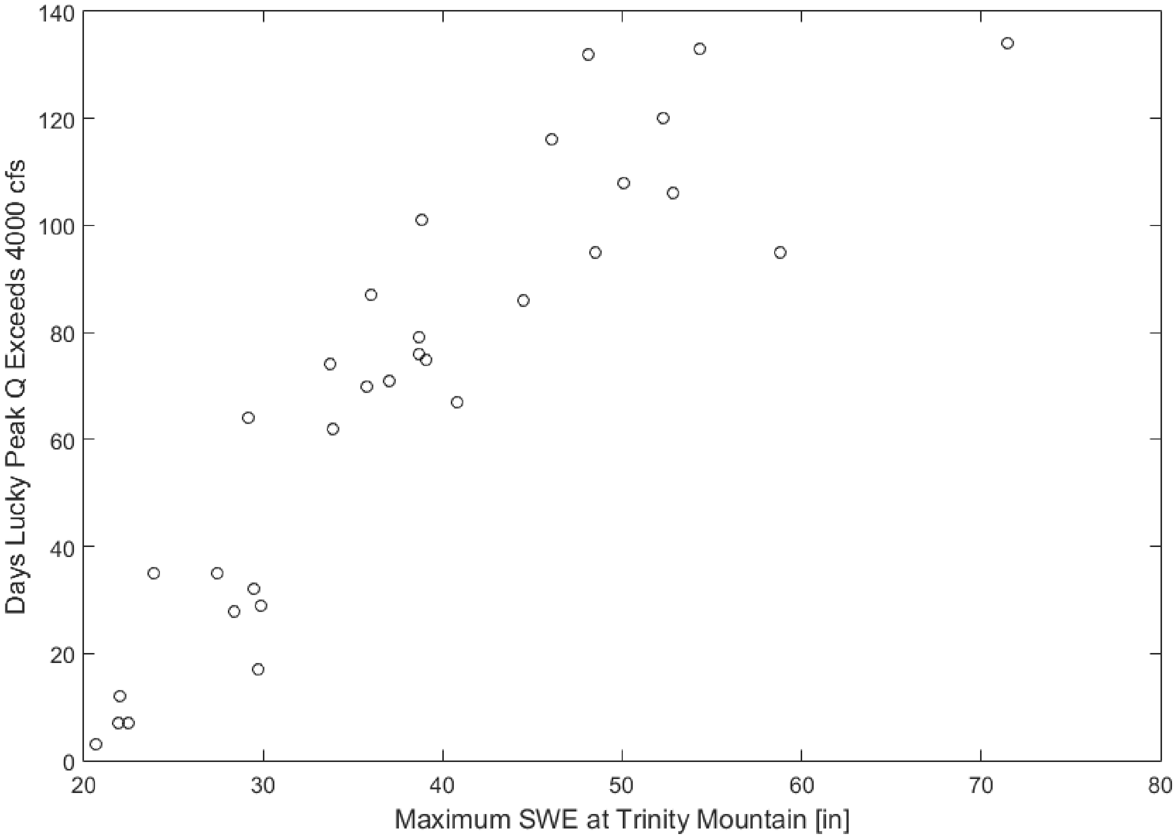


Figure 9 Maximum SWE values relate to a duration above specific flow thresholds. The maximum SWE and flow thresholds are shown for the Boise River.

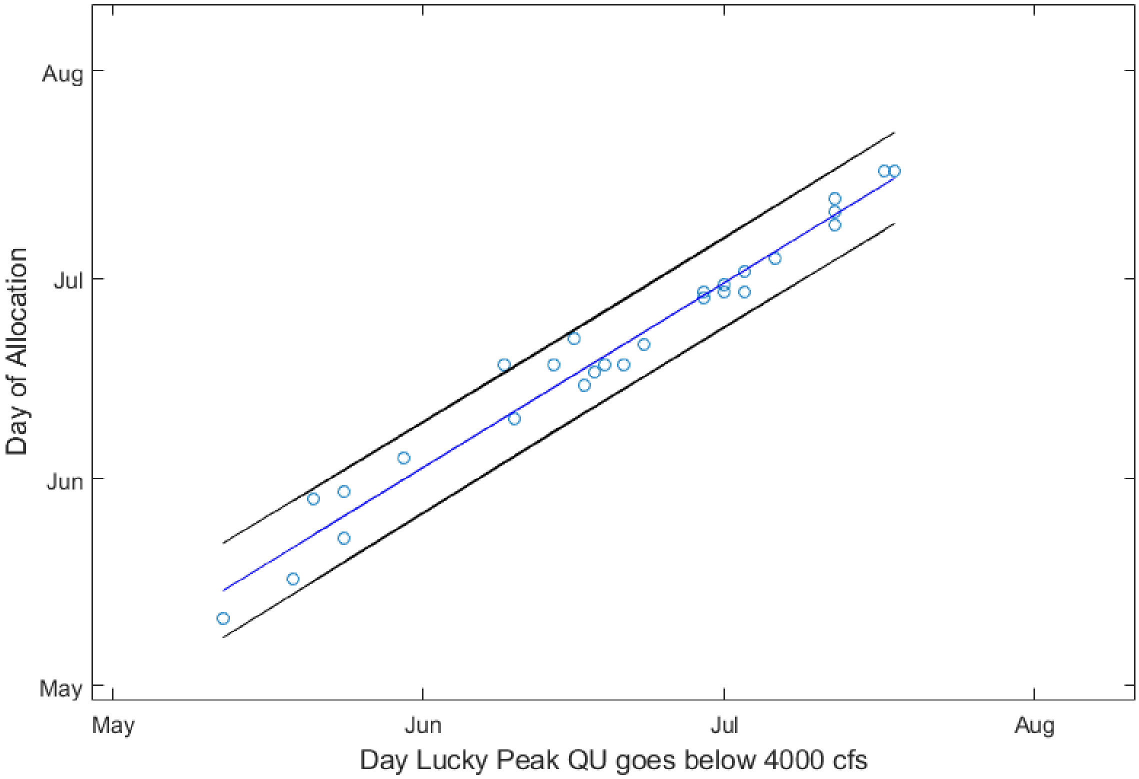


Figure 10 Specific flows during recession on the Boise River correspond to the day of allocation. The R^2 is 0.96. The trendline is the blue line, and the black lines are confidence intervals of 95%.

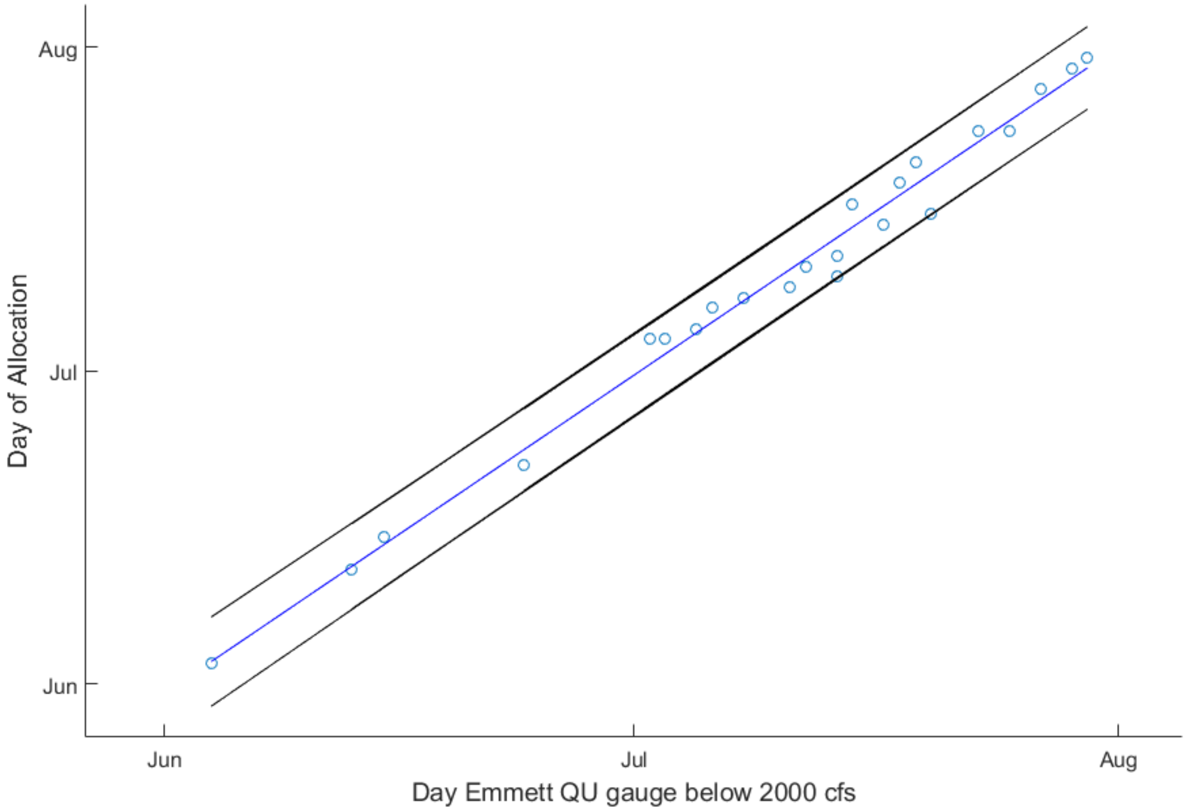


Figure 11 Specific flows during recession on the Payette River correspond to the day of allocation. The R^2 is 0.99. The trendline is the blue line, and the black lines are confidence intervals of 95%.

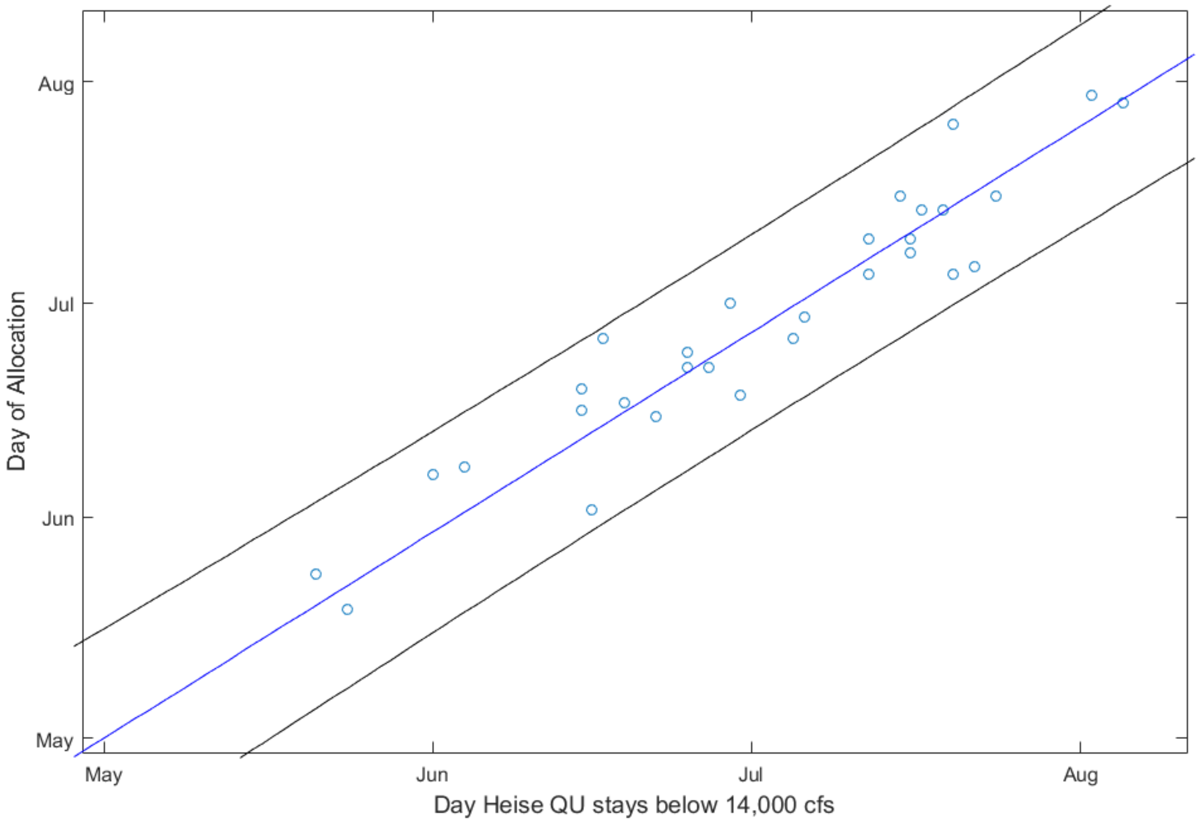


Figure 12 Specific flows during recession on the Upper Snake River correspond to the day of allocation. The R^2 is 0.90. The trendline is the blue line, and the black lines are confidence intervals of 95%.

