IMPLICATIONS OF INCREASING SNOW EPHEMERALITY FOR GREAT BASIN HYDROLOGY AND VEGETATION

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**ABSTRACT**

Ephemeral snow is defined in a common persistence threshold as snowpack that persists for less than 60 consecutive days. Current observation and modeling techniques for ephemeral snowpack are lacking or underutilized. Remote sensing is a promising technique for mapping ephemeral snow but only gridded data products that have daily temporal resolution can be used due to the short timespan of ephemeral events.

We used the Great Basin U.S.A. as a case study because the lack of cloud cover, the climate and the corresponding vegetation gradient from arid to montane make it an optimal location for studying snow seasonality. We also developed two classification techniques for differentiating ephemeral snow from seasonal snow: The maximum consecutive snow duration and the snow seasonality metric (SSM). In Chapter 1, we used moderate resolution spectroradiometer (MODIS) and snow data assimilation system (SNODAS) data to answer the following questions: 1) How would shifts from seasonal to ephemeral snowpacks affect the availability of melt water? 2) How does topography affect snow seasonality and 3) What mechanisms cause ephemeral snowpacks and how does that vary with climate? We noted the differences in snowpack and soil moisture dynamics between ephemeral and seasonal snow cover at snow telemetry (SNOTEL) and soil climate analysis network (SCAN) stations. Then, we compared maximum consecutive snow duration against elevation and aspect. Lastly, we created a process to categorize ephemeral snowpack based on the dominant mechanism limiting snow cover.
In Chapter 2, we used MODIS data and a Random Forest (RF) model to answer the following questions: 1) What topographic and climatic variables are the most influential when predicting snow ephemerality?, 2) Will increases in the average winter temperature lead to a shift from seasonal to ephemeral snowpack?, and 3) What vegetation types are most at-risk to extreme changes in ephemerality relative to their historic conditions? We incorporated topographic and climate variables into our Random Forest model to evaluate which variables were the most influential. We then adjusted the average winter temperature by 2°C and 4°C, and noted how much of the Great Basin shifted from seasonal to ephemeral snow. We also brought in Landfire vegetation classification data to determine what vegetation types are most at-risk from a seasonal-ephemeral shift. In Chapter 4 we summarize the advancements offered by this thesis, but also note the many limitations in our current observations and modeling of ephemeral snow that require future research.
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CHAPTER 1
INTRODUCTION

Much of the world's snow is ephemeral, which means that it does not persist for the entire snow season. A common persistence threshold defines ephemeral snow as snowpack that persists for less than 60 consecutive days. Unlike seasonal snow, ephemeral snow does not provide reliable water inputs related to the warming and spring melt of seasonal snowpacks. A seasonal-ephemeral shift in snowpack threatens water availability to vegetation. Yet despite the importance of ephemeral snowpack, current observation and modeling techniques are lacking or underutilized. Most ground-based snow observations are in locations that predominantly have seasonal snow. Commonly used modeling techniques often neglect ground heat flux and do not account for small temperature and radiation changes. Remote sensing is a promising technique for mapping ephemeral snow but only gridded data products that have daily temporal resolution like moderate resolution imaging spectroradiometer (MODIS) products can be used due to the short timespan of ephemeral events.

We used the Great Basin U.S.A. as a case study because the lack of cloud cover, the climate and the corresponding vegetation gradient from arid to montane make it an optimal location for studying snow seasonality. We also developed two classification techniques for differentiating ephemeral snow from seasonal snow: The maximum consecutive snow duration and the snow seasonality metric (SSM). The maximum consecutive snow duration is the greatest number of consecutive snow covered days in a given water year. The SSM is a -1 to 1 scale made by subtracting the days containing ephemeral snow from the days containing seasonal snow, and dividing by the total number of days containing snow.
In Chapter 1, we used MODIS and snow data assimilation system (SNODAS) data to answer the following questions: 1) How would shifts from seasonal to ephemeral snowpacks affect the availability of melt water? 2) How does topography affect snow seasonality and 3) What mechanisms cause ephemeral snowpacks and how does that vary with climate? We noted the differences in snowpack and soil moisture dynamics between ephemeral and seasonal snow cover at snow telemetry (SNOTEL) and soil climate analysis network (SCAN) stations. Then, we compared maximum consecutive snow duration against elevation and aspect. Lastly, we created a process to categorize ephemeral snowpack based on the dominant mechanism limiting snow cover.

In Chapter 2, we used MODIS data and a Random Forest (RF) model to answer the following questions: 1) What topographic and climatic variables are the most influential when predicting snow ephemerality?, 2) Will increases in the average winter temperature lead to a shift from seasonal to ephemeral snowpack?, and 3) What vegetation types are most at-risk to extreme changes in ephemerality relative to their historic conditions? We incorporated topographic and climate variables into our Random Forest model to evaluate which variables were the most influential. We then adjusted the average winter temperature by 2°C and 4°C, and noted how much of the Great Basin shifted from seasonal to ephemeral snow. We brought in Landfire vegetation classification data to determine what vegetation types are most at-risk from a seasonal-ephemeral shift.

Together Chapters 2-3 represent a large step forward in our understanding of snow seasonality in the Great Basin, with potential application of our seasonality metrics and classification systems to other areas. Then, in Chapter 4 we summarize the advancements offered by this thesis, but also note the many limitations
in our current observations and modeling of ephemeral snow that require future research.
2.1 Abstract

Ephemeral snowpacks, or those that persist for less than 60 consecutive days, are challenging to observe and model. Ephemeral snowmelt delivers water earlier and with less deep soil moisture than seasonal snow melt; however little is known about the spatial and temporal distribution of ephemeral snow. We used data from moderate resolution imaging spectroradiometer (MODIS) and Snow Data Assimilation System (SNODAS) data from water years 2005-2014 to map the extent of ephemeral snowpack across the Great Basin. During this time period, Great Basin snowpack was highly variable. The maximum seasonal snow cover in the Great Basin was 64% in 2010 and the minimum seasonal snow cover was 24% in 2014. We found that elevation had a strong control on snow ephemerality, and nearly all snowpacks over 2500 m were seasonal. Aspect had a smaller influence, but snowpacks were more likely to be ephemeral on south facing slopes than north facing slopes at high elevations. Additionally, we used SNODAS-derived estimates of melt, sublimation, blowing snow sublimation, and we used solid/liquid precipitation to define the mechanisms of snow ephemerality. In warm years like 2014, the Great Basin shifts from being seasonally dominant to ephemerally dominant as the rain-snow transition moves up in elevation and melt increases. Given that snow ephemerality is generally expected to increase as a consequence of climate change, we put forward several challenges and recommendations necessary for predicting and managing the effects of ephemeral snow on hydrology.
2.2 Introduction

Seasonal snowmelt supplies water to 1/6 of the world’s population, which supports 1/4 of the global economy (Barnett et al., 2005; Sturm et al., 2017). Seasonal snowpack provides predictable melt timing and volumes in the spring, which influences streamflow timing, surface water and groundwater availability (Jasechko et al., 2014; Stewart et al., 2005). Reliable spring snowmelt also provides a strong control on vegetation phenology and productivity in many ecosystems (Parida and Buermann, 2014; Trujillo et al., 2012). Despite the importance of seasonal snow to water supplies, much of the world’s snow is ephemeral, which means it melts and sublimes throughout the snow cover season instead of having one consistent period of snowmelt. Even small shifts from historically seasonal to ephemeral snowpack due to regional warming could disrupt snowmelt timing in ways that could alter summer productivity, soil temperature, and soil moisture regimes (Hamlet et al., 2005; Harpold and Molotch, 2015; Jefferson, 2011; Parida and Buermann, 2014; Regonda et al., 2005; Stielstra et al., 2015; Trujillo et al., 2012). A shift from seasonal to ephemeral snowpacks will have negative implications for the winter tourism, water management, hydropower, and forest management sectors in particular (Schmucki et al., 2014; Sturm et al., 2017). Despite the hydrological and ecological importance of ephemeral snow, we lack widely accepted methodologies to classify, map, and model snow ephemerality.

One widely accepted snowpack classification system in snow hydrology by Sturm et al. (1995) divides snowpack into six categories: Tundra, Taiga, Alpine, Maritime, Ephemeral, and Prairie. In that system, ephemeral snowpacks are defined as all snowpacks that persist for less than 60 consecutive days, are less than 50 cm depth, and have less than three different snow layers (Sturm et al., 1995). The
Sturm et al. (1995) classification system is also incorporated into physical snowpack models, such as SnowModel (Liston and Elder, 2006), to separate seasonal and ephemeral snowpacks. Models often separate the calculation of seasonal and ephemeral snowpack energetics because ephemeral snowpacks are much more sensitive to basal melt from ground heat flux. Additionally, cold content varies more in deeper, seasonal snowpacks. Although not much is known about their hydrological impacts, ephemeral snowpacks modify the intensity and duration of precipitation inputs by storing and releasing water in a less predictable way than seasonal snow. In this paper, we take a broader perspective on ephemeral snowpacks using the definition of snow persisting for short durations (<60 days).

Ground-based and remote sensing observations have their own strengths and weaknesses for observing ephemeral snowpacks. Most ground-based snow measurement stations (e.g. the National Resource Conservation Snow Telemetry SNOTEL network) in the Great Basin–and the rest of the Western United States–are built to observe seasonal snow (Figure 2.1). This is because sites are typically placed in topographically sheltered forest gaps that retain snow longer than nearby terrain. This improves the skill in streamflow forecasting, the primary goal of the SNOTEL network, but means that most SNOTEL sites only have ephemeral snow cover in exceptionally dry or warm years (Serreze et al., 1999). The scarcity of ground-based ephemeral snow data has changed slightly in recent years with additional measurements at NRCS SCAN (Figure 2.1) and within research watersheds (Anderton et al., 2002; Jost et al., 2007). However, the lack of field observations from ephemeral snowpacks has limited previous investigations (e.g. Sturm et al. 2010).

Spectral remote sensing collects observations over all cloud-free area–including both seasonal and ephemeral snow zones–but has its own sets of advantages and
challenges. There are multiple methods to define the start and end of the observed snow covered period. Often, it is defined as the date of the first and last remotely sensed observations of snow cover (e.g. Choi et al. 2010; Kimball et al. 2004; Nitta et al. 2014). Because this approach does not account for intermittent snow free periods, it tends to overestimate snow duration and miss important ephemeral dynamics Thompson and Lees (2014). Snow persistence thresholds can be used to define snow ephemerality, but no standard persistence threshold exists (e.g. Gao et al. 2011; Karlsen et al. 2007). Given the intermittent nature of ephemeral snow, observations must be daily or finer to capture its dynamics Wang et al. (2014). Consequently, products like Landsat that have a 16-day overpass do poorly at estimating snow seasonality compared to products like the moderate-resolution imaging spectroradiometer (MODIS). Moreover, high cloud cover reduces observation frequency, and limits the ability to observe ephemeral snow events. Like with ground-based snow research, some remote-sensing based studies often exclude ephemeral events altogether (e.g Sugg et al. 2014). The algorithm developed by Thompson and Lees (2014) removed most of the methodological flaws mentioned above by using daily MOD10A1 data and accounting for snow absences in the middle of the snow season, but their study was challenging to verify and applied only in a small area of Australia. Given the current lack of ground-based observations (Figure 2.1), remote sensing is one path forward for observing ephemeral snow.

