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RESEARCH ARTICLE

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The sensitivity of snow ephemerality to warming climate across an arid to montane vegetation gradient

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Abstract

Shifts from longer seasonal snowpacks to shorter, ephemeral snowpacks (snowpacks that persist for <60 days) due to climate change will alter the timing and rates of water availability. Ephemeral snowmelt has less predictable timing and lowers soil water availability during the growing season. The Great Basin, United States is an ideal system to study snow ephemerality across a broad climate gradient. To identify the climatic controls on snow ephemerality, we analysed moderate resolution imaging spectroradiometer (MODIS) snow-covered products from water years 2001–2015 using an object-based mapping approach and a random forest model. Winter temperature and precipitation were the most influential variables on the maximum snow duration. We predict that warming the average winter air temperature by 2 and 4°C would reduce the areal extent of seasonal snow by 14.7 and 47.8%, respectively (8.8% of the Great Basin's areal extent is seasonal in the historical record), with shifts to ephemeral snowpack concentrated in lower elevations and warmer regions. The combination of warming and interannual precipitation variability (i.e., reductions of 25%) had different effects on vegetation types. Vegetation types that have had consistent seasonal snow cover in their historical record are likely to have lower resilience to a new hydrologic regime, with earlier and more intermittent snowmelt causing a longer but drier growing season. Implications of increased snow ephemerality on vegetation productivity and susceptibility to disturbance will depend on local topography, subsurface water storage, and physiological adaptations. Nevertheless, patterns found in this study can help target management intervention to species that are most at risk.

KEYWORDS

climate change, ephemeral snow, ecohydrology, great basin usa, remote sensing, snow hydrology

1 | INTRODUCTION

Seasonal snowpacks are 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 & Buermann, 2014; Trujillo, Molotch, Goulden, Kelly, & Bales, 2012). The predominant focus of hydrological and snow observations has been in the seasonal snow zone where water is stored for long periods of time before being released at predictable intervals to downstream ecosystems and communities. However, much of the snow-covered Western United States does not have consistent seasonal snowpacks and is instead characterized by ephemeral snowpacks that disappear and reappear by losing water to melt and sublimation throughout the winter. Warming temperatures are expected to increase snow ephemerality by shifting snow to rain (Hinckley et al., 2014; Klos, Link, & Abatzoglou, 2014) and increasing the energy available to ablate snowpacks (Harpold & Brooks, 2018).

Because snowmelt is the primary control on peak soil moisture timing in seasonal snow zones (Harpold & Molotch, 2015), increased ephemeral snowmelt and more winter rain will cause earlier and more sporadic water inputs (Petersky & Harpold, 2018). In turn, early snow disappearance, lower soil water storage, and increasing summer water demand result in more water stress for vegetation later in the growing season (Harpold, 2016). Ephemeral snowpacks are the dominant source of water inputs for a large geographic area of semiarid Western United States rangeland, woodlands, and forests (Anderson & Mills, 2016; Kormos et al., 2014), but their areal extent, sensitivity to climate change, and effects on vegetation are not well quantified.

Earlier water inputs from ephemeral snowmelt lengthen the potential growing season (Hu, Moore, Burns, & Monson, 2010) but causes trees to experience earlier and longer periods of climatic water deficit during the growing season (Harpold, 2016; Stephenson, 1990; Tague & Peng, 2013). Melt from seasonal snowpack is released slower and later than incoming precipitation, causing water inputs to be more coincident with incoming water demand that is driven primarily by increasing solar angles (day length) in the spring. Carbon uptake rates by conifer forests are highest on a per-day basis during snowmelt (Winchell, Barnard, Monson, Burns, & Molotch, 2016). Snow water also makes up an important portion of transpiration late in the growing season, months after snowmelt has ended (Hu et al., 2010). Therefore, as water inputs shift earlier in the year from earlier melt and winter rain, carbon uptake by montane forests early in the year may not offset reduced late season uptake (Knowles, Molotch, Trujillo, & Litvak, 2018). In addition to less net carbon uptake during earlier snow water inputs, carbon allocation at the tree scale has important controls for resisting forest disturbance like drought (Hart, Veblen, Eisenhart, Jarvis, & Kulakowski, 2014; Knowles, Lestak, & Molotch, 2017; Williams et al., 2013) and impacts net partitioning to transpiration (Garcia, Tague, & Choate, 2016). These differences in ecophysiological adaptations to earlier water inputs are likely to vary substantially based on species and traits, with conifer forests showing higher ability to utilize earlier water inputs (Kelly & Goulden, 2016).