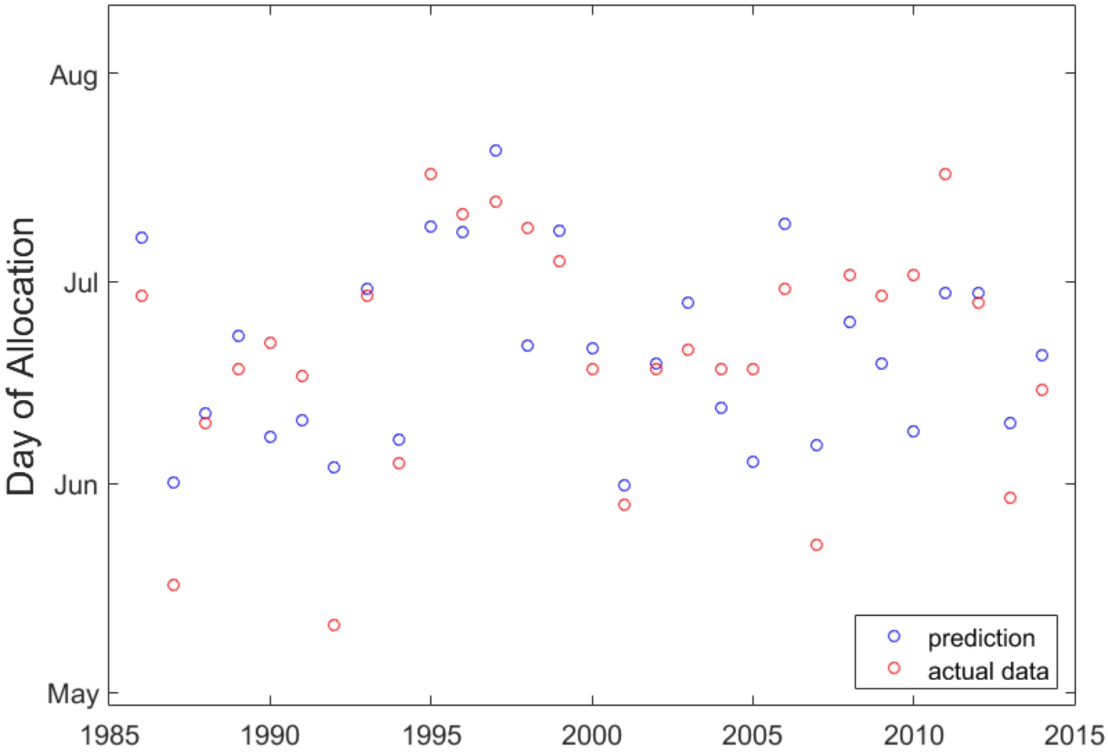


Figure 13 Model 1 for the Boise River Basin is used to generate predictions for past years. The blue circles represent predictions, and the red circles represent the actual DOA. The average deviation from actual DOA for Model 1 is 8.67 days.

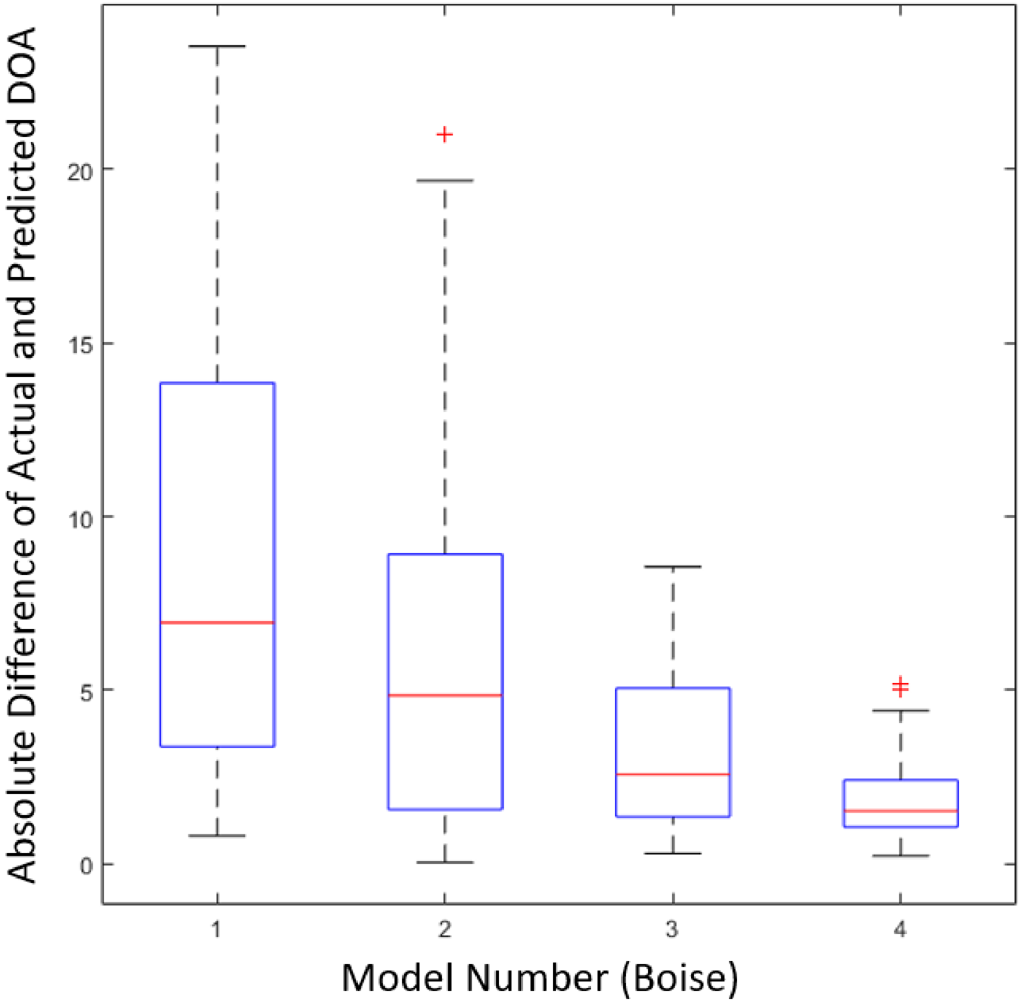


Figure 14 The absolute value of the models' predictions and the actual DOA for the respective years are determined for the Boise River Basin models. With an increase in information, the differences between the actual and predicted DOA decrease. However, further verification is needed since the data used was used to build the models.

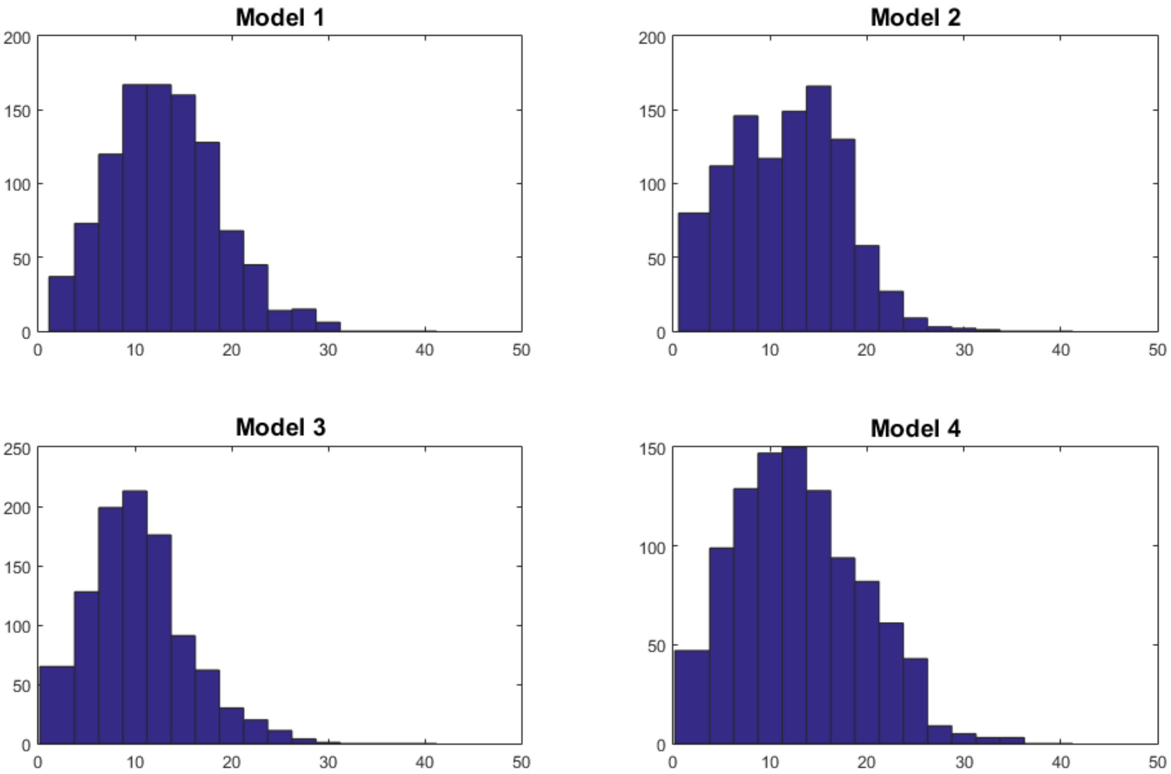


Figure 15 RMSE bootstrap verification for the 4 models on the Boise River. Models 1 and 3 perform the best, but the data for Model 3 is not ready until after the month of May, when day of allocations begin to occur in the period of record.