Modeling ephemeral snowpacks is challenging and has not received the same attention as modeling more persistent, seasonal snowpacks. Most physics-based models (e.g. Liston and Elder 2006), are optimized for seasonal snow, and produce less accurate results over ephemeral snow (Kelleners et al., 2010; Kormos et al., 2014). As stated previously, however, there is a lack of field observations to inter-
Figure 2.1: (a) Locations of and (b) Number of Snow Telemetry (SNOTEL) and Soil Climate Analysis Network (SCAN) stations in the Great Basin, USA that are located in ephemeral and seasonal snow as defined by $<60$ or $\geq 60$ days of maximum consecutive snow duration respectively. Snow duration data collected using the Snow Data Assimilation System model. 

There are a variety of underlying processes that cause ephemeral snowpacks, which challenge snow models and increase uncertainty. Based on previous classification systems, we define three mechanisms by which areas receiving snowfall can experience ephemeral snowpacks: 1) Rainfall limiting the accumulation of snowpack, 2) Snowpack ablation from melt or sublimation, and 3) Wind scour removing snowpacks. All of these mechanisms have a variety of underlying atmospheric and snowpack processes that challenge prediction with snow models. At rain-snow transition elevations, even small temperature variations and other atmospheric variables can alter the mixture of rainfall and snowfall (Henderson and Leathers, 2010; Jefferson, 2011; Klos et al., 2014; Regonda et al., 2005). Complete snow water equivalent (SWE) removal from melt or sublimation is also another common cause of snow ephemerality (Clow, 2010; Leathers et al., 2004; Mote et al., 2005; Sospedra-Alfonso and Merryfield, 2017). Typically, physics-based models overestimate modeled SWE in ephemeral snowpack, due to neglect or underestimation of ground heat flux and the challenges of tracking cold content in shallow
snowpacks (Cline, 1997; Hawkins and Ellis, 2007; Kelleners et al., 2010; Kormos et al., 2014; LaMontagne, 2009; Şensoy et al., 2006). Models parameterize energy fluxes differently, which can lead to differences in model estimates of sublimation and melt (Essery et al., 2009; Schmucki et al., 2014; Sospedra-Alfonso et al., 2016). Removal of snowpack from wind scour is a very important factor on snow accumulation in alpine regions, but is often neglected in models altogether (e.g. Mernild et al. 2017; Pomeroy 1991; Winstral et al. 2013. Widespread evidence exists that wind redistribution of snow can cause ephemeral snowpacks that are consistent from year to year because of topography and dominant wind directions (Hood et al., 1999). The three mechanisms causing ephemeral snow (i.e. rain-snow transition, ablation by sublimation and melt, and wind scour) have fundamentally different underlying causes, with different and poorly quantified sensitivity to climate and land cover variability.

The goal of this paper is to use the Great Basin as a case study to estimate the distribution, hydrological consequences, and mechanisms of ephemeral snowpacks using both ground-based and remote sensing observations. We adapt a classification from Sturm et al. (1995) to map snow across the Great Basin, compare remotely sensed and modeled estimates of ephemeral snow, and develop our own metric to further classify snow seasonality. The Great Basin is ideal for this investigation because it spans dramatic gradients of elevation and hydroclimatology. This prototypical area depends disproportionately on mountain snowpack for water supplies, contains few ground-based observations, and there is relatively little winter cloud cover to limit spectral remote sensing techniques. Three research questions guide our analyses of ephemeral snowpacks in the Great Basin: 1) What are the implications for soil moisture from seasonal to ephemeral snow melt? 2) How does topography affect snow seasonality, and 3) What mechanisms
cause ephemeral snowpacks and how does that vary with climate? We find that ephemeral snowmelt leads to fundamentally different water availability than seasonal snow and that warmer years cause the melt and rain-snow transition to shift lower in elevation.

2.3 Study Area

The Great Basin is the closed basin between the Wasatch and southern mountain ranges in Utah and the eastern slope of the Sierra Nevada mountain range in California. The region is known for having “internal drainage,” which means that none of the waterways travel to the ocean (Svejcar, 2015). The climate is semi-arid and the ecosystem is shrub-dominated (Svejcar, 2015; West, 1983; Wigand et al., 1995). We defined the Great Basin region based on the Hydrologic Unit Code (HUC) Region 16 adapted from Seaber et al. (1987) by the United States Geological Survey (USGS) (Figure 2.2). Overall, the Great Basin has a mean winter precipitation of 12 cm and a mean winter temperature of 0.4 degrees C (Figure 2.3) (Abatzoglou, 2012).

2.4 Methods

In order to compare the effect of snow ephemerality on soil moisture patterns, we first took coordinates for SNOTEL and SCAN stations within the Great Basin. To evaluate how soil moisture varies based on snowpack parameters during a drought year (water year 2015) and a non-drought year (water year 2016), we chose two SNOTEL stations: Porter Canyon (ID: 2170, Elevation 2191m) and Big Creek
Figure 2.2: Map of the Great Basin region, USA as defined by the United States Geological Survey (USGS) Hydrologic Unit Code (HUC) Region 16 along with major cities and mountain ranges. The Sierra Nevada and Wasatch/Uinta mountain ranges defined using the US EPA L4 ecoregion classifications of "Sierra Nevada" and "Wasatch Uinta" respectively. Ruby Mountains were defined using a combination of "Mid-Elevation Ruby Mountains" and "High Elevation Ruby Mountains" in the US EPA L3 classification Omernik (1987). Elevation contours at 1000 m intervals.

Summit (ID: 337, Elevation 2647m) that differ in elevation but are in close proximity. We then used average snow water equivalent (SWE) data across water years 2005-2014 from the snow data assimilation (SNODAS) model to categorize each SNOTEL and SCAN station as being in ephemeral or seasonal snow if the dura-
Figure 2.3: (a) Average winter temperature, (b) average winter precipitation, and (c) average winter radiation across water years 2001-2015 along with elevation in the Great Basin.

The duration of continuous snow cover was less or more than 60 days, respectively. For these stations, we compared percent soil moisture, soil temperature at 5 and 50 cm soil depth along with snow depth, and SWE. We also acquired soil moisture and SWE data at 5 and 50 cm for all the SNOTEL and SCAN stations in the Great Basin in water years 2014-2016. We discarded years and stations containing more than 7 days of continuous missing data or soil moisture values that were 0%. To compare the timing of snow and peak soil moisture, we then took the difference between the day of last snow and the day with peak median 10 day soil moisture for each year at each site. We also calculated the coefficient of variation (one standard deviation divided by the mean) of soil moisture for each year at each station. We used the maximum length of continuous SWE that was greater than 0.2 in to categorize years as containing ephemeral or seasonal snow.

We mapped ephemeral snow across the Great Basin using two methods: spec-
tral remote sensing with moderate imaging spectroradiometer (MODIS) data and the snow data assimilation system (SNODAS) model. We used Google Earth Engine to analyze the data, which is a cloud-based computing platform optimized for mapping large datasets. The MODIS dataset we used was the 2010 MODIS/Terra Snow Cover Daily L3 Global 500 m Grid (MOD10A) and we used the Normalized Difference Snow Index (NDSI) with parameters outlined in Hall et al. (2006) to find fractional snow covered data. The equation for calculating NDSI in MOD10 is:

\[
NDSI = \frac{\text{Band}4 - \text{Band}6}{\text{Band}4 + \text{Band}6}
\] (2.1)

A pixel is then mapped as containing fractional snow based on the NDSI value and the percent reflectance value in Band 2. If the reflectance is less than 10%, the pixel won’t be mapped as containing snow regardless of the NDSI value (Hall et al., 2001). We classified all pixels with a snow fraction of 30-100 as Snow, pixels with snow fractions between 0 and 30 as No Snow, and pixels that had all other designations as Other. We also used an algorithm derived from Sturm et al. (1995) to minimize the impact of cloud cover in our MODIS data. The algorithm ‘grows’ the boundaries of all areas containing snow and reclassifies pixels that were classified as Other to Snow if the corresponding pixels in the previous image were classified as Snow. It also reclassifies pixels that were classified as Other to No Snow if the corresponding pixels in the previous image were No Snow. For places where there are clouds, the algorithm uses values from the previous day. To determine the number of ephemeral and seasonal snow events, we used a Google Earth Engine function to note the day of the Water Year when snow appeared (when a pixel went from classified as No Snow in the previous day to classified as Snow in the current day) and when snow disappeared (a pixel went from classified as
Snow in the previous day to being classified as No Snow in the current day), and determined the length of snow cover by subtracting the day of snow appearance from the day of snow disappearance. If the length of snow cover was <60 days, then the snow event was classified as ephemeral. Otherwise, if the length of snow cover was ≥60 days, the snow event was categorized as seasonal. In addition to these metrics, we derived a snow seasonality metric (SSM) to quantify a MODIS pixel’s tendency to have ephemeral or seasonal snow, rather than a binary metric like <60 days. The SSM is depicted in Equation 2.2 and it works by classifying every day where there was seasonal snow present as 1 and every day where there was ephemeral snow present as -1, and then averaging all -1 and +1 values. This created a -1 to 1 scale, where -1 signifies that all the snow covered days in a given pixel within one water year were ephemeral and +1 signifies that they were all seasonal.

\[
SSM = \frac{Days_{Seasonal} - Days_{Ephemeral}}{Days_{Total}}
\]  

(2.2)

Additionally, we discarded all instances where snow was absent for one day only from the overall record of snow disappearance and appearance because we found numerous artifacts from the MOD10A NDSI processing that lead to single day snow disappearance during long stretches of snow cover. One day snow events were also removed from the SNODAS algorithm to make both algorithms more consistent. For each water year from 2001 to 2015, we recorded the maximum total number of days where snow was present (to be referred to as the maximum snow duration).

To determine the relationship between elevation and snow seasonality, we took
the average maximum snow duration across water years 2001-2015 and used elevation, and aspect as measured by a digital elevation model (DEM) obtained from the Shuttle Topography Mission resampled to the same resolution with bilinear sampling (Farr et al., 2007). To calculate northness, we used the equation:

\[
\text{Northness} = \cos\left(\frac{\text{aspect} \times \pi}{180}\right)
\] (2.3)

We then categorized each MODIS pixel based on five 500 m elevation bins from a range of 1000 to >3000 m. Then, to remove bias based on the size of each bin, we used random sampling to make each bin contain the same number of points as the least full bin (13548 points that were >3000 m). Then we combined each resampled bin into one dataset and created heatmaps to compare the elevation vs. the average maximum snow duration. We also use the same method to compare aspect to average maximum snow duration with aspect using eight 45 degree bins from a range of 0 to 360 degrees. We randomly sampled 195163 points from each bin (the size of the bin from 315 to 360 degrees). After resampling, we combined all the bins together and split them into three elevation categories: Low Elevation (Elevation <1500 m), Medium Elevation (1500 ≥ Elevation <2500), and High Elevation (Elevation ≥ 2500m). Then, we resampled again to 82823 points per bin (the size of the High Elevation bin).

We used SNODAS data to simply differentiate the mechanisms that cause snow to become ephemeral. The four mechanisms were assigned if the net ablation (or rain) exceeded 50% of the total winter precipitation (Figure 2.4): 1) A mixture of rain and snow limiting snow accumulation (the rain-snow transition), 2) snowpack loss due to sublimation, 3) snowpack loss due to melt, and 4) snowpack loss due
to wind scour. We determined the prevailing mechanism in each 1000 m SNODAS pixel in each year.

![Flowchart](image)

Figure 2.4: Diagram of the process for the ephemeral snow mechanism model. Seasonal snow outputs were rejected, all other outputs were categorized.

We used Earth Engine to execute the modeled algorithm on each 1000 m SNODAS pixel in the Great Basin. We then chose six years (2009-2014) and created histograms of each mechanism by elevation for each year.
2.5 Results and Discussion

2.5.1 Ephemeral Snow and Soil Water Inputs

Snowmelt influences a variety of terrestrial hydrological processes and states, but it has a dominant influence on infiltration and soil moisture dynamics in areas with low summer precipitation (Harpold and Molotch, 2015). Soil moisture is a primary control on rainfall-runoff response and water availability for vegetation (McNamara et al., 2005; Schwinning and Sala, 2004).

We quantified differing response of soil moisture between seasonal and ephemeral snowpacks that have important ecohydrological implications. McNamara et al. (2005) described soil moisture in semi-arid watersheds with seasonally-dominant snowmelt as going through five phases: (1) a summer dry period, (2) a transitional fall wetting period, (3) a winter wet, low-flux period, (4) a spring wet, high-flux period, and (5) a transitional late-spring drying period. We use the McNamara et al. (2005) framework for soil moisture response to seasonal snowmelt to illustrate differences with soil moisture response to ephemeral snow melt. First using two nearby sites with differing snow regimes. Then second, using all of the soil moisture records available in the Great Basin (Figure 2.5).

We contrast soil moisture response at two adjacent SNOTEL stations that differ in elevation by >500 m (Figure 2.1) to illustrate differences between ephemeral and seasonal snowmelt. Soil moisture at 5 and 50 cm were used to represent a shallow and deep response during a drought year (water year 2015) and a typical year (water year 2016). Porter Canyon had ephemeral snow (28 days maximum duration) in 2015 and seasonal snow (116 days) in 2016 (Figure 2.5a). Big Creek
had seasonal snowpack both years, although much shallower snowpack in 2015 (Figure 2.5b). When seasonal winter snowpack is present at both sites in 2016, soil moisture follows the phases outlined by McNamara et al. (2005) for a semi-arid, snowmelt driven environment. Shallow and deep soil moisture was in a low-flux state during December-February (DJF) at Big Creek in 2016 (Figure 2.5f). During March-May (MAM), soil moisture increased substantially and was in a high-flux state. Average shallow soil moisture was similar in the MAM period (24.4% and 24.8%, respectively) and DJF period (11.3% and 19.8%) between 2015 and 2016, suggesting that snow storage and melt negates differences in early season soil moisture between years with very different winter precipitation. Porter Canyon also showed a similar soil moisture increase in the MAM period after a stable low-flux pattern in the DJF period during water year 2016 when it had seasonal snow. Both sites also reach their near maximum annual soil moisture coincident with snow (Harpold and Molotch, 2015) in 2016, but Porter Canyon has snow disappearance in both years that preceded peak soil moisture by several months. The deeper 50 cm soil moisture had a smaller and shorter peak during 2015 at Porter Canyon as compared to 2016 and Big Creek response.

In addition to comparing soil moisture responses for two sites, we also analyzed 328 site years (50 ephemeral and 278 seasonal site years) from all SNOTEL and SCAN sites in the Great Basin (Figure 2.1) over water year 2014, 2015, and 2016 in order to illustrate the broader patterns of soil moisture between ephemeral and seasonal snow melt. We found that soil moisture peaked on average 5 and 7 days prior to snow disappearance for shallow and deep soil moisture, respectively. This confirms previous findings that seasonal snow melt drives coincident wetting and deeper water percolation (Harpold and Molotch, 2015; McNamara et al., 2005). In contrast, the median difference between peak soil moisture and snow disappearan-
Figure 2.5: (a,b) Snow depth, (c,d) Snow Water Equivalent and (e,f) Soil Moisture measured at Porter Canyon and Big Creek Snow Telemetry (SNOTEL) stations for water years 2015-2016, which were a drought year and a typical year respectively.

ance from ephemeral snow melt was 79 and 48 days for shallow and deep soil moisture, respectively (Figure 2.6a). Shallow soil moisture in ephemeral snowmelt had a coefficient of variation (CV) of 0.2 compared to 0.4-0.5 for seasonal snowmelt (Figure 2.6). The lower CV for deep ephemeral snow compared to deep seasonal snow is consistent with a low water flux state for most of the year and reduced deep percolation to groundwater and streamflow.

The differences in soil moisture response between seasonal and ephemeral snow-packs across the Great Basin could have important consequences for vegetation
Figure 2.6: (a) The difference between date of peak soil moisture and last day of snow (Days) for shallow (5 cm) and deep (50 cm) soil moisture during water years 2014-2016 in Great Basin SNOTEL stations. (b) The coefficient of variation (CV) for shallow (5 cm) and deep (50 cm) soil moisture during water years 2014-2016 in Great Basin SNOTEL and SCAN stations.

Phenology and runoff generation. For example, the timing of soil moisture is a strong control on the timing and amount of net ecosystem productivity (Inouye, 2008), with earlier snowmelt causing an earlier and longer growing season with reduced carbon uptake (Hu et al., 2010; Winchell et al., 2016). Harpold (2016) also showed that earlier snow disappearance generally led to more days of soil moisture below wilting point at SNOTEL sites across the Western U.S. Our finding that soil moisture peaked earlier in ephemeral snow melt than seasonal snowmelt is thus likely to be correlated with reduced vegetation productivity and increase late season water stress in many areas. In addition to stressing local vegetation, ephemeral snowmelt may reduce groundwater recharge and streamflow. For example, baseflow contributions to streamflow and overall water yield declined when snowmelt rates were smaller (Barnhart et al., 2016; Earman et al., 2006; Trujillo and Molotch, 2014). Changes in percolation patterns also affect the distribution of more shallow rooting plants versus deeper rooting plants that need
long duration pulses to grow and reproduce (Schwinning and Sala, 2004). These consequences of ephemeral snow, as illustrated when compared to seasonal soil moisture response, provide a strong motivation to understand the distribution and causes of ephemeral snowpacks across the Great Basin.
2.5.2 Topographic Controls on Snow Seasonality

In a typical year, much the Great Basin experiences ephemeral snow (Figure 2.7) that is neither observed with standard ground stations (Figure 2.1) nor quantified with standard metrics. Using MODIS imagery and an object-based approach, we employ two new metrics to estimate snow ephemerality with daily snow cover products: 1) The maximum consecutive snow duration and 2) The snow seasonality metric or SSM. The SSM describes both the consecutive snow season length and shoulder-season ephemerality. A SSM value $<1$ means an area experiences at least one ephemeral snow event. Maximum consecutive snow duration can be compared to the Sturm et al. (1995) 60-day threshold for ephemeral snow, but it is flexible enough to include a threshold of any day length. The average maximum consecutive snow duration in the Great Basin from MODIS data was 42.1 days (Figure 2.7). The average SSM was -0.4 in the Great Basin (Figure 2.7). We found the average maximum consecutive snow duration measured using SNODAS data was 62.9 days and the average snow seasonality metric (SSM) was -0.4 (Figure 2.7), which was very similar to those found with MODIS remote sensing. However, the SNODAS model over estimates snow duration and does not capture the elevation caused patterns (Figure 2.7). The results of both metrics and both snow datasets are consistent with how the Great Basin experiences mostly ephemeral snowpacks but contains areas of persistent seasonal snow (Figure 2.7).

While we can use remote sensing to map snow ephemerality, it is still an incomplete tool for understanding the mechanisms causing it. Therefore, we investigate elevation and aspect as proxies for snowpack mass and energy dynamics. Elevation is a primary control on near surface air temperature due to the lapse rate (Bishop et al., 2011; Greuell and Smeets, 2001; Nolin and Daly, 2006) and aspect (Nolin and
Figure 2.7: Average maximum consecutive snow duration (Maximum snow duration) and snow seasonality metric (SSM) for the Great Basin measured using moderate resolution imaging spectroradiometer (MODIS) and snow data assimilation system (SNODAS) data in the Great Basin, USA. MODIS data is from water years 2001-2015 and SNODAS data is from water years 2005-2014.

Daly, 2006). Prior research has found that there is a strong elevation dependence on snowmelt timing, runoff generation, snow water equivalent (SWE), and snow season length (Hunsaker et al., 2012; Jefferson, 2011; Jost et al., 2007; Molotch and Meromy, 2014). These elevation effects likely sum a variety of factors, including temperature controls on the rain-snow transition, longwave radiation in cloudy areas, and sensible heat flux. Aspect is often a secondary control on snow distributions because it influences incoming shortwave radiation (Jost et al., 2007; Pomeroy et al., 2003) and wind patterns (Knowles et al., 2015; Leathers et al., 2004; Winstal et al., 2013). Shortwave radiation is the primary driver of ablation via melt and
sublimation (Cline, 1997; Marks and Dozier, 1992).

Figure 2.8: Heatmaps of the relationship between elevation and average maximum consecutive snow duration at (a) all slopes,(b) north-facing slopes only, and (c) south facing slopes only in the Great Basin, USA. North facing was defined as Northness >0.25 and south facing was defined as Northness<-0.25. Average maximum snow duration data obtained from moderate-resolution imaging spectroradiometer (MODIS) data, elevation and northness from Shuttle Topography Mission data.