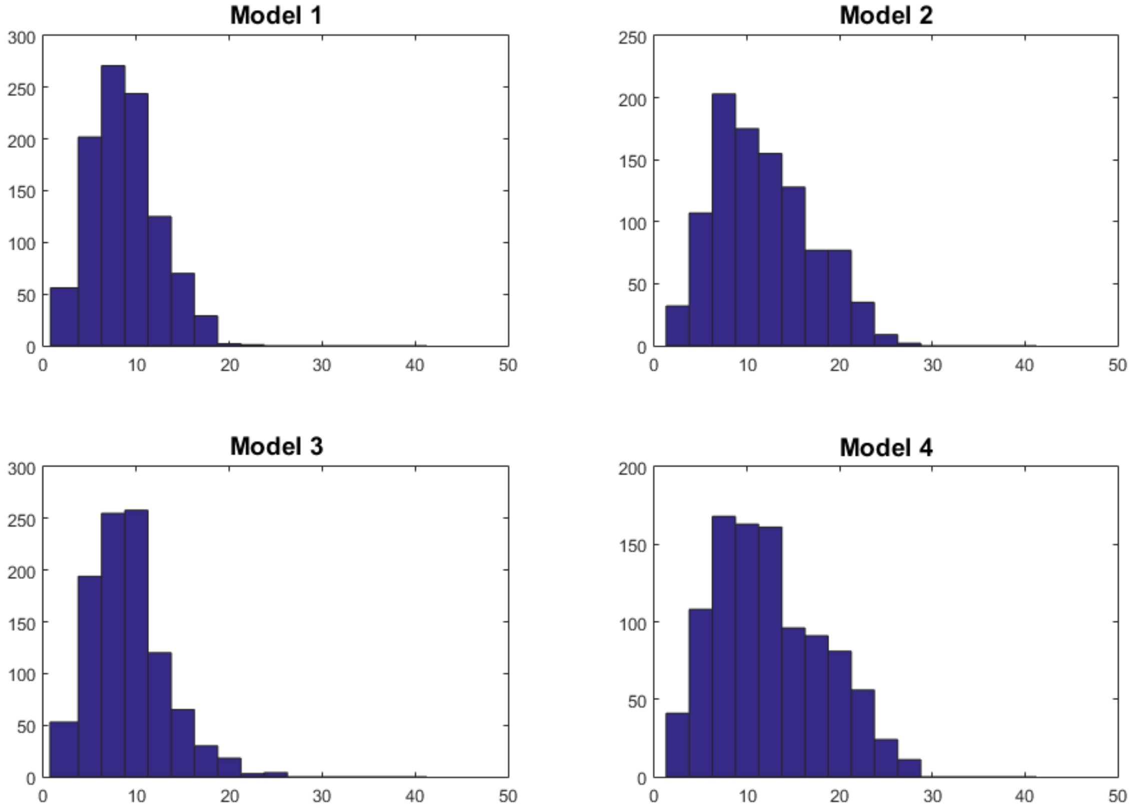
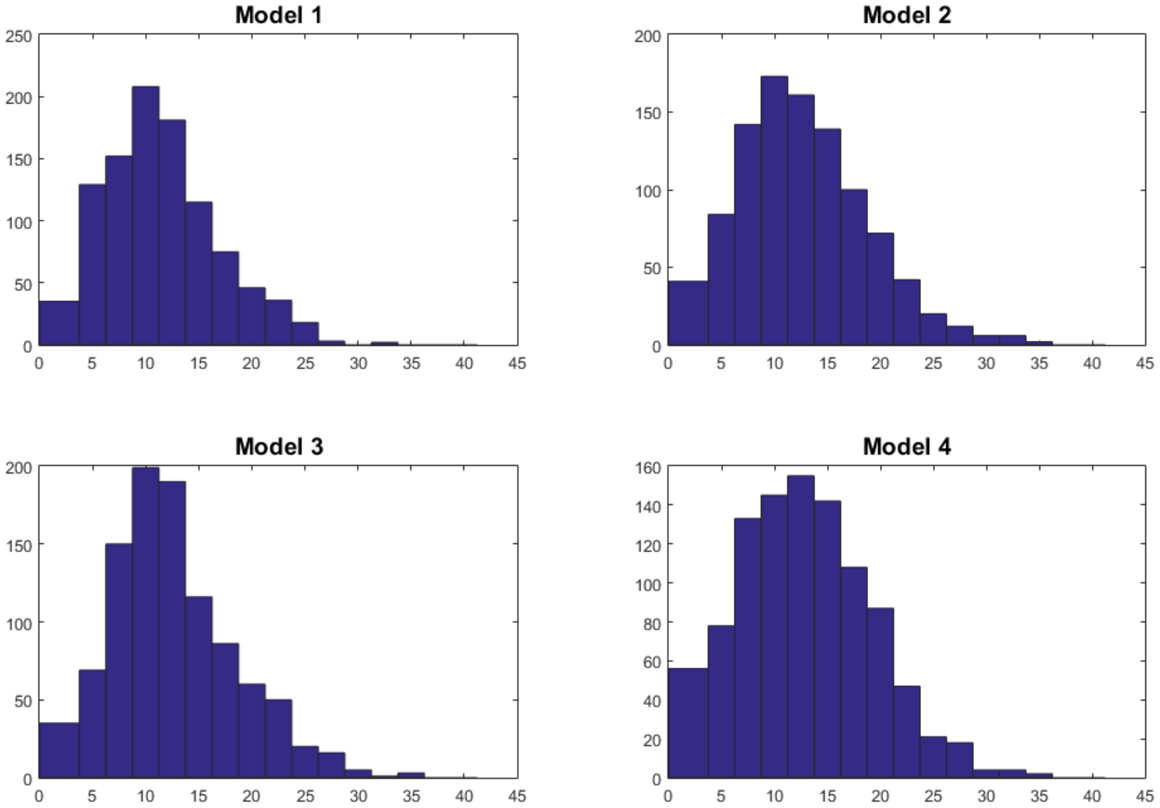


Figure 16 RMSE bootstrap verification for the 4 models on the Payette River. Model 1 shows the least amount of spread of distribution of RMSE. The distribution of error in Model 1 is the smallest, even though the other 3 models use more information based on how the snowpack melts.



Model 1

Model 2

Model 3

Model 4

Figure 17 RMSE bootstrap verification for the 4 models on the Snake River. The distribution of Model 1 is the tightest, with more smaller error values. The distribution gets more error with the additional data of Models 2, 3, and 4.

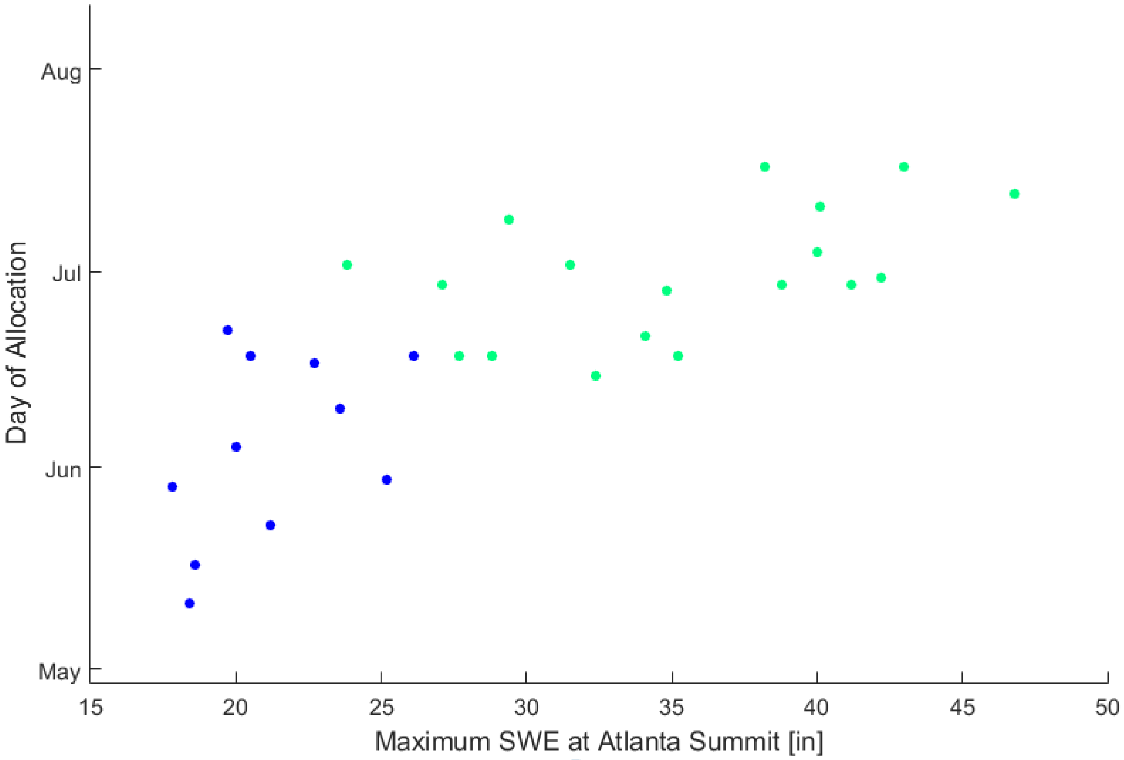


Figure 18 Maximum SWE at Atlanta Summit and day of allocation in a given year with water shortages represented in blue and surplus in green. Not only can maximum SWE values help determine when the day of allocation will be, but they can also help determine if there will be a water shortage.

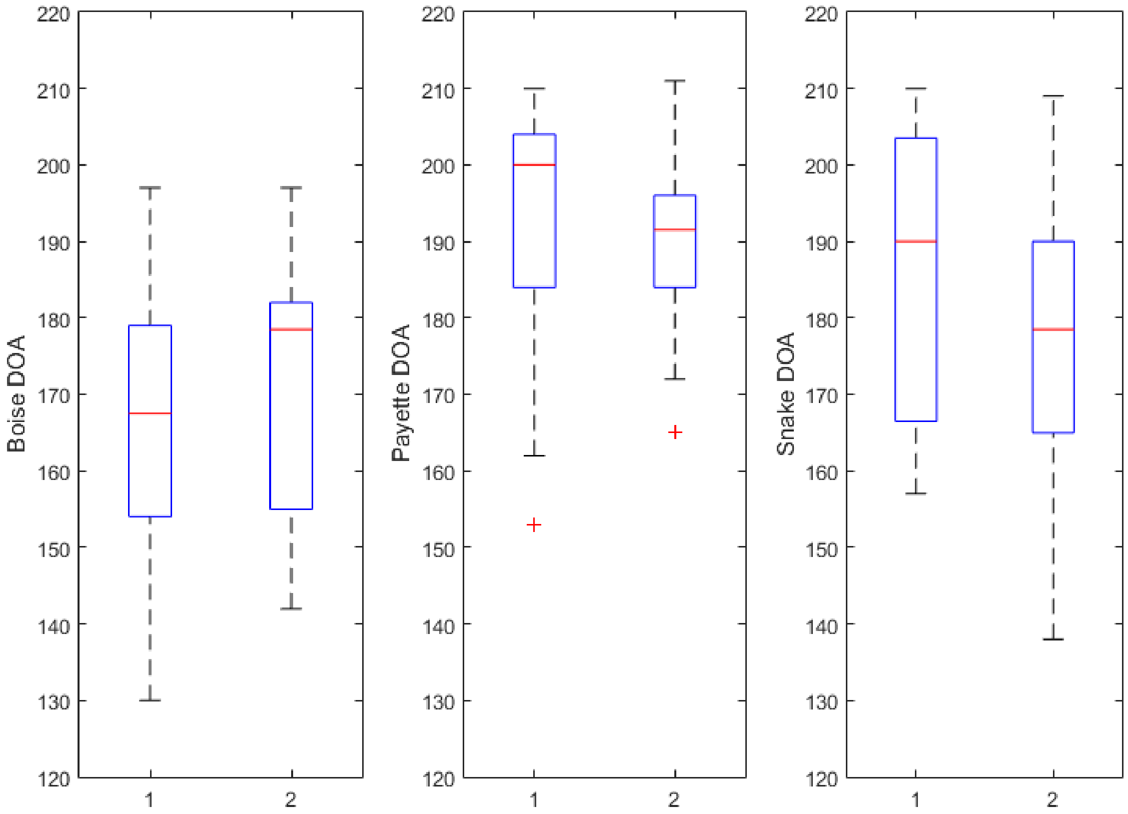


Figure 19 Box and whisker plots for the first 10 and last 10 years of day of allocation data for the three basins. The Boise River Basin shows no trend of earlier or later day of allocation. However, both the Payette and Snake River basins show trends moving toward an earlier day of allocation. ‘1’ on the x-axis refers to the first 10 years of data, and ‘2’ on the x-axis refers to the last 10 years of data.

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Katzfey, J. J. (1995b). Simulation of Extreme New Zealand Precipitation Events. Part II: Mechanisms of Precipitation Development. *Monthly Weather Review*. http://doi.org/10.1175/1520-0493(1995)123<0755:SOENZP>2.0.CO;2