Splitting the Great Basin into low elevations (<1500 m), mid elevations (1500-2500 m), and high elevations (>2500 m) illustrated the dominant role that elevation has on snow cover duration (Figure 2.8). In our area normalized sample, 96.2% of low elevation area and 75.2% of medium elevation area (between 1500 and 2500 m) had a maximum consecutive snow duration of less than 60 days. Only 10.5% of high elevations had a maximum consecutive snow duration of less than 60 days on average (Figure 2.8). The results suggest that mid and low elevations of the Great Basin are more likely to be ephemerally-dominant. The heat maps illustrate that elevation alone is not a strong predictor of maximum consecutive snow cover days.

We use three smaller ecoregions that are focused on three mountain ranges (see Figure 2.2) to illustrate variability in elevation effects (Figure 2.9). There were very similar average maximum snow duration values in the Ruby Mountains (Figure 2.9a), eastern Sierra Nevada (Figure 2.9b), and western Wasatch/Uinta ecoregion (Figure 2.9c) (107, 100, and 95 days, respectively). However, the Ruby Mountains tended to have longer persisting snow than the Sierra Nevada and Wasatch/Uinta
ecoregions. The Sierra Nevada ecoregion was also poorly related to elevation above 2500 m, while the Wasatch were more poorly predicted by elevation below 2500 m (Figure 2.9). These differing relationships with elevation point to other factors effecting snow duration.

Figure 2.9: Heat maps of the relationship between elevation and average maximum snow duration for three seasonally-dominant ecoregions in the Great Basin: (a) The Ruby mountains, (b) the Sierra Nevada mountains, and (c) the Wasatch/Uinta mountains.

Aspect is also an important control on snow seasonality in the Great Basin, but its importance is limited to mid and high elevations. We find that there are shorter maximum snow durations in south-facing aspects at elevations >1500 m (Figure 2.10). At low elevations, the difference in average maximum snow duration between north and south facing slopes was 0.4 days, while for mid and high elevations, it was 2 and 5 days, respectively (Figure 2.10). This is consistent with aspect being a control for solar radiation, and how it changes the energetics of snowpacks that persist long enough to undergo mass changes. These deeper, high elevation snowpacks likely melt and sublimate in response to greater solar radiation and corresponding warmer temperature on south facing hillslope (Hinckley et al., 2014; Kormos et al., 2014). In contrast, lower elevation areas appear to have maximum snow duration caused by factors other than aspect. This is consistent
with the amplified importance of other energy fluxes and factors, like ground heat flux and the rain-snow transition, that are not captured with simple topographic relationships (Figure 2.8, 9 and 10).

Figure 2.10: Heatmaps of the relationship between aspect and average maximum consecutive snow duration at (a) low elevations (0-1500 m), (b) medium elevations (1500-2500 m) and (c) high elevations (2500 m+). Average maximum snow duration data obtained from moderate-resolution imaging spectroradiometer (MODIS) data, aspect from Shuttle Topography Mission data.
2.5.3  Proximate Mechanisms Controlling Snow Ephemerality

Deciphering the causes and climate sensitivity of ephemeral snowpacks is challenged by a lack of models and observations. However, we propose a three-mechanism classification scheme to help frame future research directions: 1) rain-snow transitions limit snow accumulation, 2) snowpack ablation from melt and sublimation, and 3) wind scour and redistribution. Probably the most explored and observed mechanism is the potential for rising rain-snow transition elevations to limit snow accumulation and duration (Bales et al., 2006; Klos et al., 2014; Knowles et al., 2006; Mote, 2006; Mote et al., 2005). Reduction in snow duration can also be caused by the melt of snowpack (Mote, 2006) and losses from sublimation (Harpold et al., 2012; Hood et al., 1999), however, much less is known about the role and distribution of these processes outside of the seasonal snowpack zone. Finally, wind scour can reduce snowpacks by redistributing it to other areas or by increasing sublimation via blowing wind (Knowles et al., 2015; Leathers et al., 2004).

We chose six years to evaluate the dominant mechanisms causing snowpack ephemerality using a new classification systems (Figure 2.3) based on SNODAS data that compared favorably to estimates from MODIS (Figure 2.7). In that six year period, the year with the lowest average winter temperature using GRID-MET estimates was 2013 at -0.9°C while the year with the highest average winter temperature was 2014 at 1.0°C (Abatzoglou, 2012) (Table 2.1). In water year 2013 and water year 2010, the two coldest years, seasonal snowpacks were dominant in most of the Great Basin and Western United States (Figure 2.11-12). Ephemeral snowpacks were caused primarily by rain-snow transitions, but melt made up a greater proportion in the colder 2010 year (Figure 2.12). In the coldest years, the rain-snow transition and melt caused ephemerality shift lower in elevation (Figure
In the warmest year (2014), seasonal snowpack was lowest in all Western US mountain ranges (Figure 2.11), including the Great Basin where ephemeral snowpacks increased in middle and higher elevations due to the rain-snow mechanism (Figure 2.11 and 12). Melt caused ephemerality also increased in the warm 2014, but ephemerality remained low above 2500 m in all years. Sublimation was only present as a limiting mechanism in 2010 and only for a small area (Figure 2.11). Blowing sublimation was not the dominant cause of snow ephemerality in the Great Basin for any year.

Table 2.1: Average winter temperature (°C) and average elevation (m) for both dominant mechanisms of snow ephemerality and seasonal snow from 2009-2014.

<table>
<thead>
<tr>
<th>Water Year</th>
<th>Average Winter Temp (deg C)</th>
<th>Mean Elev for Rain Snow Transition (m)</th>
<th>Mean Elev for Melt (m)</th>
<th>Mean Elev for Seasonal Snow (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2009</td>
<td>0.1</td>
<td>1806.3</td>
<td>1750.8</td>
<td>1728.4</td>
</tr>
<tr>
<td>2010</td>
<td>-0.6</td>
<td>1811.3</td>
<td>1747.1</td>
<td>1761.3</td>
</tr>
<tr>
<td>2011</td>
<td>-0.2</td>
<td>1803.7</td>
<td>1765.6</td>
<td>1699.6</td>
</tr>
<tr>
<td>2012</td>
<td>0.4</td>
<td>1803.7</td>
<td>1745.2</td>
<td>1709.8</td>
</tr>
<tr>
<td>2013</td>
<td>-0.9</td>
<td>1815.6</td>
<td>1709.8</td>
<td>1754.1</td>
</tr>
<tr>
<td>2014</td>
<td>1.0</td>
<td>1789.9</td>
<td>1748.9</td>
<td>1731.5</td>
</tr>
</tbody>
</table>

The mechanisms inferred from the SNODAS model have important implications for snow ephemerality in the Great Basin, but we lack confidence in the modeling of these shallow snowpacks. These limitations are present in all snowpack energy models because the models were developed for deeper snowpacks where terms like ground heat flux and albedo-depth relationships can be ignored (Cline, 1997; Harstveit, 1984; LaMontagne, 2009; Liang et al., 1994). In shallow snowpacks, these terms are more critical (Hawkins and Ellis, 2007; LaMontagne, 2009; Şensoy et al., 2006), and the lack of SWE means the internal energy state of the snowpack (i.e. cold content) is more easily varied by short term climate forcing (e.g. warm, sunny days) (Liston, 1995). Ephemeral snowpacks also exist at lower elevations with warmer soils and increased ground heat flux (LaMontagne, 2009). Uncer-
Figure 2.11: Dominant mechanisms for snow ephemerality from water years 2009-2014 in the Western United States. Data obtained from the snow data assimilation system (SNODAS) model. Areas with seasonal snow, no snow, and water bodies are also depicted. The Great Basin region is outlined in yellow.

tainty in the rain-snow transition principally arises from predicting climate forcing and in particular temperature. However, the underlying method and other ancillary data can also be important for the quality of precipitation phase prediction (Harpold et al., 2017). Further complicating rain-snow transition mechanisms is
Figure 2.12: Histograms of the relationship between elevation and the dominant mechanisms for snow ephemerality in the Great Basin from water years 2009-2014. Snow data obtained from the snow data assimilation system (SNODAS) model.

how rain can be stored in existing snowpacks or drained to the soil surface depending on the snowpack mass and energy states (Lundquist et al., 2008; Marks et al., 2001). Although SNODAS assimilates MODIS imagery into the model, it does not appear to capture the finer elevation patterns we found using the MOD10A product (Figure 2.7), which is consistent with challenges reported by other SNODAS verification efforts in complex terrain (Clow, 2010; Hedrick et al., 2015). The Great Basin shows tremendous sensitivity to snow ephemerality from topography and elevation (Figure 2.11-12) and thus, represents an area where improvements in the physically-based modeling of shallow snow and rain-snow transition elevations will be critical to predicting snow water resources under variable and changing climate.
2.6 Conclusions

Mapping, measuring, and modeling ephemeral snow is challenging with current techniques, but will be vital for understanding how water resources and vegetation will respond to a future climate regime. Ephemeral snowpacks do not have distinct accumulation and ablation periods, which means the timing of soil moisture input varies and has less impacts. Therefore, as snowpacks shift from seasonal to ephemeral, there are potential ecohydrological consequences such as changes to vegetation response, vegetation distribution, hydraulic conductivity, lateral flow, and solute transport.

Our work shows that while topography and climate variability have strong controls on the distribution of ephemeral snowpacks (Figure 2.8 and 11), they will not be sufficient for predicting snow ephemerality under extreme and changing climate. Instead, we will need physics-based models capable of capturing the three broad mechanisms identified by this study: 1) rain-snow transitions limit snow accumulation, 2) snowpack ablation from melt and sublimation, and 3) wind scour and redistribution. These classifications could help better identify local and regional sensitivity to increased snow ephemerality (Figure 2.11 and 12). This work has also highlighted major weaknesses in the observational infrastructure, data analysis and modeling techniques needed to support the growing importance of ephemeral snowpacks.
CHAPTER 3
THE SENSITIVITY OF SNOW EPHEMERALITY TO WARMING CLIMATE ACROSS AN ARID TO MONTANE VEGETATION GRADIENT

3.1 Abstract

Shifts from seasonal snowpacks that persist all winter to shorter, ephemeral snowpacks threaten to alter the timing and amount of melt water available to vegetation. The Great Basin, USA is an ideal system for studying snow ephemerality, as both seasonal and ephemeral snow are prevalent. We analyzed 2001-2015 Moderate-Resolution Imaging Spectroradiometer (MODIS) snow cover products using an object-based mapping approach and a Random Forest (RF) model to identify the sensitivity to increased ephemerality under warming scenarios in the Great Basin. Key factors explaining the duration of maximum continuous snowpack were average winter temperature, average winter precipitation and elevation, which suggests rain-snow transitions and ablation from melt are the primary causal mechanisms driving the transition from seasonal to ephemeral snow. We also identified three ecoregions where the shifts are especially pronounced. Our models predict that warming the average winter temperature by 2°C and 4°C, respectively, will cause a shift in 1.4% and 8.1% of the total snow-covered area in the Great Basin shifting from seasonal to ephemeral snow. Predicted snow ephemerality under a 4°C warming scenario was associated with the maximum snow ephemerality observed over the historical record. All forest classes showed some sensitivity to summer greenness as measured with the normalized difference vegetation index (NDVI) from maximum snow duration. Warming scenarios predict >4°C warming in the Great Basin by end of the 21st century would cause unprecedented snow
ephemerality and possibly decrease net primary productivity in semi-arid montane forests.