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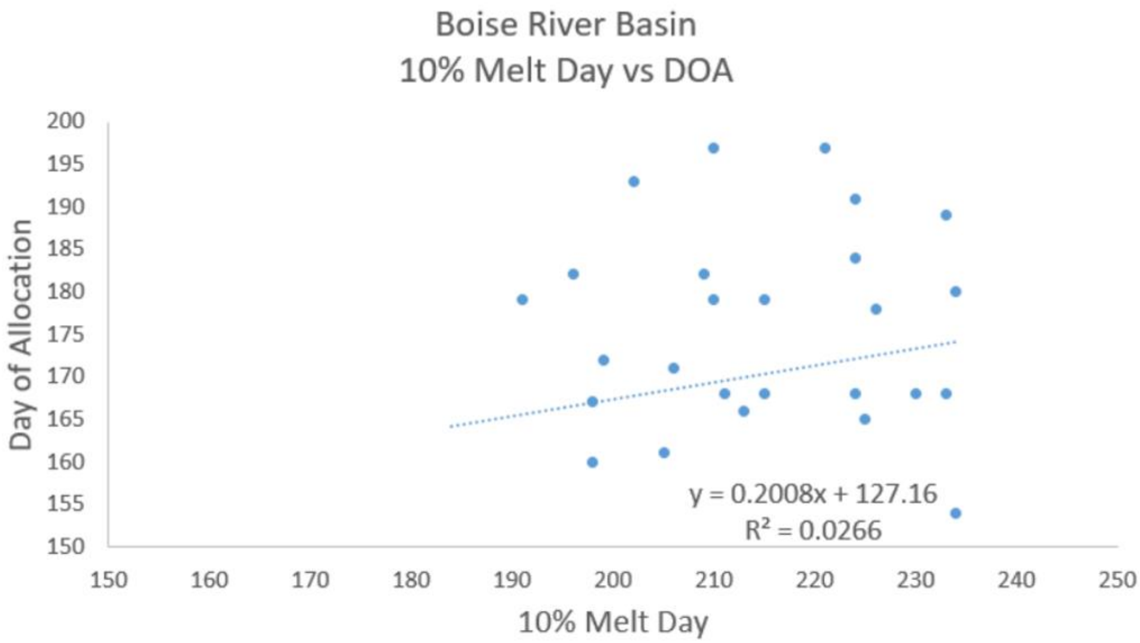
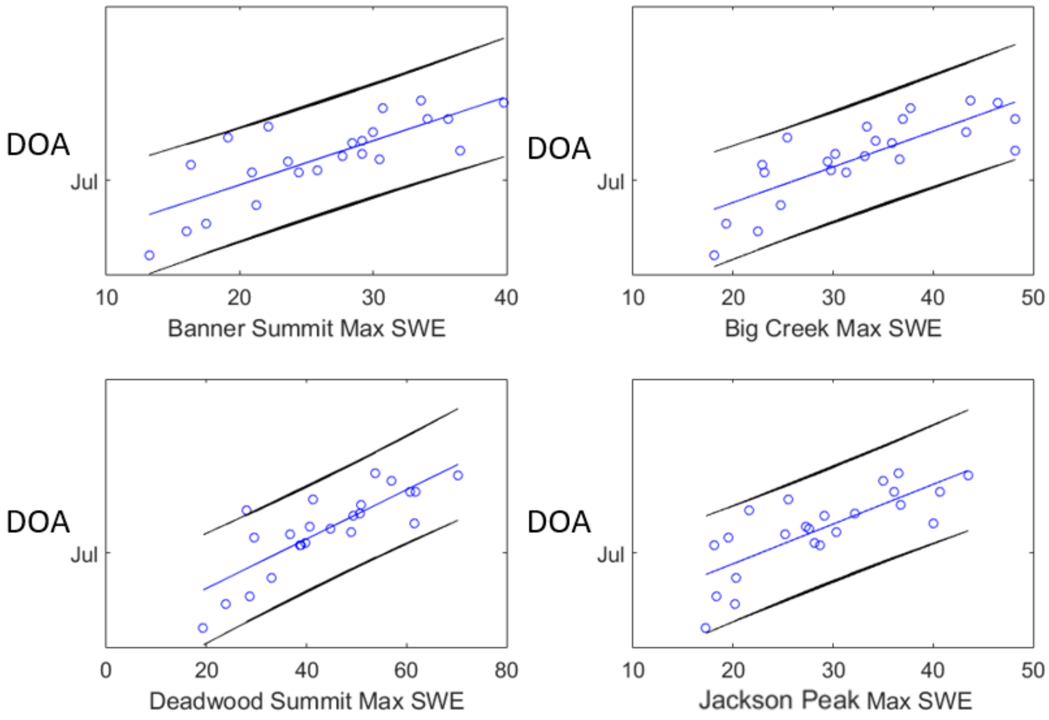
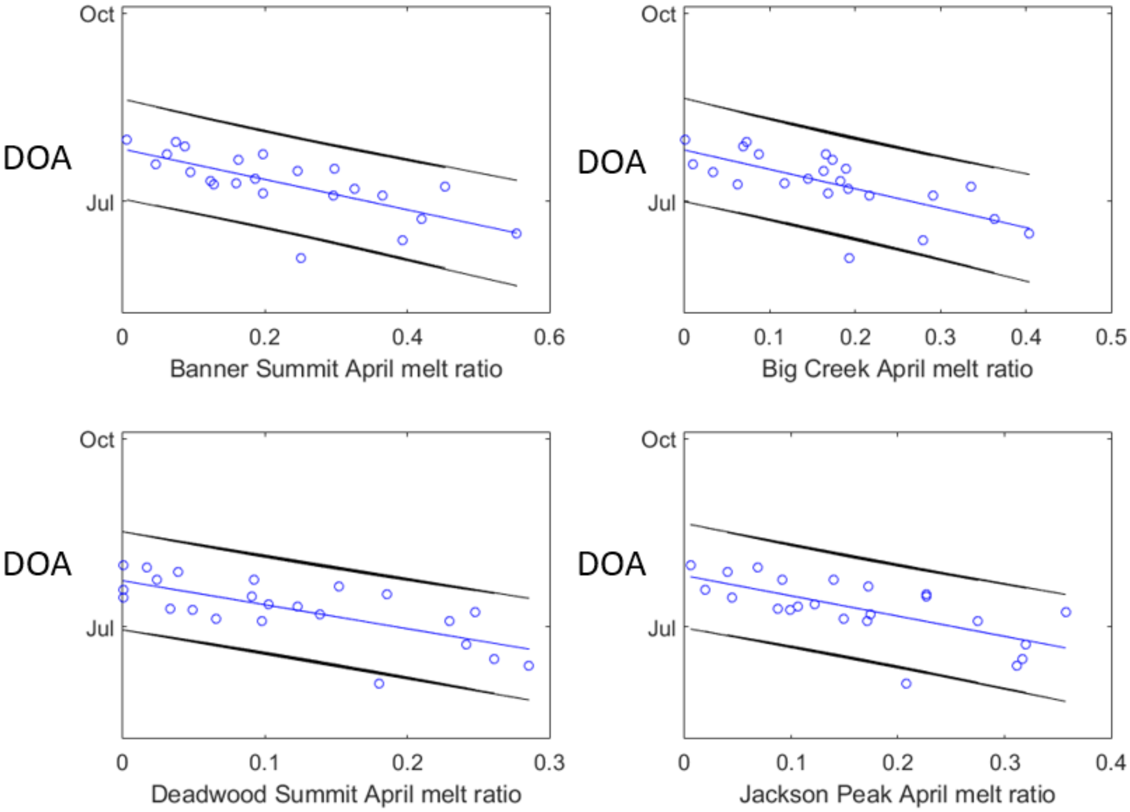
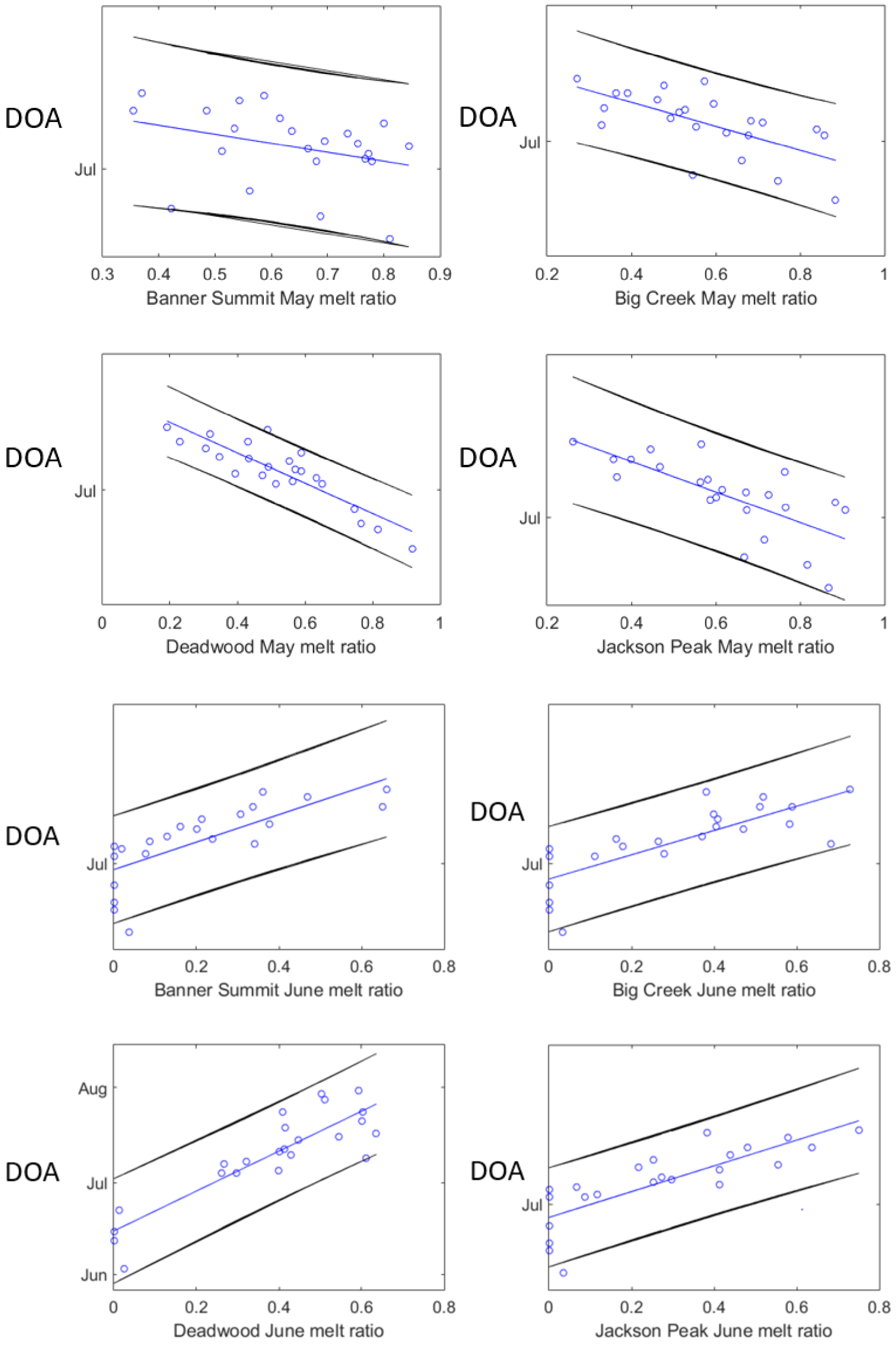
APPENDIX A

Correlations of SWE Parameters to Day of Allocation





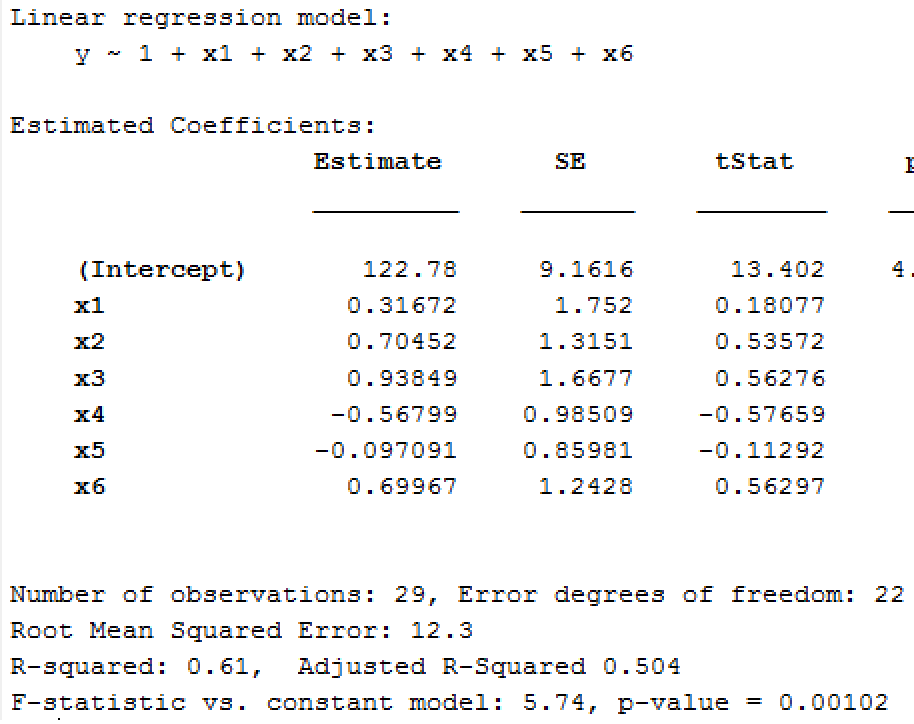

Oct
Jul
DOA
0
0.2
0.4
0.6
Banner Summit April melt ratio
Oct
Jul
DOA
0
0.1
0.2
0.3
0.4
0.5
Big Creek April melt ratio
Oct
Jul
DOA
0
0.1
0.2
0.3
Deadwood Summit April melt ratio
Oct
Jul
DOA
0
0.1
0.2
0.3
0.4
Jackson Peak April melt ratio


DOA
Jul
0.3
0.4
0.5
0.6
0.7
0.8
0.9
Banner Summit May melt ratio
DOA
Jul
0.2
0.4
0.6
0.8
1
Big Creek May melt ratio
DOA
Jul
0
0.2
0.4
0.6
0.8
1
Deadwood May melt ratio
DOA
Jul
0.2
0.4
0.6
0.8
1
Jackson Peak May melt ratio
DOA
Jul
0
0.2
0.4
0.6
0.8
Banner Summit June melt ratio
DOA
Jul
0
0.2
0.4
0.6
0.8
Big Creek June melt ratio
DOA
Aug
Jul
Jun
0
0.2
0.4
0.6
0.8
Deadwood June melt ratio
DOA
Jul
0
0.2
0.4
0.6
0.8
Jackson Peak June melt ratio

Statistics for Final Models

Table A.14 Constants for Model 1 of the Boise River

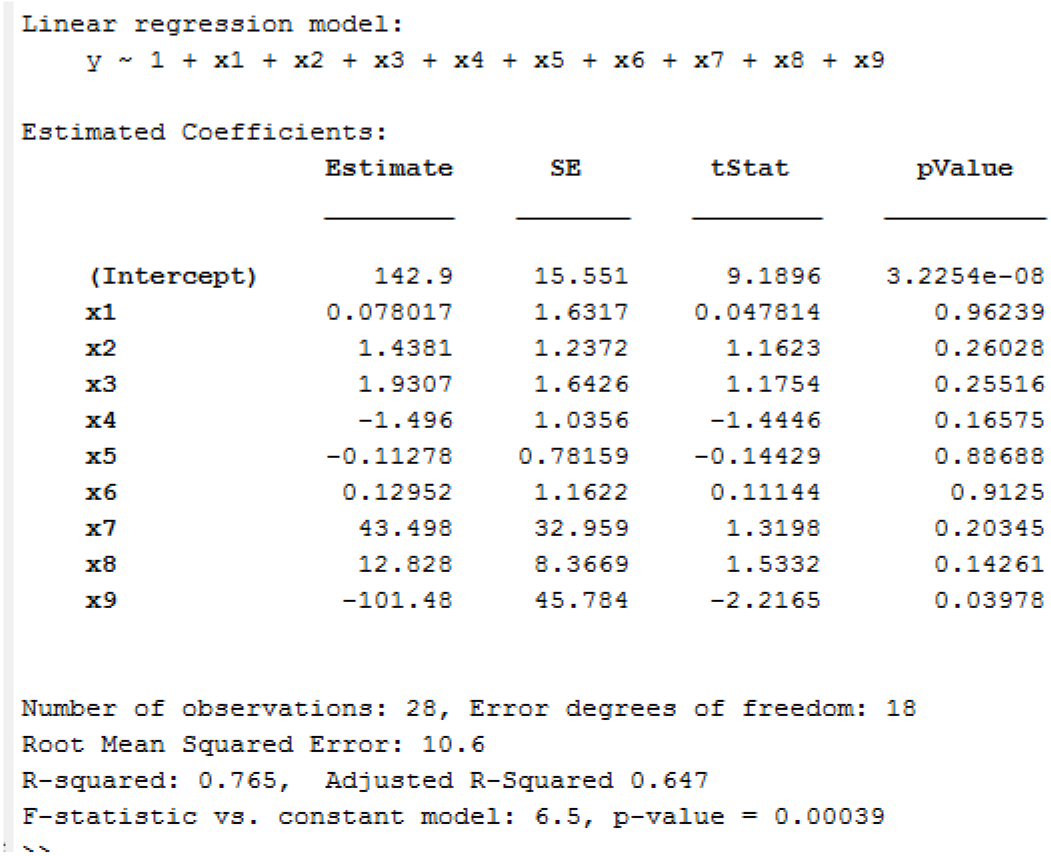
Boise 1	Atlanta	Graham	Jackson	Mores	Trinity	Vienna
Max SWE	.32	.70	.94	-.57	-.1	.70



```
Linear regression model:
    y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6

Estimated Coefficients:
                     Estimate       SE        tStat       pValue
                     ________    _______    ________    _________

    (Intercept)        122.78     9.1616      13.402    4.631e-12
    x1                0.31672      1.752     0.18077       0.8582
    x2                0.70452     1.3151     0.53572      0.59752
    x3                0.93849     1.6677     0.56276      0.57929
    x4               -0.56799    0.98509    -0.57659      0.57007
    x5              -0.097091    0.85981    -0.11292      0.91112
    x6                0.69967     1.2428     0.56297      0.57915


Number of observations: 29, Error degrees of freedom: 22
Root Mean Squared Error: 12.3
R-squared: 0.61,  Adjusted R-Squared 0.504
F-statistic vs. constant model: 5.74, p-value = 0.00102
```

Table A.15 Constants for Model 2 of the Boise River

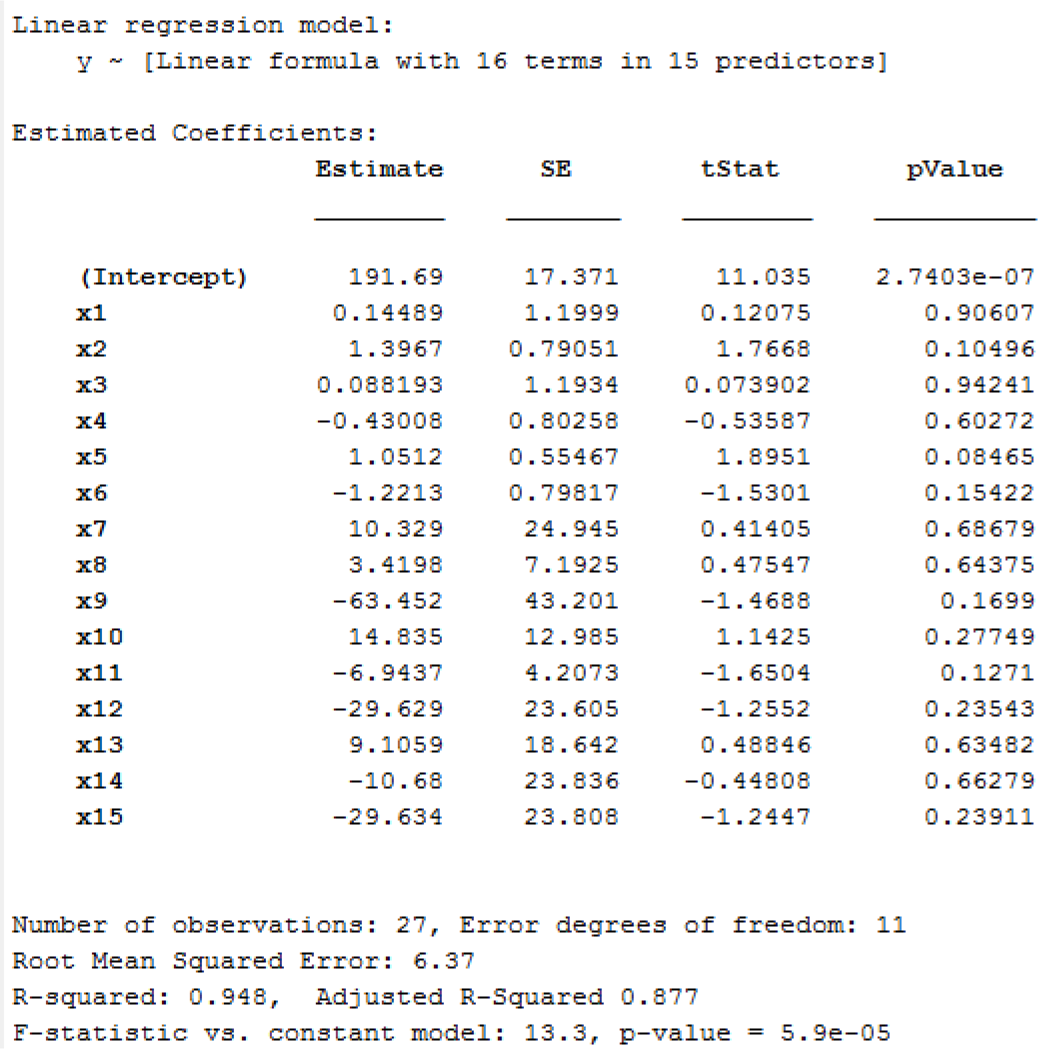
Boise 2	Atlanta	Graham	Jackson	Mores	Trinity	Vienna
Max SWE	.08	1.4	1.9	-1.4	-.11	.13
April Melt	43.5	12.8	-101.5	N/A	N/A	N/A



```
Linear regression model:
    y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9

Estimated Coefficients:
                   Estimate       SE        tStat        pValue
                   ________    _______    ________    __________

    (Intercept)       142.9     15.551      9.1896    3.2254e-08
    x1             0.078017     1.6317    0.047814       0.96239
    x2               1.4381     1.2372      1.1623       0.26028
    x3               1.9307     1.6426      1.1754       0.25516
    x4               -1.496     1.0356     -1.4446       0.16575
    x5             -0.11278    0.78159    -0.14429       0.88688
    x6              0.12952     1.1622     0.11144        0.9125
    x7               43.498     32.959      1.3198       0.20345
    x8               12.828     8.3669      1.5332       0.14261
    x9              -101.48     45.784     -2.2165       0.03978


Number of observations: 28, Error degrees of freedom: 18
Root Mean Squared Error: 10.6
R-squared: 0.765,  Adjusted R-Squared 0.647
F-statistic vs. constant model: 6.5, p-value = 0.00039
```

Table A.16 Constants for Model 3 of the Boise River

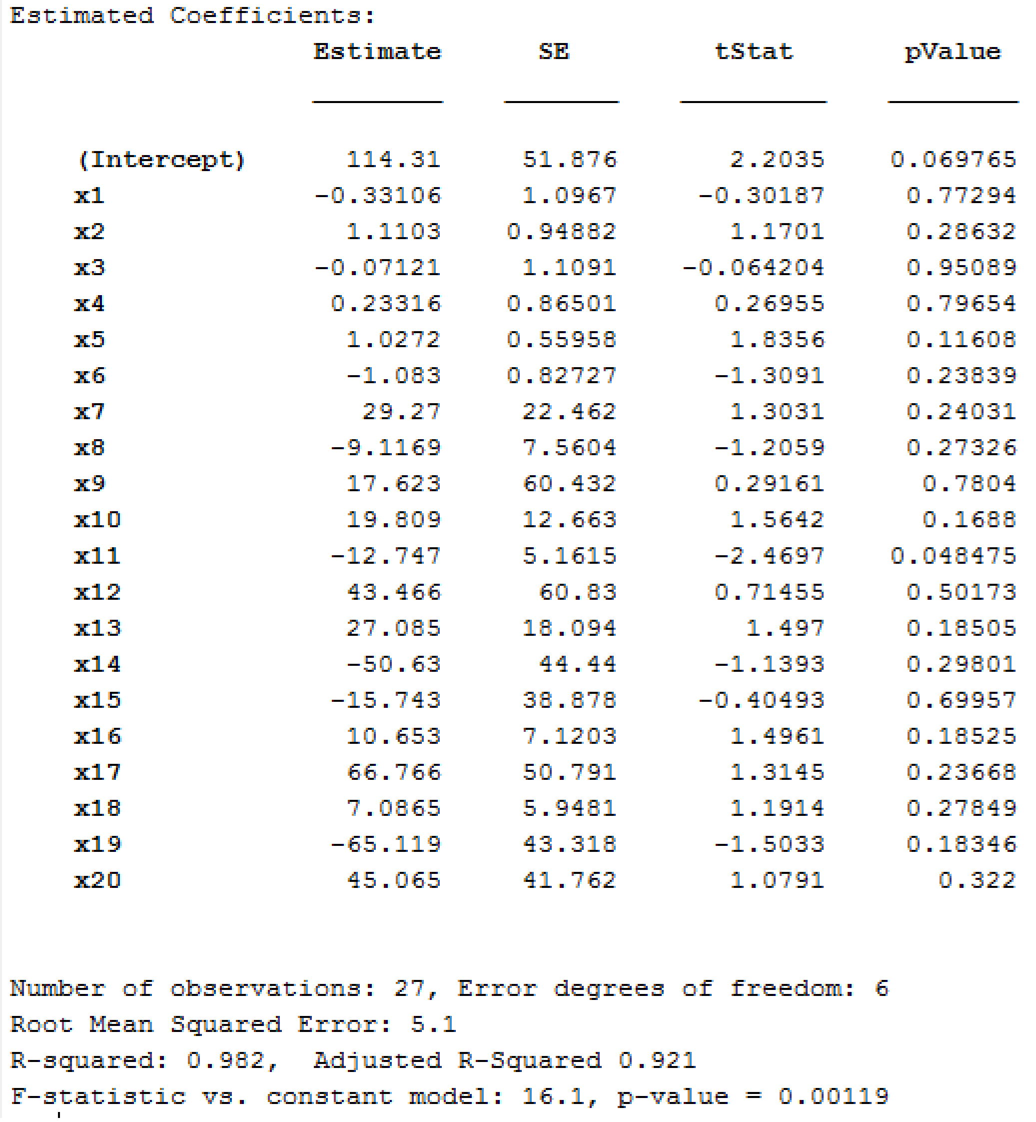
Boise 3	Atlanta	Graham	Jackson	Mores	Trinity	Vienna
Max SWE	.14	1.4	.09	-.43	1.1	-1.2
April Melt	10.3	3.4	-63.5	N/A	N/A	N/A
May Melt	14.8	-6.9	-29.6	9.1	-10.7	-29.6



```
Linear regression model:
    y ~ [Linear formula with 16 terms in 15 predictors]

Estimated Coefficients:
                   Estimate      SE         tStat        pValue  
                   ________    _______    ________    __________

    (Intercept)      191.69     17.371      11.035    2.7403e-07
    x1              0.14489     1.1999     0.12075       0.90607
    x2               1.3967    0.79051      1.7668       0.10496
    x3             0.088193     1.1934    0.073902       0.94241
    x4             -0.43008    0.80258    -0.53587       0.60272
    x5               1.0512    0.55467      1.8951       0.08465
    x6              -1.2213    0.79817     -1.5301       0.15422
    x7               10.329     24.945     0.41405       0.68679
    x8               3.4198     7.1925     0.47547       0.64375
    x9              -63.452     43.201     -1.4688        0.1699
    x10              14.835     12.985      1.1425       0.27749
    x11             -6.9437     4.2073     -1.6504        0.1271
    x12             -29.629     23.605     -1.2552       0.23543
    x13              9.1059     18.642     0.48846       0.63482
    x14              -10.68     23.836    -0.44808       0.66279
    x15             -29.634     23.808     -1.2447       0.23911


Number of observations: 27, Error degrees of freedom: 11
Root Mean Squared Error: 6.37
R-squared: 0.948,  Adjusted R-Squared 0.877
F-statistic vs. constant model: 13.3, p-value = 5.9e-05
```