3.2 Introduction

Seasonal snowpacks are a reliable source of water storage for more than 60 million people in the Western United States (Service, 2004). Snowpacks also provide a strong control on the timing of surface water availability, as well as vegetation phenology and productivity (Jefferson, 2011; Parida and Buermann, 2014; Trujillo et al., 2012). The predominant focus of hydrological and snow observations have been in the seasonal snow zone where water storage is important for downstream communities. However, much of the snow covered Western U.S. does not have consistent seasonal snowpacks, and is instead characterized by ephemeral snowpacks that release water as melt and sublimation throughout the winter. Soil water availability is likely to be fundamentally different in ephemeral zones where water is released intermittently than in seasonal zones where water is released more evenly over a spring melt season (Harpold and Molotch, 2015; McNamara et al., 2005). Ephemeral snowpacks are important for large portions of semi-arid Western U.S. rangeland, woodlands, and forests (Anderson and Mills, 2016; Kormos et al., 2014). Expected warming temperatures are likely to increase snow ephemerality and reduce snow seasonality, but we have few predictions of how these important snowpack changes will impact water and ecological resources.

Several tools have been developed to classify snowpack but they have yet to be applied in the context of increased snow ephemerality under climate change. A widely accepted classification system divides snowpack into six categories based
on duration, depth, temperature, and grain size: Tundra, Taiga, Alpine, Maritime, Ephemeral, and Prairie (Sturm et al., 1995). In the system developed by Sturm et al. (1995), ephemeral snowpack is all snowpack that persists for less than 60 days. Characteristics of ephemeral snowpack include experiencing snow accumulation and snowmelt at the same time, sensitivity to ground heat fluxes, a shallow snow depth, and a high correlation between snow cover area (SCA) and snow water equivalent (SWE) (Liston and Elder, 2006; Sanecki et al., 2006; Schmucki et al., 2014; Zaitchik and Rodell, 2009). Those characteristics are difficult to model because ablation and accumulation can occur simultaneously and ground heat flux must be more accurately estimated (Pomeroy et al., 1998; Schmucki et al., 2014). As a consequence, most physics-based snow models exclude ephemeral snow (Kormos et al., 2014; Rittger et al., 2012; Sturm et al., 1995).

Remote sensing observations of snow cover offer a relatively underused opportunity for mapping ephemeral snowpacks. However, common snow remote sensing challenges, such as long periods of cloudiness, can be even more acute for mapping short-lived snow presence and absence. Moreover, it is common for remote sensing studies to define the snow-covered period as the difference between the first and last days of observed snow, which therefore assumes no ephemeral snow disappearance (Thompson and Lees, 2014). Another common method of defining the snow-covered period is through using snow persistence thresholds. For example, Gao et al. (2011) defined the beginning and end of the snow-covered period as the first and last observations containing >13 consecutive days of snow or clouds. However, there is no standard for what threshold to use and, given the intermittent nature of ephemeral snow, only daily observations can be used to map snow seasonality (Wang et al., 2014). New object-based approaches are improving our ability to map ephemeral snowpacks by creating multi-pixel
snow regions across both the spatial and temporal domains (Blaschke, 2010; Duro et al., 2013; Thompson and Lees, 2014). Yet, Thompson and Lees (2014) is the only study that applied these approaches to ephemeral snow, which means the study requires additional verification and novel applications. For example, no study has yielded needed insights into the distribution of ephemeral snow and its sensitivity to warming.

The consequences of increased snow ephemerality on vegetation and carbon-water cycles are currently not well understood. Shallow snowpacks give less insulation to the soil, which can lower soil temperature and respiration rates (Williams et al., 1998). Carbon uptake rates by vegetation are higher during later snowmelt (Winchell et al., 2016) and potentially greater when supplied by snow water versus rain water (Hu et al., 2010). Small-scale measurements of carbon fluxes are supported by decreases in remotely-sensed forest greenness in the summer following poor snowpack years (Parida and Buermann, 2014; Trujillo et al., 2012). Despite the relationship between snow and forest productivity, the effects of increased snow ephemerality on forest productivity are generally unexplored.

In this paper, the Great Basin, USA is used as a case study for understanding the sensitivity of snowpack ephemerality to warming temperatures and the potential implications for vegetation species spanning arid to montane conditions. This region is ideal for a remote-sensing investigation of snowpack ephemerality because it relies on variable montane snow melt for its water supply, lacks ground observations to train physically-based models, and there is relatively little cloud cover. We use an object-based methodology to map ephemeral snow developed by Thompson and Lees (2014), a new snow seasonality metric, and a Random Forest (RF) model to answer three questions: 1) What topographic and climatic variables are
the most influential when predicting snow ephemerality?, 2) Will increases in the average winter temperature lead to a shift from seasonal to ephemeral snowpack?, and 3) What vegetation types are most at risk for extreme changes in ephemerality relative to their historic conditions? Our study is the first to quantify and project snow ephemerality as a function of climate warming, and to characterize the degree to which snowmelt regimes are likely to be altered for montane vegetation communities.

3.3 Study Area

The Great Basin is the hydrologic region draining between the Wasatch and southern mountain ranges in Utah and the eastern slope of the Sierra Nevada mountain range in California. The region is known for having internal drainage, which means that none of the waterways travel to the ocean (Svejcar, 2015). The climate is semi-arid and the ecosystem is shrub-dominated (Svejcar, 2015; West, 1983; Wigand et al., 1995). Due to climate change, communities in the Great Basin and other areas of the Western United States are expecting a temperature rise of 2-5°C and an increase in rain dominated extent of at least 53% (Chambers and Pellant, 2008; Klos et al., 2014). We defined the Great Basin region based on the Hydrologic Unit Code (HUC) Region 16 adapted from Seaber et al. (1987) by the United States Geological Survey (USGS) (Figure 3.1).
3.4 Methods

We used 2010 MODIS/Terra Snow Cover Daily L3 Global 500 m Grid (MOD10A) gridded data and a Normalized Difference Snow Index (NDSI) with parameters outlined in Hall et al. (2006) to find fractional snow covered data. The equation for calculating NDSI in MOD10A is:
\[ NDSI = \frac{\text{Band4} - \text{Band6}}{\text{Band4} + \text{Band6}} \] 

Each pixel was then mapped as containing fractional snow based on the NDSI value and the % reflectance value in Band 2. If the % reflectance is less than 10\%, the pixel was not mapped as containing snow regardless of the NDSI value (Hall et al., 2001). We made a snow duration algorithm in Google Earth Engine to categorize each MOD10 pixel. Google Earth Engine is a cloud-based computing platform optimized for mapping large datasets. We classified all pixels with a snow fraction of 30-100\% as Snow, pixels with snow fractions between \( \leq 30\% \) as No Snow, and pixels that had all other values as Other.

For each day, we then used edge delineation and region growing to grow the boundaries of all areas containing snow. The methodology for this was derived from the Thompson and Lees (2014) edge delineation and region growing algorithm and adapted for Google Earth Engine. The temporal region-growing algorithm reclassified pixels that were classified as Other to Snow if the corresponding pixels in the previous image were classified as Snow. It also reclassified pixels that were classified as Other to No Snow if the corresponding pixels in the previous image were No Snow. Additionally, if no data was found for a pixel, the algorithm used the value for the previous day.

To determine the number of ephemeral and seasonal snow events, we used a Google Earth Engine function to note the day of the Water Year when snow appeared (when a pixel went from classified as No Snow in the previous day to classified as Snow in the current day) and when snow disappeared (a pixel went from classified as Snow in the previous day to being classified as No Snow in the
current day), and determined the length of snow cover by subtracting the day of snow appearance from the day of snow disappearance. If the length of snow cover was <60 days, then the snow event was classified as ephemeral. Otherwise, if the length of snow cover was ≥60 days, the snow event was categorized as seasonal. This conformed to the 60 day snow threshold used in Sturm et al. (1995). Additionally, we discarded all instances where snow was absent for one day only from the overall record of snow disappearance and appearance because we found numerous artifacts from the MOD10A NDSI processing that lead to single day snow disappearance during long stretches of snow cover.

For each water year from 2001 to 2015, the number of ephemeral and seasonal events, we recorded the total number of days where snow was present and the average duration of a snow event. In addition to these metrics, we derived a snow seasonality metric (SSM) that was used to quantify a MODIS pixels tendency to have ephemeral or seasonal snow. This metric worked by classifying every day where there was seasonal snow present as positive one and every day where there was ephemeral snow present as negative one, and then averaging these -1 and +1 (Equation 3.2). This created a -1 to 1 scale, where -1 signifies that all the snow covered days in a given pixel within one water year were ephemeral and +1 signifies that they were all seasonal. If a pixel contained no seasonal or ephemeral events during the water year, that pixel was classified as No Snow.

\[
SSM = \frac{Days_{Seasonal} - Days_{Ephemeral}}{Days_{Total}}
\]  

\hspace{1cm} (3.2)

We obtained precipitation and temperature for each year, along with the 30 year normals for these parameters from GRIDMET data (Abatzoglou, 2012) and
we determined aspect and elevation for each MODIS pixel by using ArcGIS Spatial Analyst tools on a 30 m elevation model estimated from the Shuttle Topography Mission (Farr et al., 2007). We estimated northness using the equation:

\[ \text{Northness} = \cos \left( \frac{\text{aspect} \times \pi}{180} \right) \] (3.3)

We then re-scaled the aspect, and northness rasters to the same 500 m resolution as the MODIS imagery using bilinear sampling. Additionally, we averaged the values of the snow seasonality metric for each year in order to estimate the tendency of each MODIS pixel to contain a seasonal or an ephemeral snow event.

Random Forest (RF) modeling uses decision tree learning to build a robust predictive model, rank variable importance, and find and visualize bivariate interactions (Breiman, 2001). In this project, we used the three topographic variables (elevation, aspect, and northness) and three climatic variables (average winter precipitation, average winter temperature, and average net radiation) as predictors for our first RF model. For this analysis, winter was defined as between December 1st and March 31st. The climatic variables came from the Gridded Surface Meteorological Dataset (GRIDMET) (Abatzoglou, 2012). The response variable for this model was the average maximum consecutive snow duration in days. For our second RF model, we used the predicted maximum number of snow covered days from our first model as a seventh predictor variable in a second model. The response variable for this model was our snow seasonality metric (SSM). For both RF models, we used 0.6 as the fraction of number of observations to draw without replacement and 500 as the number of trees.