Table A.17 Constants for Model 4 of the Boise River

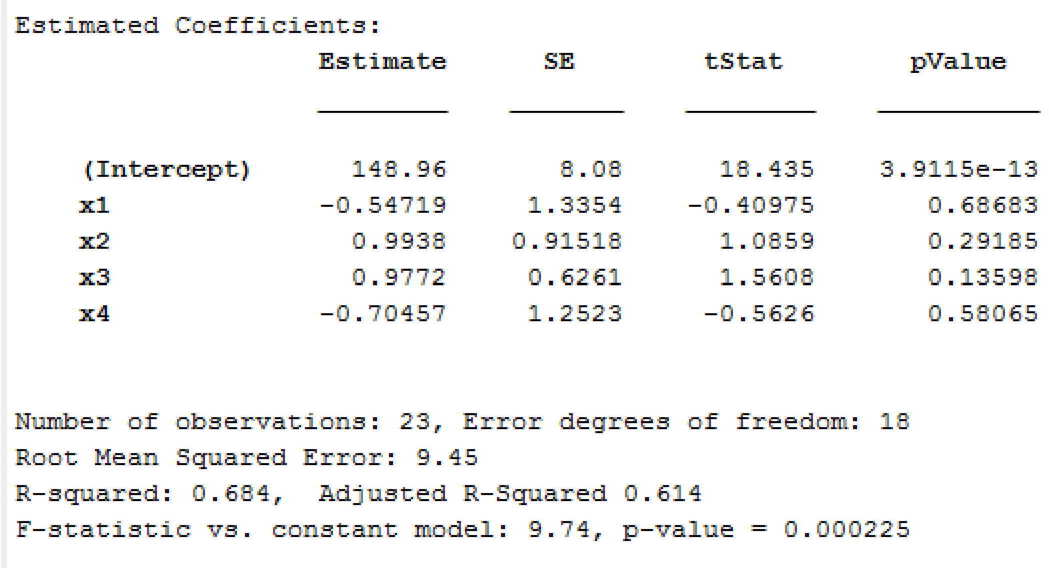
Boise 4	Atlanta	Graham	Jackson	Mores	Trinity	Vienna
Max SWE	-.3	1.1	-.1	-.2	1.0	-1.1
April Melt	29.3	-9.1	17.6	N/A	N/A	N/A
May Melt	19.8	-12.7	43.5	27.1	-50.6	-15.7
June Melt	10.7	N/A	66.8	7.1	-65.1	45.1



```
Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)      114.31     51.876      2.2035    0.069765
    x1             -0.33106     1.0967    -0.30187     0.77294
    x2               1.1103    0.94882      1.1701     0.28632
    x3             -0.07121     1.1091   -0.064204     0.95089
    x4              0.23316    0.86501     0.26955     0.79654
    x5               1.0272    0.55958      1.8356     0.11608
    x6               -1.083    0.82727     -1.3091     0.23839
    x7                29.27     22.462      1.3031     0.24031
    x8              -9.1169     7.5604     -1.2059     0.27326
    x9               17.623     60.432     0.29161      0.7804
    x10              19.809     12.663      1.5642      0.1688
    x11             -12.747     5.1615     -2.4697    0.048475
    x12              43.466      60.83     0.71455     0.50173
    x13              27.085     18.094       1.497     0.18505
    x14              -50.63      44.44     -1.1393     0.29801
    x15             -15.743     38.878    -0.40493     0.69957
    x16              10.653     7.1203      1.4961     0.18525
    x17              66.766     50.791      1.3145     0.23668
    x18              7.0865     5.9481      1.1914     0.27849
    x19             -65.119     43.318     -1.5033     0.18346
    x20              45.065     41.762      1.0791       0.322


Number of observations: 27, Error degrees of freedom: 6
Root Mean Squared Error: 5.1
R-squared: 0.982,  Adjusted R-Squared 0.921
F-statistic vs. constant model: 16.1, p-value = 0.00119
```

Table A.18 Constants for Model 1 of the Payette River

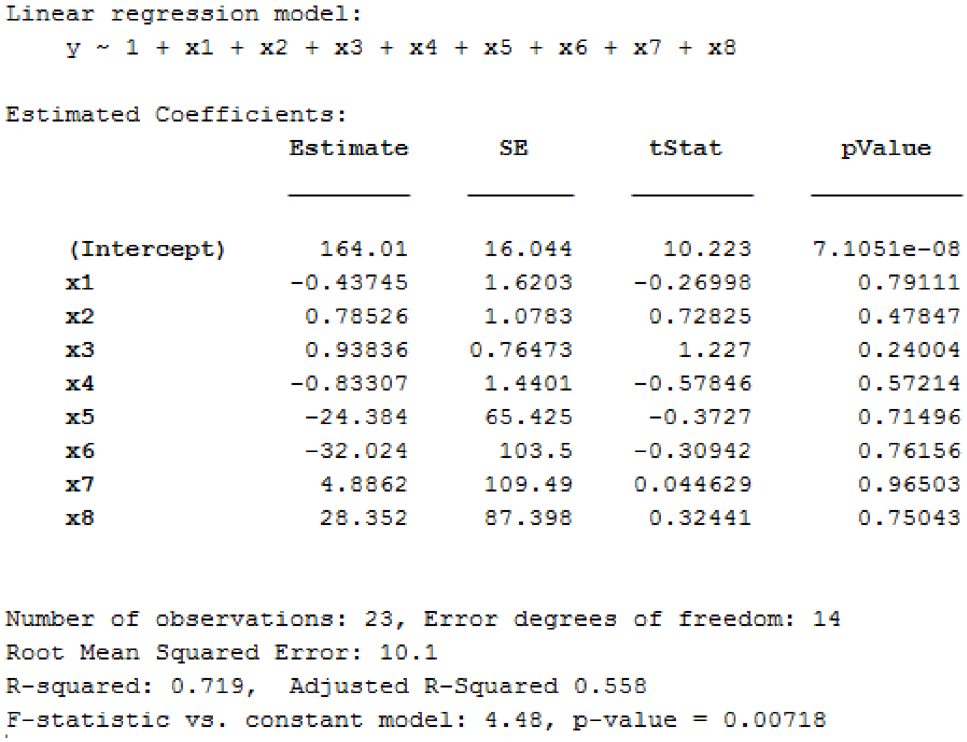
Payette 1	Banner	Big Creek	Deadwood	Jackson
Max SWE	-.55	.99	.98	-.70



```
Estimated Coefficients:
                    Estimate       SE        tStat       pValue  
                    ________    _______    ________    __________

    (Intercept)       148.96       8.08      18.435    3.9115e-13
    x1              -0.54719     1.3354    -0.40975       0.68683
    x2                0.9938    0.91518      1.0859       0.29185
    x3                0.9772     0.6261      1.5608       0.13598
    x4              -0.70457     1.2523     -0.5626       0.58065


Number of observations: 23, Error degrees of freedom: 18
Root Mean Squared Error: 9.45
R-squared: 0.684,  Adjusted R-Squared 0.614
F-statistic vs. constant model: 9.74, p-value = 0.000225
```

Table A.19 Constants for Model 2 of the Payette River

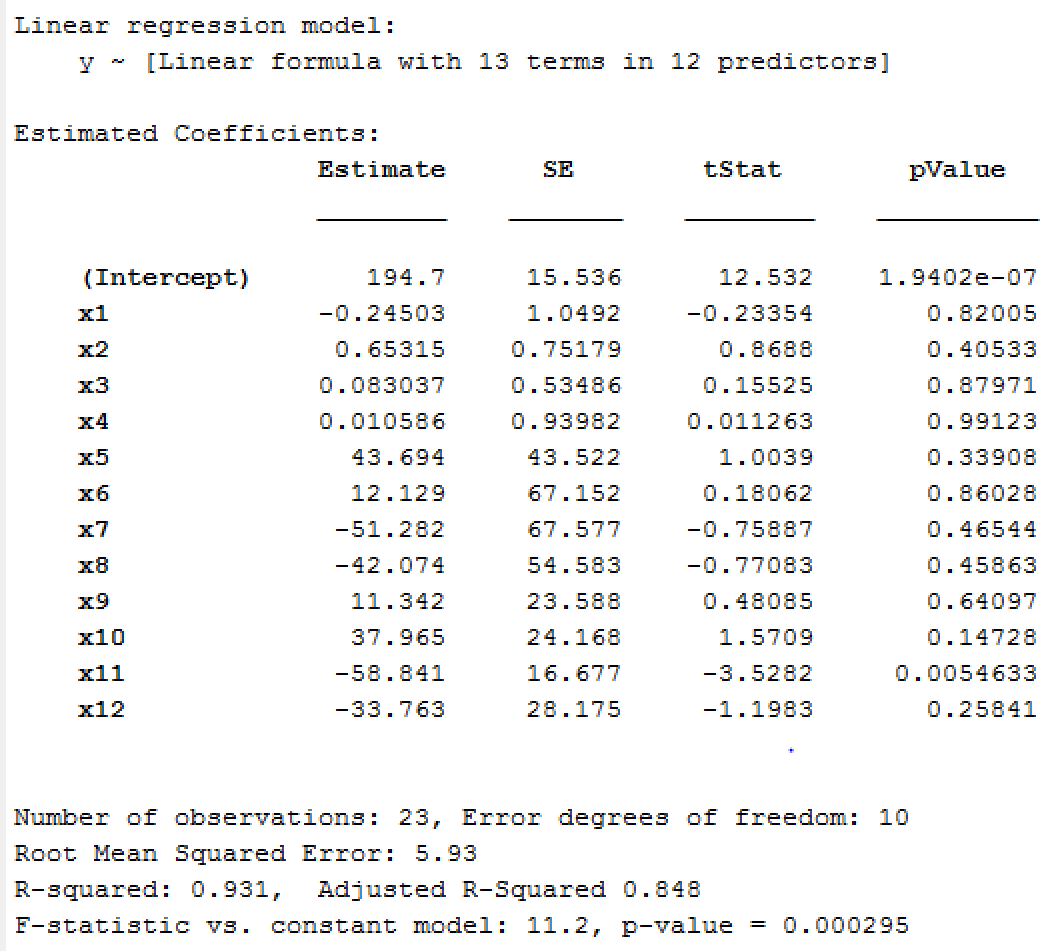
Payette 2	Banner	Big Creek	Deadwood	Jackson
Max SWE	-.44	.78	.94	-.83
April Melt	-24.4	-32.0	4.9	28.4



```
Linear regression model:
    y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8

Estimated Coefficients:
                   Estimate       SE         tStat       pValue
                   ________    ________    ________    __________

    (Intercept)      164.01      16.044      10.223    7.1051e-08
    x1             -0.43745      1.6203    -0.26998       0.79111
    x2              0.78526      1.0783     0.72825       0.47847
    x3              0.93836     0.76473       1.227       0.24004
    x4             -0.83307      1.4401    -0.57846       0.57214
    x5              -24.384      65.425     -0.3727       0.71496
    x6              -32.024       103.5    -0.30942       0.76156
    x7               4.8862      109.49    0.044629       0.96503
    x8               28.352      87.398     0.32441       0.75043


Number of observations: 23, Error degrees of freedom: 14
Root Mean Squared Error: 10.1
R-squared: 0.719,  Adjusted R-Squared 0.558
F-statistic vs. constant model: 4.48, p-value = 0.00718
```

Table A.20 Constants for Model 3 of the Payette River

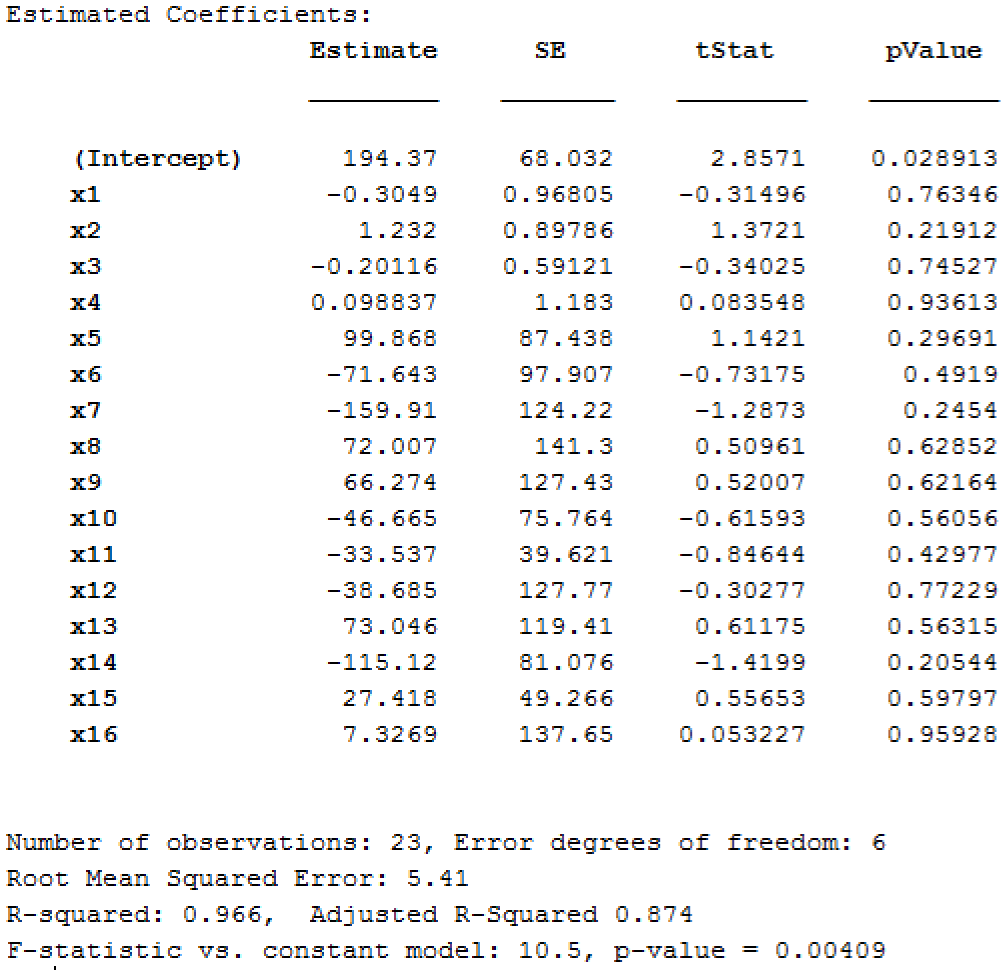
Payette 3	Banner	Big Creek	Deadwood	Jackson
Max SWE	-.24	.65	.08	.01
April Melt	43.7	12.1	-51.3	-42.1
May Melt	11.3	38.0	-58.8	-33.8



```
Linear regression model:
    y ~ [Linear formula with 13 terms in 12 predictors]

Estimated Coefficients:
                     Estimate      SE        tStat       pValue
                    ________    _______    ________    __________

    (Intercept)        194.7     15.536      12.532    1.9402e-07
    x1              -0.24503     1.0492    -0.23354       0.82005
    x2               0.65315    0.75179      0.8688       0.40533
    x3              0.083037    0.53486     0.15525       0.87971
    x4              0.010586    0.93982    0.011263       0.99123
    x5                43.694     43.522      1.0039       0.33908
    x6                12.129     67.152     0.18062       0.86028
    x7               -51.282     67.577    -0.75887       0.46544
    x8               -42.074     54.583    -0.77083       0.45863
    x9                11.342     23.588     0.48085       0.64097
    x10               37.965     24.168      1.5709       0.14728
    x11              -58.841     16.677     -3.5282     0.0054633
    x12              -33.763     28.175     -1.1983       0.25841


Number of observations: 23, Error degrees of freedom: 10
Root Mean Squared Error: 5.93
R-squared: 0.931,  Adjusted R-Squared 0.848
F-statistic vs. constant model: 11.2, p-value = 0.000295
```

Table A.21 Constants for Model 4 of the Payette River

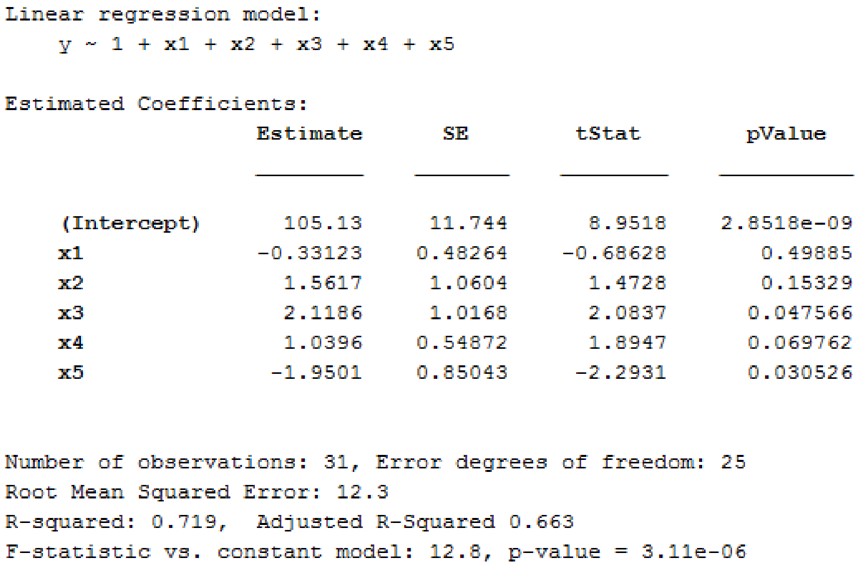
Payette 4	Banner	Big Creek	Deadwood	Jackson
Max SWE	-.3	1.2	-.2	.1
April Melt	100.0	-71.6	-160.0	72.0
May Melt	66.3	-46.7	-33.5	-38.7
June Melt	73.0	-115.1	27.4	7.3



```
Estimated Coefficients:
                   Estimate       SE        tStat       pValue
                   ________    _______    ________    ________

    (Intercept)      194.37     68.032      2.8571    0.028913
    x1              -0.3049    0.96805    -0.31496     0.76346
    x2                1.232    0.89786      1.3721     0.21912
    x3             -0.20116    0.59121    -0.34025     0.74527
    x4             0.098837      1.183    0.083548     0.93613
    x5               99.868     87.438      1.1421     0.29691
    x6              -71.643     97.907    -0.73175      0.4919
    x7              -159.91     124.22     -1.2873      0.2454
    x8               72.007      141.3     0.50961     0.62852
    x9               66.274     127.43     0.52007     0.62164
    x10             -46.665     75.764    -0.61593     0.56056
    x11             -33.537     39.621    -0.84644     0.42977
    x12             -38.685     127.77    -0.30277     0.77229
    x13              73.046     119.41     0.61175     0.56315
    x14             -115.12     81.076     -1.4199     0.20544
    x15              27.418     49.266     0.55653     0.59797
    x16              7.3269     137.65    0.053227     0.95928


Number of observations: 23, Error degrees of freedom: 6
Root Mean Squared Error: 5.41
R-squared: 0.966,  Adjusted R-Squared 0.874
F-statistic vs. constant model: 10.5, p-value = 0.00409
```

Table A.22 Constants for Model 1 of the Snake River

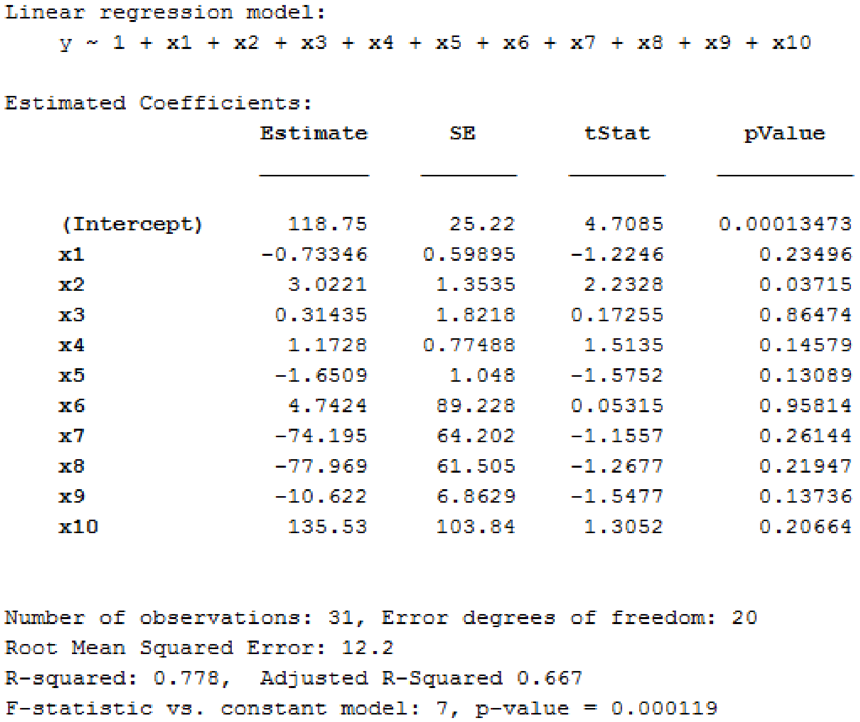
Snake 1	Black Bear	Grassy Lake	2 Ocean Pl.	Phillips	Lewis
Max SWE	-.33	1.6	2.1	1.0	-2.0



```
Linear regression model:
    y ~ 1 + x1 + x2 + x3 + x4 + x5

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    ________    __________

    (Intercept)      105.13     11.744      8.9518    2.8518e-09
    x1             -0.33123    0.48264    -0.68628       0.49885
    x2               1.5617     1.0604      1.4728       0.15329
    x3               2.1186     1.0168      2.0837      0.047566
    x4               1.0396    0.54872      1.8947      0.069762
    x5              -1.9501    0.85043     -2.2931      0.030526


Number of observations: 31, Error degrees of freedom: 25
Root Mean Squared Error: 12.3
R-squared: 0.719,  Adjusted R-Squared 0.663
F-statistic vs. constant model: 12.8, p-value = 3.11e-06
```