We created the RF models using a stratified random sample based on eleva-
tion. We used 500 m elevation bins, with the first bin containing elevations under 1500 m and the last bin containing elevations above 3000 m. To reduce substantial computational requirements, we sampled 5000 pixels per water year for each bin, which brought the total sample size to 75,000 pixels. We repeated the sampling process 10 times in order to check for consistency. Because they were nearly identical, we randomly chose one model out of the ten to be the final sampling protocol and used this final model to make predictions across the entire dataset.

After running the RF models with the historical climate data, we ran two additional sets of RF models in which we raised the average winter temperature by +2°C and +4°C respectively. The results of these models were then compared to the additional dataset to determine if each MOD10A pixel either remained ephemeral snow (SSM remained below -0.5), remained seasonal snow (SSM remained above 0.5), shifted from seasonal to ephemeral snow (SSM went from +0.5 to -0.5), shifted from ephemeral to seasonal snow (SSM went from -0.5 to +0.5), or varied inter-annually (stayed between -0.5 and 0.5). We also highlighted the Sierra Nevada, Wasatch/Uinta, and Ruby Mountains as regions of importance for a seasonal to ephemeral shift. We defined the Sierra Nevada and Wasatch/Uinta regions as all areas of the Great Basin with the US EPA L4 ecoregion classifications of Sierra Nevada and Wasatch Uinta respectively. We defined the Ruby Mountain region as the combination of Mid-Elevation Ruby Mountains and High Elevation Ruby Mountains in the US EPA L3 classification (Omernik, 1987) (Figure 3.7).

We selected 13 vegetation types using the Landfire gridded dataset (?) (Figure 3.2; Table 3.1) based on both their prevalence in the region and their importance in explaining the full elevational gradient of vegetation types. We then determined the maximum consecutive snow duration, the difference between the
average snow duration from the measured dataset and the average snow duration for each climate model and the percent change in extent from seasonal to ephemeral for each vegetation type. We used the 10th percentile as a baseline for the most ephemeral dominant each 500 m MODIS pixel has been across water years 2001-2015 both in terms of maximum consecutive snow duration and SSM. We could then compare the change in ephemerality from warming against the 10th percentile as a way to gauge the magnitude of change.

We calculated the annual maximum summer normalized difference vegetation index (NDVI) using the MODIS 16-Day L3 Global 500 m (MOD13A1) product from July 1st to September 30th. This is a common definition of summer in studies that analyze summer greenness (Winchell et al., 2016). We then used a multiple linear regression to determine what type of control winter maximum consecutive snow duration had on summer NDVI. In addition to maximum consecutive snow duration, the other predictor variables we used were total winter precipitation, average winter temperature, average radiation, and two interaction terms: Average winter temperature x maximum snow duration and total winter precipitation x average winter temperature. We ran a separate regression model for areas containing each of the 13 vegetation types we used. To evaluate what type of control maximum snow duration had on summer NDVI for each vegetation type, we used the standardized regression coefficient, which normalizes all regression coefficients so that they can be compared to one another. If maximum snow duration’s standardized regression coefficient had the largest absolute value, we categorized it as a primary control for the given vegetation type. Otherwise, we categorized it as a secondary control unless the greatest absolute value was winter temperature x maximum snow duration, which we then categorized as the interaction term having primary control. We also recorded the adjusted R² values for each linear model.
3.5 Results

Snowpack seasonality varied considerably in the Great Basin over the period of 2001-2015. On average the basin was dominated by ephemeral snow. Approximately 77.6% of the basin had a maximum consecutive snow duration that was less than 60 days and about 54.6% of the basin had a snow seasonality metric (SSM) of less than -0.5. Conversely, about 8.8% of the basin had a SSM of greater than 0.5, or was more likely to experience seasonal snowpack than ephemeral snowpack (Figure 3.3). The rest of the basin, about 37%, varied between ephemeral and seasonal depending on the year (Figure 3.3). Ephemeral snow was more prevalent in the low elevations of Central Nevada and Utah while seasonal snow was greatest in the Sierra, Ruby, and Wasatch/Uinta mountain ranges (Figures 2.1 and 2.3). Overall, ephemeral snowpacks were greatest in the low elevations and southern portions of
the study range (Figure 3.3). The proportions of ephemeral snow varied depending on the year with drier years having greater ephemeral snow extents than wet years (Figure 3.4).

![Figure 3.3: Maximum consecutive snow durations (left) and snow seasonality metrics (SSM) (right) in the Great Basin from water years 2001-2015. The 60 day threshold for maximum consecutive snow duration is adapted from Sturm et al. (1995). Seasonal Snow is average Maximum Consecutive Snow Duration ≥60 Days and Ephemeral Snow is average Maximum Consecutive Snow Duration <60 Days. Always Seasonal is average SSM >0.5, Always Ephemeral is average SSM <0.5 and Varies Interannually is -0.5 < average SSM < 0.5. No Snow is SSM=0 for all years.](image)

The RF models were able to effectively predict the historical snow ephemerality. The Root Mean Square Error (RMSE) for the maximum consecutive snow duration was 16.0 days and the RMSE for the snow seasonality metric (SSM) was 0.41. The performance (RMSE) was similar across vegetation types and varied between -4 and 15 days in maximum consecutive snow duration. The largest errors were with Lodgepole Pine (average 15 days) and Engelmann Spruce (average 9 days) (Appendix). These results give us confidence in applying the RF model to understand the effects of warming on snow ephemerality.

The RF model showed that winter temperature and precipitation were the most important climatic variables for predicting maximum consecutive snow duration, while elevation was an important topographical variable. Winter temperature was five times more important than winter precipitation in predicting maximum con-
Figure 3.4: Maximum consecutive snow durations (top) and snow seasonality metrics (SSM) (bottom) in the Great Basin in a wet year (2008), and a dry year (2015). The 60 day threshold in (a) is adapted from Sturm et al. (1995). Seasonal Snow is Maximum Consecutive Snow Duration $>$ 60 Days and SSM $>$ 0. Ephemeral Snow is Maximum Consecutive Snow Duration $\leq$ 60 Days and SSM $<$ 0. No Snow is SSM=0.

The predicted maximum consecutive snow duration with the RF model (Figure 3.5). For the RF model that predicted the snow seasonality metric (SSM), the most important variable was the predicted maximum consecutive snow duration. Both RF models had the same order of importance for the six climatic and topographic variables.

The 2 and 4°C warming experiments using our RF models caused shifts from seasonal to ephemeral snowpacks and an increase in overall ephemerality. Nearly 1.5% of the Great Basin shifted from seasonal to ephemeral with an increase of 2°C in winter temperature. With an increase of 4°C in average winter temperature, 8.1% of the Great Basin shifted from seasonal to ephemeral, which caused the extent of seasonal snow to decline to less than 0.1%. In the Sierra Nevada moun-
Figure 3.5: (a) Influence of topographic and climactic variables on the maximum consecutive snow duration and (b) snow seasonality metric (SSM) as calculated by a Random Forest (RF) model. The index of overall importance is a normalized estimate of variable importance based on the importance estimate described in Breiman (2001).

tains (Figure 3.1), 22% of the extent shifted from seasonal to ephemeral with the 2°C model and 38% shifted with the 4°C model. In the Wasatch-Uinta mountains, 6% of the extent shifted from seasonal to ephemeral with the 2°C model and 43% shifted with the 4°C model. In the Ruby Mountains, 10% of the extent shifted from seasonal to ephemeral with the 2°C model and 42% shifted with the 4°C model.

Snow duration and SSM varied substantially among the different vegetation types but the distribution was uneven across elevations. Saltbush-Greasewood, Sagebrush, and Blackbrush (average elevations 1583-1833m) have historical average maximum snow durations of under 30 days and their median SSMs were below -0.5. White Fir, Juniper Pinyon Woodland, Gambel Oak, Jeffrey/Ponderosa Pine, Interior Douglas-Fir and Mountain Sagebrush (average elevations 1950-2299m) had average maximum snow durations between 30 and 90 days, and their median SSMs was between -0.5 and 0.5. Red Fir, Aspen, Engelmann Spruce, and Lodgepole Pine (average elevations 2451-2772,) had historical average maximum snow durations above 120 days and their median SSMs were above 0.5 (Figure 3.7; Table 3.1). Given that information, we classified the first group of vegetation (histori-
Figure 3.6: Where the snow seasonality is Always Ephemeral (SSM < -0.5), Always Seasonal (SSM > 0.5), shifted from seasonal to ephemeral (SSM_{Observed} > 0.5 & SSM_{Modeled} < -0.5), or varied interannually (-0.5 < SSM < 0.5) for the RF model that increased average winter temperature by 2°C (left) and 4°C (right). Pie charts represent the proportions of each category and are rounded to the nearest 1%. Snow that shifted from ephemeral to seasonal was >0.1% for both models.

Figure 3.7: The historical average maximum consecutive snow durations (top) and snow seasonality metrics (bottom) for Great Basin vegetation types. Error bars on the top graph represent the standard deviation (Days).

Model predictions caused most montane vegetation types to experience shorter maximum consecutive snow durations and more snow ephemerality than found
Table 3.1: Vegetation types (Landfire), their average elevations, total area extents, average maximum consecutive snow durations, average snow seasonality metrics (SSM), and average maximum summer NDVI across the Great Basin, USA from water years 2001-2015.

<table>
<thead>
<tr>
<th>Common Name</th>
<th>Latin Name</th>
<th>Average Elevation (m)</th>
<th>Area (km²)</th>
<th>Average Maximum Snow Duration (Days)</th>
<th>Average SSM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Saltbush-Greasewood</td>
<td><em>Atriplex sp.</em> &amp; <em>Sarcobatus vermiculatus</em></td>
<td>1583.2</td>
<td>339820.2</td>
<td>26.1</td>
<td>-0.7</td>
</tr>
<tr>
<td>Sagebrush</td>
<td><em>Artemisia tridentata tridentata</em> &amp; <em>A. tridentata wyomingensis</em></td>
<td>1796.9</td>
<td>485971.2</td>
<td>39</td>
<td>-0.5</td>
</tr>
<tr>
<td>Blackbrush</td>
<td><em>Coleogyne ramosissima</em></td>
<td>1832.9</td>
<td>74852.1</td>
<td>9.4</td>
<td>-0.6</td>
</tr>
<tr>
<td>White Fir</td>
<td><em>Abies concolor</em></td>
<td>1950</td>
<td>12616.2</td>
<td>89.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Juniper Pinyon Woodland</td>
<td><em>Juniperus osteosperma</em> &amp; <em>Pinus edulis</em></td>
<td>2003.8</td>
<td>206244.9</td>
<td>46.9</td>
<td>-0.4</td>
</tr>
<tr>
<td>Gambel Oak</td>
<td><em>Quercus gambelii</em></td>
<td>2006</td>
<td>11571.3</td>
<td>83.5</td>
<td>-0.2</td>
</tr>
<tr>
<td>Jeffrey/ Ponderosa Pine</td>
<td><em>Pinus jeffreyi</em> &amp; <em>Pinus Ponderosa</em></td>
<td>2062</td>
<td>7133.4</td>
<td>60.9</td>
<td>-0.2</td>
</tr>
<tr>
<td>Interior Douglas-Fir</td>
<td><em>Pseudotsuga menziesii</em> var. glauca*</td>
<td>2190.4</td>
<td>2609.1</td>
<td>101</td>
<td>0.2</td>
</tr>
<tr>
<td>Mountain Sagebrush</td>
<td><em>A. tridentata vaseyana</em></td>
<td>2298.7</td>
<td>70667.1</td>
<td>81.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Red Fir</td>
<td><em>Abies magnifica</em></td>
<td>2450.9</td>
<td>4995.9</td>
<td>124.5</td>
<td>0.5</td>
</tr>
<tr>
<td>Aspen</td>
<td><em>Populus tremuloides</em></td>
<td>2522.9</td>
<td>45166.5</td>
<td>120.8</td>
<td>0.5</td>
</tr>
<tr>
<td>Engelmann Spruce</td>
<td><em>Picea engelmannii</em></td>
<td>2727.8</td>
<td>6715.8</td>
<td>146.6</td>
<td>0.5</td>
</tr>
<tr>
<td>Lodgepole Pine</td>
<td><em>Pinus contorta</em></td>
<td>2771.7</td>
<td>2646.9</td>
<td>142.6</td>
<td>0.6</td>
</tr>
</tbody>
</table>

in the historical record. The changes in maximum consecutive snow duration and average median SSM did not exceed the 10th percentile threshold for Predominantly Ephemeral vegetation for the 2°C warming. No change in average maximum consecutive snow duration exceeded the historic 10th percentile threshold for the 2°C warming. Under the 4°C warming scenario, all vegetation types exceeded the maximum consecutive snow duration threshold, while only Juniper Pinyon Woodland did not exceed the SSM threshold. Only Red Fir had an aver-
Table 3.2: The minimum and maximum change in average maximum consecutive snow duration (MCSD) and median snow seasonality metric (SSM) with Random Forest models increasing average winter temperature by 2 and 4°C for each vegetation category based on historical seasonality (in parenthesis).

<table>
<thead>
<tr>
<th>Vegetation Category</th>
<th>Change in Avg. MCSD (Days) with 2°C warming</th>
<th>Change in Avg. MCSD (Days) with 4°C warming</th>
<th>Change in Median SSM with 2°C warming</th>
<th>Change in Median SSM with 4°C warming</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predominantly Ephemeral</td>
<td>(2.2,-10.4)</td>
<td>(5.5,-22.2)</td>
<td>(-0.17,-0.32)</td>
<td>(-0.25,-0.36)</td>
</tr>
<tr>
<td>Variable Seasonality</td>
<td>(-17.6,-39.1)</td>
<td>(-30.7,-79.7)</td>
<td>(-0.28,-0.79)</td>
<td>(-0.51,-1.28)</td>
</tr>
<tr>
<td>Predominantly Seasonal</td>
<td>(-52.3,-83.4)</td>
<td>(-102.6,-123.4)</td>
<td>(-0.08,-1.33)</td>
<td>(-1.41,-1.71)</td>
</tr>
</tbody>
</table>

Average change in maximum consecutive snow duration and a median SSM that exceeded the 10th percentile for the 2°C warming. Conversely, all vegetation types had changes in maximum consecutive snow duration and SSM that exceeded the threshold for a 4°C warming. Red Fir was the most sensitive to 2°C warming across all vegetation classes (Figure 3.8; Table 3.2).

Figure 3.8: Changes in the historical average maximum consecutive snow durations and snow seasonality metrics for Great Basin vegetation types based on warming the average winter temperature by 2 and 4°C respectively. Red lines denote each of the vegetation categories based on historical seasonality.
In addition to changes in maximum consecutive snow duration and seasonality, there were also variable changes to the extent of ephemeral snow. Red Fir had seasonal-ephemeral shifts of 41% and 56% for the 2°C and 4°C models respectively. The large shifts in extent for this vegetation type are due to its historically seasonal snow extent in the Sierra Nevada mountains, which experienced a large shift in extent from seasonal to ephemeral under warming. The two Sierra Nevada conifer vegetation types that occupy lower average elevations—White Fir, and Jeffrey/Ponderosa Pine—had more modest seasonal-ephemeral shifts (between 8 and 10% for the 2°C model and between 10 and 18% for the 4°C model). Gambel Oak, Interior Douglas-Fir, and Mountain Sagebrush, which are mid-elevation vegetation types that can be found throughout the Great Basin, also had lower seasonal-ephemeral shifts (between 4% and 5% for the 2°C model and between 8% and 13% for the 4°C model) than the mid-elevation vegetation types that are exclusive to the Sierra Nevada. However, the mid-elevation forests and woodlands had larger seasonal-ephemeral shifts compared to the low-elevation shrubs and Pinyon-Juniper Woodland (less than 1% for all vegetation types and both models). The highest elevation montane vegetation species, Aspen, Engelmann Spruce, and Lodgepole Pine, had seasonal-ephemeral shifts for the 2°C model below 10% and above 29% for the 4°C model (Figure 3.9). High elevation vegetation was the most sensitive to snow ephemerality, especially with the 4°C increase.

To evaluate the influence of maximum snow duration on average summer NDVI, we used multiple linear regression and standardized (beta) regression coefficients to rank the influence of average winter temperature, average radiation, total winter precipitation and snow duration. The regression models also incorporated temperature x precipitation and snow duration x temperature as interaction terms. For two vegetation types—Blackbrush and Engelmann Spruce—maximum snow dura-
Figure 3.9: Percent of extent for Great Basin vegetation types that shifted from Seasonal snow (SSM > 0.5) to Ephemeral snow (SSM < -0.5).

...ition was the primary control on summer NDVI. However the variance explained was low. For an additional three types—Juniper Pinyon Woodland, Aspen, and Lodgepole Pine—the interaction between maximum snow duration and average winter temperature was the primary control. The majority of sites had maximum snow duration as a secondary control. At these sites, either total winter precipitation or total winter precipitation x temperature was the primary control. Overall these results suggest widespread and consistent sensitivity to decreased peak summer vegetation greenness from increased snow ephemerality for a substantial number of Great Basin vegetation types.
Figure 3.10: NDVI (Normalized Difference Vegetation Index) multiple linear regression model results for each vegetation type. "Primary" refers to maximum snow duration having a primary control on summer NDVI, "Secondary" refers to it having a secondary control, and "Interaction" refers to when the interaction between maximum snow duration and temperature was the primary control.
3.6 Discussion

The Great Basin represents a unique region to study the effects of increased snow ephemerality on vegetation response because the proportion of seasonal and ephemeral snowpacks is strongly sensitive to climate and topography. On average, ephemeral snow characterizes about 55% of Great Basin snowpack and seasonal snow makes up about 9%, with seasonally dominant snow being more common in high elevation mountain ranges. Seasonal snowmelt releases water in fundamentally different ways compared to ephemeral snow. Ephemeral snowmelt is more episodic, less intense, and earlier (Grant et al., 2004; Seyfried et al., 2009). Based on both remote and field observations, we expect increased snow ephemerality to alter vegetation phenology (Parida and Buermann, 2014; Trujillo et al., 2012). Smaller snowpacks and earlier water inputs generally lead to greater soil water stress at the end of the growing season and both shifts in the timing and amount of estimated forest productivity (Harpold, 2016; Trujillo et al., 2012; Winchell et al., 2016). Our research into how snow ephemerality responds to warming in the Great Basin is the first to explicitly show the potential role of increased snow ephemerality from regional warming on water availability for diverse montane vegetation.

Investigations into the sensitivity of snow ephemerality to environmental and climatic conditions are rare. This is because there are few field observations in ephemerally dominant snowpack and current physical models tend to underperform for predicting ephemerality. (Kelleners et al., 2010; Kormos et al., 2014) Statistical approaches enable researchers to take advantage of the richness of remote sensing and gridded climate data and avoid the inherent challenges of physical modeling for shallow snowpacks, like the increased importance of ground heat flux and rapidly changing cold content. Although statistical models like RF lack a
direct physical interpretation, sensitivity to winter temperature suggests that the rain-snow transition and winter melt are the predominant mechanisms driving increased snow ephemerality. This is supported by the geographic extent of the changes (Figure 3.6), which are focused along the lower elevations of the larger mountain ranges. Many of these areas in the Wasatch and Sierra mountain ranges have been shown to have historical changes in snow-rain elevations (Knowles et al., 2006; Safeeq et al., 2016). However, we cannot rule out increased ablation of shallow snowpacks during warmer conditions from both melt and sublimation (Harpold et al., 2012) in possible future changes. Despite the challenges of interpreting complex statistical models, our results have highlighted a potential hierarchy of controls, which we can use to infer possible ecohydrological risks from increasing ephemerality. Future improvements to our statistical model approach will involve adding eastness along with northness as a variable, and removing elevation due to the incorporation of precipitation and temperature.

Our RF predictions to 2-4°C warming suggest that most montane conifer forest types are expected to have unprecedented snow ephemerality under reasonable warming scenarios for the Great Basin (Eyring et al., 2016). The most at-risk vegetation types in the Great Basin are Red Fir, Lodgepole Pine, and Engelmann Spruce, which had snow durations that were, on average, 65 and 118 days less than the historical extreme for the 2°C and 4°C models respectively. Although we cannot directly link our results back to forest productivity and carbon uptake, historical analysis has shown that NDVI is a strong proxy for this metric (Trujillo et al., 2012). Our step-wise regression results for the lower elevation vegetation types (Figure 3.10) were consistent with previous investigations showing the importance of precipitation over temperature in controlling NDVI response in the Great Basin (Tang et al., 2015). However, that previous work did not include NDVI analysis in Great
Basin conifer forests. Our results show that peak summer NDVI is sensitive to snow duration at most vegetation types, but in complex ways that were difficult to disentangle with our statistical approach (Figure 3.10). Given that all lower vegetation types already experience widespread ephemerality, their adaptability to utilize ephemeral snow melt and weather long, dry growing seasons is likely high. Conversely, montane conifer forests experienced snow ephemerality that was well-beyond the extremes seen in the last 15 years, which includes one of the most severe droughts in the Sierra Nevada (Belmecheri et al., 2016). Consequently, there is more concern that these higher elevation montane forests will be forced to adapt to new water availability regimes, which generally lead to earlier and longer growing seasons and negative consequences for forest productivity such as increased late-season water stress (Bales et al., 2011; Harpold, 2016; Winchell et al., 2016). Although montane conifer forests cover a small area of the Great Basin (Table 3.1 and Figure 3.2), they remain ecologically important because they grow at high-elevations, and the asymmetrical response to climate change by vegetation type makes them difficult to replace Beniston (2003).