Table A.23 Constants for Model 2 of the Snake River

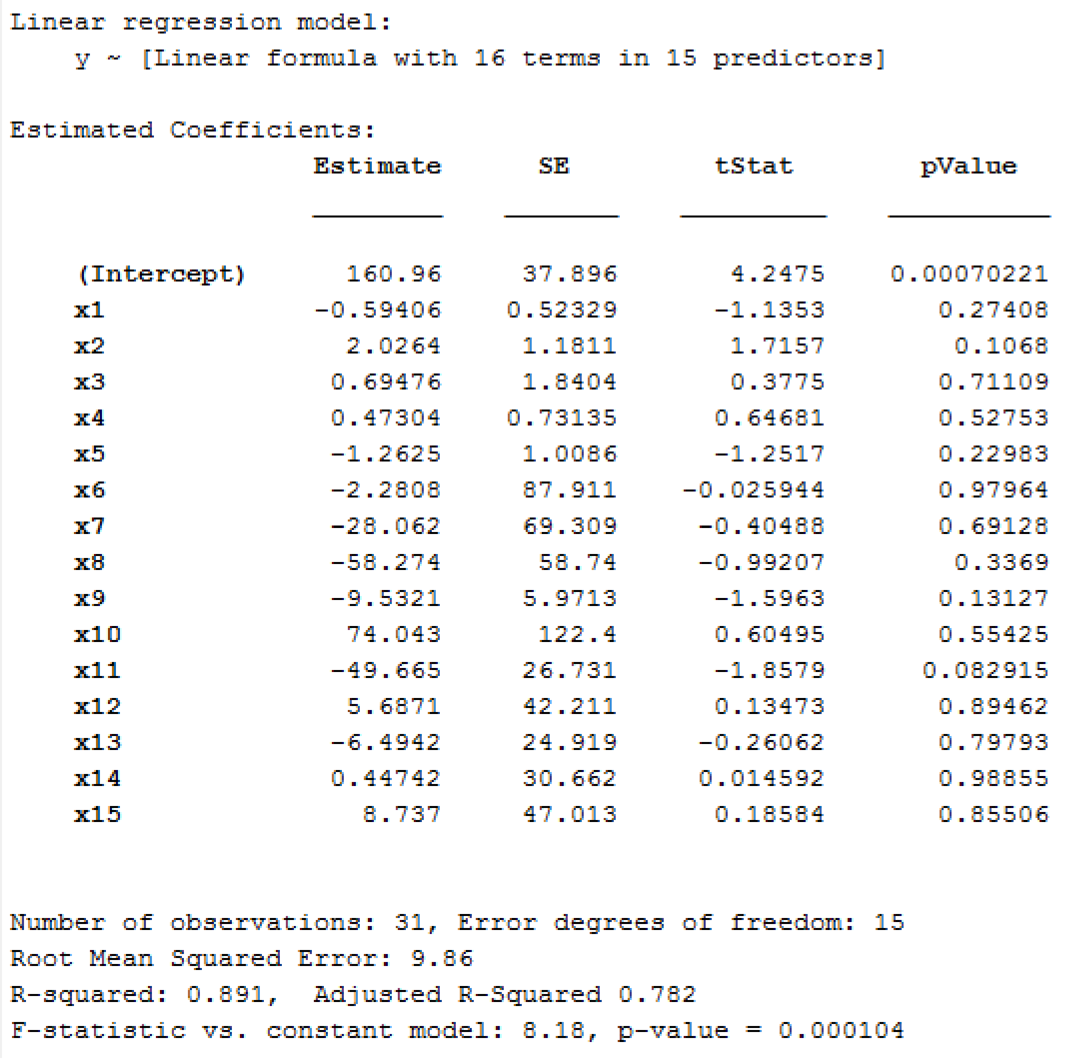
Snake 2	Black Bear	Grassy Lake	2 Ocean Pl.	Phillips	Lewis
Max SWE	-.73	3.0	.31	1.20	-1.7
April Melt	4.7	-74	-77	-10	135



```
Linear regression model:
    y ~ 1 + x1 + x2 + x3 + x4 + x5 + x6 + x7 + x8 + x9 + x10

Estimated Coefficients:
                   Estimate      SE        tStat       pValue
                   ________    _______    _______    __________

    (Intercept)      118.75      25.22     4.7085    0.00013473
    x1             -0.73346    0.59895    -1.2246       0.23496
    x2               3.0221     1.3535     2.2328       0.03715
    x3              0.31435     1.8218    0.17255       0.86474
    x4               1.1728    0.77488     1.5135       0.14579
    x5              -1.6509      1.048    -1.5752       0.13089
    x6               4.7424     89.228    0.05315       0.95814
    x7              -74.195     64.202    -1.1557       0.26144
    x8              -77.969     61.505    -1.2677       0.21947
    x9              -10.622     6.8629    -1.5477       0.13736
    x10              135.53     103.84     1.3052       0.20664


Number of observations: 31, Error degrees of freedom: 20
Root Mean Squared Error: 12.2
R-squared: 0.778,  Adjusted R-Squared 0.667
F-statistic vs. constant model: 7, p-value = 0.000119
```

Table A.24 Constants for Model 3 of the Snake River

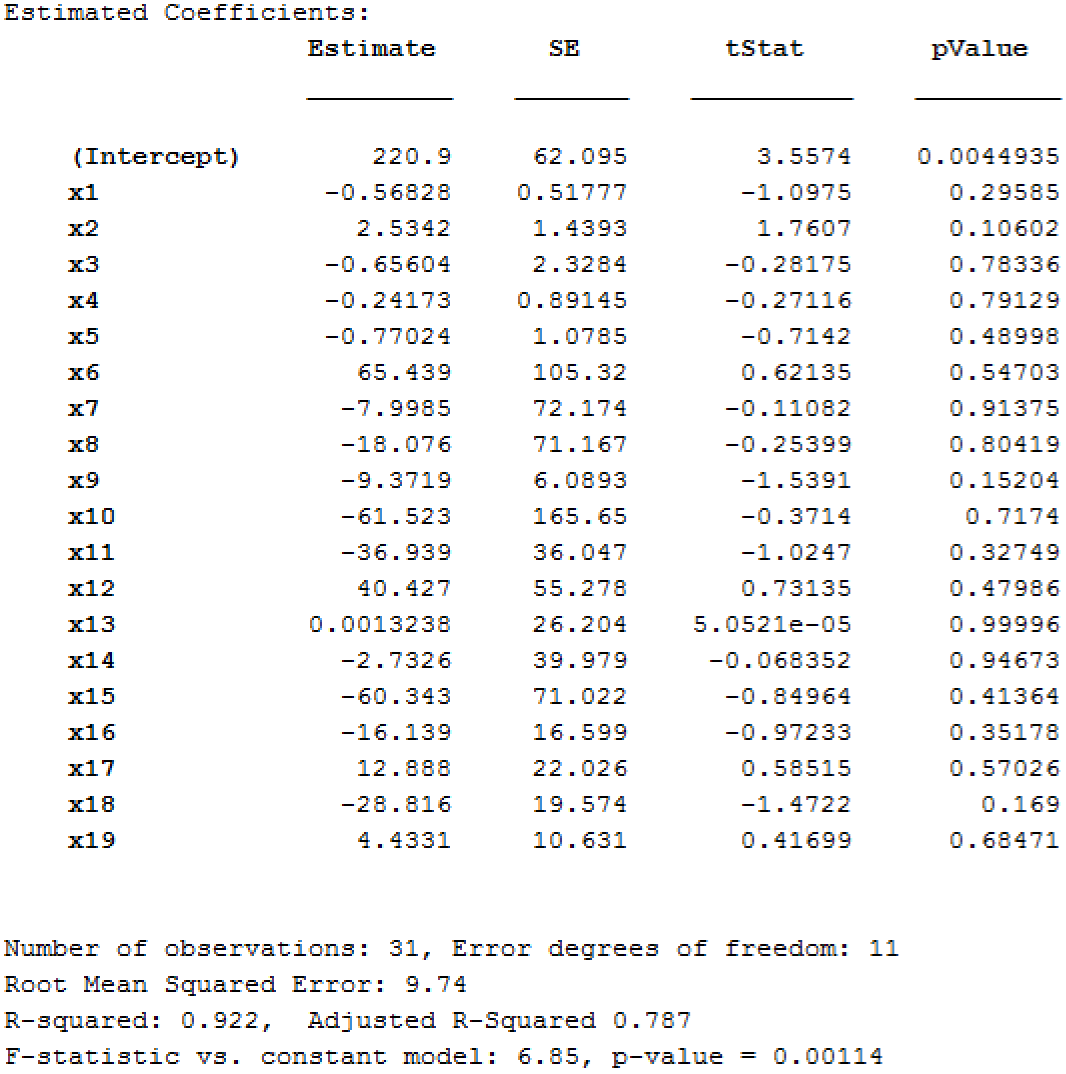
Snake 3	Black Bear	Grassy Lake	2 Ocean Pl.	Phillips	Lewis
Max SWE	-.59	2.02	.69	.47	-1.2
April Melt	-2.2	-28.1	-58.3	-9.5	74.0
May Melt	-49.7	5.7	-6.5	.44	8.7



```
Linear regression model:
    y ~ [Linear formula with 16 terms in 15 predictors]

Estimated Coefficients:
                   Estimate       SE        tStat        pValue
                   ________    ________    _________    __________

    (Intercept)      160.96      37.896       4.2475    0.00070221
    x1             -0.59406     0.52329      -1.1353       0.27408
    x2               2.0264      1.1811       1.7157        0.1068
    x3              0.69476      1.8404       0.3775       0.71109
    x4              0.47304     0.73135      0.64681       0.52753
    x5              -1.2625      1.0086      -1.2517       0.22983
    x6              -2.2808      87.911    -0.025944       0.97964
    x7              -28.062      69.309     -0.40488       0.69128
    x8              -58.274       58.74     -0.99207        0.3369
    x9              -9.5321      5.9713      -1.5963       0.13127
    x10              74.043       122.4      0.60495       0.55425
    x11             -49.665      26.731      -1.8579      0.082915
    x12              5.6871      42.211      0.13473       0.89462
    x13             -6.4942      24.919     -0.26062       0.79793
    x14             0.44742      30.662     0.014592       0.98855
    x15               8.737      47.013      0.18584       0.85506


Number of observations: 31, Error degrees of freedom: 15
Root Mean Squared Error: 9.86
R-squared: 0.891,  Adjusted R-Squared 0.782
F-statistic vs. constant model: 8.18, p-value = 0.000104
```

Table A.25 Constants for Model 4 of the Snake River

Snake 4	Black Bear	Grassy Lake	2 Ocean Pl.	Phillips	Lewis
Max SWE	-.57	2.5	-.7	-.2	-.8
April Melt	65.4	-8.0	-18.1	-9.4	-61.5
May Melt	-36.9	40.4	.001	-2.7	-60.3
June Melt	N/A	-16.1	12.9	-28.8	4.4



```
Estimated Coefficients:
                   Estimate      SE         tStat         pValue
                   _________   _______   ___________   _________

    (Intercept)        220.9    62.095        3.5574   0.0044935
    x1              -0.56828   0.51777       -1.0975     0.29585
    x2                2.5342    1.4393        1.7607     0.10602
    x3              -0.65604    2.3284      -0.28175     0.78336
    x4              -0.24173   0.89145      -0.27116     0.79129
    x5              -0.77024    1.0785       -0.7142     0.48998
    x6                65.439    105.32       0.62135     0.54703
    x7               -7.9985    72.174      -0.11082     0.91375
    x8               -18.076    71.167      -0.25399     0.80419
    x9               -9.3719    6.0893       -1.5391     0.15204
    x10              -61.523    165.65       -0.3714      0.7174
    x11              -36.939    36.047       -1.0247     0.32749
    x12               40.427    55.278       0.73135     0.47986
    x13            0.0013238    26.204    5.0521e-05     0.99996
    x14              -2.7326    39.979     -0.068352     0.94673
    x15              -60.343    71.022      -0.84964     0.41364
    x16              -16.139    16.599      -0.97233     0.35178
    x17               12.888    22.026       0.58515     0.57026
    x18              -28.816    19.574       -1.4722       0.169
    x19               4.4331    10.631       0.41699     0.68471


Number of observations: 31, Error degrees of freedom: 11
Root Mean Squared Error: 9.74
R-squared: 0.922,  Adjusted R-Squared 0.787
F-statistic vs. constant model: 6.85, p-value = 0.00114
```