Even within vegetation types, we expect snow ephemerality will be uneven based on local climate and physiological conditions. Elevation was a primary control on snow ephemerality (Figure 3.5), which suggests that lower elevation ranges of these vegetation types might be more at risk. Moreover, more local topographic effects like slope also affected snow ephemerality, which may lead to localized effects on vegetation based on those factors.

Because increased snow ephemerality is expected to cause earlier and more episodic water inputs, we suspect that these changes will most impact places with low soil storage and/or shallow rooting depths because these areas cannot store
snow melt water effectively to buffer late summer water stress (Bales et al., 2011; Harpold, 2016). The ability of vegetation to use early snow melt water inputs to maintain productivity is an area of active research (Scott-Denton et al., 2013; Winchell et al., 2016), however earlier water inputs are consistently associated with a greater duration of soil moisture below wilting point water content Harpold (2016). The implications of the seasonal to ephemeral shift for vegetation will require sophisticated models that can account for two main challenges: 1) issues associated with modeling the cold content and ground heat flux to shallow snowpacks and 2) ecophysiological parameters on rooting depth and water use strategies. New work has suggested that uncertainty of ecophysiological parameters in mountain conifers was sufficient to alter biomass accumulation and even water losses that form streamflow (Garcia et al., 2016).

Our results may show that widespread sensitivity of Great Basin snow to increased ephemerality will have negative impacts on vegetation. This justifies both more field and remote observations, and improved process-based modeling approaches. Statistically based approaches would benefit from daily data at a finer spatial resolution than MODIS because increasing the spatial resolution would reduce uncertainty related to topographical variation. For example, we had difficulty accurately validating our snow cover duration results at 500 m scales to snow pillows that are 3m in width (Appendix). Fractional snow cover estimates could be more accurate with improved mixing models (MODSCAG) has shown improved accuracy over NDSI approaches, although this would not solve the issue of having to assign an arbitrary threshold to define snow disappearance (Nolin, 2010; Painter et al., 2009). Improving physically-based modeling approaches must go in concert with increased snow measurement instrumentation at lower elevations and ephemeral snowpacks. Currently, only soil climate analysis network
(SCAN) has any significant instrumentation in ephemeral snow (Figure 2.1). Ultimately, building physics-based predictive models will require a renewed commitment by snow hydrologists. Our results suggest that this will be a needed effort as ephemeral snowpacks become more typical in places we have long relied on for seasonal snowmelt. Models that accurately capture vegetation response to increased snow ephemerality are also needed. Overall, we lack both observations and process-based modeling techniques to thoroughly quantify snow ephemerality and the vegetation response to its increase.

3.7 Conclusions

The snowpack of Great Basin will become more ephemeral under reasonable scenarios of future warming. As a result, high elevation conifer forests will experience unprecedented snow conditions and potentially experience water stress. The outsized importance of average winter temperature in predicting snow ephemerality is consistent with snow-rain transitions and winter melt being the primary drivers of ephemeral snowpack in this region. We have shown that high elevation snowpack in montane conifer forests is the most sensitive to warming, which means the negative effects of earlier and inconsistent water inputs and greater water stress during the growing season might be disproportionately focused in ecologically critical areas. Future work is needed that uses a finer spatial scale to monitor snowpacks, incorporates additional ground-based observations of ephemeral snow, captures vegetation response to increased snow ephemerality, and improves the physically based snow models that are currently in operation but known to be unreliable in ephemeral conditions. While remote sensing can produce accurate ephemeral snow estimation in the Great Basin, replicating more cloudy areas with
mountain snowpack will be a challenge. Given our results suggesting that snow ephemerality will be very sensitive to warming in this region, we have demonstrated the necessity for a greater focus on its mechanisms, sensitivity, and implications for water availability for ecosystems.
CHAPTER 4

CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Mapping, measuring, and modeling ephemeral snow is challenging with current techniques, but will be vital for understanding how snowpacks and vegetation will respond to a future climate regime. Ephemeral snowpacks do not have distinct accumulation and ablation periods, which means they do not provide consistent soil moisture inputs during the spring (Figure 2.5). Therefore, as snowpacks shift from seasonal to ephemeral, there are potential ecohydrological consequences such as changes to vegetation response, vegetation distribution, hydraulic conductivity, lateral flow, and solute transport.

We found that winter temperature is the most influential variable on snow ephemerality followed by winter precipitation (Figure 3.5). This suggests that snow ephemerality will be especially sensitive to regional warming. Warming the average winter temperature by 2°C and 4°C caused 1.4% and 8.1%, of the total snow covered area in the Great Basin to shift from seasonal to ephemeral snow respectively (Figure 3.6). Elevation has a strong control on snow ephemerality in the Great Basin (Figure 2.7). Aspect becomes an important control at elevations above 2500 m with seasonal snow being more common on north-facing slopes compared to south-facing (Figure 2.9). The importance of elevation and winter temperature is underscored in how the two primary drivers of snowpack ephemerality are the rain-snow transition limiting snow accumulation and winter melt (Figure 2.10). Warmer winters lead to an upward shift in rain-snow transition and seasonal snow elevations, along with the rain-snow transition occupying a greater fraction of total Great Basin area compared to colder years (Figure 2.11).

The most sensitive snowpack in the Great Basin to seasonal-ephemeral shifts
under future warming scenarios is at high elevations containing montane conifer forests (Figures 2.8-2.9). This means the ecohydrologic implications of the seasonal-ephemeral shift such as inconsistent soil water inputs, increases in summer stress, and reductions in summer productivity, will be concentrated in the most ecologically critical parts of the Great Basin.

This work has also highlighted major weaknesses in the observational infrastructure, data analysis and modeling techniques to support the growing importance of ephemeral snowpacks. In light of the diverse needs, we have compiled a short summary of recommendations to improve snow ephemerality predictions:

- **Better and standard snow ephemerality metrics**: Our research suggests there is a snow duration threshold where snowpack and soil moisture patterns begin to resemble seasonal snow instead of ephemeral snowmelt, and perhaps a second threshold when they begin to resemble rain. Yet evidence that this threshold is the 60 days used in the Sturm et al. (1995) paper is lacking. Instead of using this arbitrary threshold, we recommend that future research use the snow properties and soil moisture response of ephemeral snowpacks combined with a sensitivity analysis to create a snow duration threshold capable of differentiating seasonal snow melt caused soil moisture responses (e.g. McNamara et al. 2005) from ephemeral effects and rain.

- **More snow and soil moisture observations in ephemeral areas**: In the Great Basin, only 2 snow telemetry (SNOTEL) stations and 26 soil climate analysis network (SCAN) stations are in ephemerally dominant snow (Figure 2.1). The lack of observations makes it more difficult to leverage the clear differences in SWE, snow depth, and shallow soil moisture between ephemeral and seasonal snow. To help develop better criteria for categorizing snowpack as ephemeral, we need
more snow and soil moisture observations in ephemeral areas. We can then also use the snow observations to verify results derived from remote sensing and snow models.

- **Improved remote sensing algorithms:** There is currently no consistent standard in remote sensing for defining the length of snow-covered periods. It is still common for papers to define the length of a snow-covered period by the first and last days with snow cover. This standard does not account for ephemeral events between those days. Additionally, there is no consistent algorithm for accounting for cloud cover. The consistency between our remotely sensed snow ephemeral-ity results and those measured by SNODAS suggests that using consecutive snow covered days to define the length of the each snow event is a better technique (Figure 2.6). More widespread use of that technique will allow us to evaluate its accuracy across multiple regions. Having satellites that both have the daily temporal resolution of MODIS and the 30 m spatial resolution of Landsat would be helpful in this endeavor.

- **Improved spatial resolution and fidelity of snow and climate data:** Moderate resolution imaging spectroradiometer (MODIS) data has a spatial resolution of 500 m. The coarse resolution made it difficult to verify our ephemeral snow results with SNOTEL observations that use 3 m pillows (Appendix). Additionally, we have demonstrated in this paper that the areas most affected by a predicted seasonal-ephemeral shift under future warming are in montane areas with topographically complex terrain (Figures 2.1, 2.6, 2.8-2.9). Topographic complexity leads to variations in climate on much finer resolutions than the 4000 m gridded meteorology (GRIDMET) climate data used for this analysis. Gridded snow and climate data should have finer spatial resolution, akin to the 30 m spatial resolution
that Landsat has.

- **Improved physics-based modeling techniques**: Because of the limitations of physics-based snow models, we did not incorporate them into the predictive portion of our analysis. Instead, we used a statistics-based Random Forest (RF) model to predict snow ephemerality under warming scenarios. It is more challenging to draw definite conclusions about snowpack changes with a statistical model compared to a physics-based one. Improving physics-based models is therefore a high priority. In shallow snow, models must be more sensitive to ground heat flux transfers, and cold content should be more important. The time step must also be smaller (<1 day) so that it can account for rapid changes in snow cover.
APPENDIX A
SUPPLEMENTAL INFORMATION

Contents of this file: Figures A.1-A.3

Introduction:
The following figures provide additional information about the ephemeral snow algorithm and modeled Random Forest (RF) ephemeral snow results across vegetation types. Figure A.1 shows how the measured number of ephemeral and seasonal snow events at SNOTEL sites corresponded to the number derived from the ephemeral snow algorithm. Figure A.2 shows how the 30% snow fraction was chosen using a sensitivity analysis. Figure A.3 shows histograms of residuals of measured and RF modeled ephemeral snow for all vegetation species.

![Figure A.1: Root Mean Square Errors between the number of observed ephemeral and seasonal snow events at Snow Telemetry (SNOTEL) stations and the number of ephemeral and seasonal snow events derived from the algorithm in Google Earth Engine in each 500 m Moderate-resolution imaging spectroradiometer (MODIS) pixel corresponding to that station. Measured SWE (Snow Water Equivalent) of 0.2 in. or greater was used to determine snow presence for SNOTEL sites.](image-url)
Figure A.2: Box plots depicting the Root Mean Square Errors between the number of observed ephemeral and seasonal snow events at Snow Telemetry (SNOTEL) stations and the number of ephemeral and seasonal snow events derived from the algorithm in Google Earth Engine in each 500 m Moderate-resolution imaging spectroradiometer (MODIS) pixel corresponding to that station at snow fractions of 1-50%. 30% (outlined in red) was the chosen snow fraction.
Figure A.3: Histogram of the residuals between the maximum consecutive snow duration measured using the Google Earth Engine algorithm and the maximum consecutive snow duration from the Random Forest (RF) model for each vegetation type (Landfire).
BIBLIOGRAPHY