The stressful effects of snowmelt-mediated changes in soil water availability on vegetation are likely to be magnified by increased summer temperatures and higher vapour pressure deficit. Numerous studies have found that the combination of low winter precipitation and hot summer droughts is correlated with widespread forest mortality events from drought, fire, and insects in the Western United States (e.g., Hart et al., 2014; Knowles et al., 2017; Westerling, Hidalgo, Cayan, & Swetnam, 2006; Williams et al., 2013). These climate-induced vegetation stressors are expected to alter semiarid vegetation distribution (Chambers & Pellant, 2008; Guardiola-Claramonte et al., 2011), by requiring upslope migration (Kelly & Goulden, 2008) or movement into areas of microrefugia (McLaughlin et al., 2017). The dual changes to water demand and water supply are likely to have uneven influences on forest species that depend on local traits and sensitivity to drought (Bréda, Huc, Granier, & Dreyer, 2006; Koepke, Kolb, & Adams, 2010). For example, the ability to use water inputs for photosynthesis during the early growing season must be balanced by water saving strategies during drier and warmer summers. Although tools for mapping vegetation productivity have shed some light on snow–forest relationships (Trujillo et al., 2012), a lack of tools for mapping snow ephemerality has limited our ability to identify montane ecosystems at risk for the greatest changes in water availability.

Several tools have been developed to classify snow cover, but our ability to quantify changes in snow ephemerality under climate change remains weak. A widely accepted classification system divides snowpack into six categories based on duration, depth, snow temperature, and grain size: Tundra, Taiga, Alpine, Maritime, Ephemeral, and Prairie (Sturm, Holmgren, & Liston, 1995). In the system developed by Sturm et al. (1995), ephemeral snowpacks persist for <60 days. There are several common characteristics of ephemeral snowpacks, including simultaneous snow accumulation and ablation, sensitivity to ground heat fluxes, low insulation properties, and a high correlation between snow-covered area and snow water equivalent (Liston & Elder, 2006; Sanecki, Green, Wood, & Lindenmayer, 2006; Schmucki, Marty, Fierz, & Lehning, 2014; Zaitchik & Rodell, 2009). Unfortunately, these characteristics are difficult to simulate with physically based models because ground heat flux becomes important and rapid changes in cold content are possible (Pomeroy et al., 1998; Schmucki et al., 2014). Consequently, most physics-based snow models either exclude or oversimplify ephemeral snow (Kormos et al., 2014; Rittger, Dozier, & Kahl, 2012; Sturm et al., 1995).

Remote sensing observations of snow cover offer an under-used resource for mapping and quantifying ephemeral snow. However, common snow remote sensing challenges become even more acute when mapping ephemeral snowpack dynamics. For example, week-long periods of cloudiness obscure the ability to resolve snowpacks that appear and disappear over that time period. Because of these limitations, it is common for remote sensing studies to define the snow-covered period as the first and last days of observed snow, which assumes no ephemeral snow disappearance (Thompson & Lees, 2014), which overestimates the duration of snow cover. Snow persistence is another common method of defining the snow-covered period that has gained recent acceptance (Wayand, Marsh, Shea, & Pomeroy, 2018). For example, Gao, Xie, and Yao (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. These observational challenges require high temporal frequency data be used to map snow ephemerality (Wang et al., 2014) and that tools be used to account for missing information. New object-based approaches are improving our ability to map ephemeral snowpacks by classifying snow responses and regions in both space and time (Blaschke, 2010; Duro, Franklin, & Dubé, 2013; Thompson & Lees, 2014). Yet, Petersky and Harpold (2018) and Thompson and Lees (2014) are the only studies that have applied these approaches to study ephemeral snow by using object-based approaches in the temporal domain. As a result, most common tools are designed for seasonal snowpacks (e.g. Hammond, Saavedra, & Kampf, 2018; Wayand et al., 2018) and are not capable of resolving relationships between snow ephemerality, climate, and topography.

In this study, we use the Great Basin, United States as a case study to explore the implications of climate warming for snow ephemerality and how these patterns in snow ephemerality overlay on an arid to montane vegetation gradient. The Great Basin is an ideal area for a remote-sensing investigation of snowpack ephemerality because it relies on winter precipitation and snowmelt, ephemeral snowpacks are common, and there is relatively little cloud cover. We use an object-based methodology to map ephemeral snow based on moderate resolution imaging spectroradiometer (MODIS) imagery to develop a new snow seasonality metric (SSM) and verify predictions from a random forest (RF) model based on climate and topography. We address three primary questions: (a) What topographic and climatic variables are the most influential when predicting snow ephemerality? (b) Where will increases in winter temperature lead to large shifts from seasonal to ephemeral snowpack? (c) What vegetation types are most at risk for unprecedented snow ephemerality relative to their historic conditions? Our study shows wide variability in warming-caused increases in snow ephemerality will increase the risk for vegetation types that have historically experienced seasonal snow.

2 | METHODS

2.1 | Study area

The Great Basin is an ~540,000-km^2 hydrologic region in the Western United States. The region is known for having "internal drainage," which means that none of the waterways travel to the ocean (Svejcar, 2015). The climate is semiarid, and the ecosystem is shrub dominated (Svejcar, 2015; West, 1983). 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 areal extent of at least 53% by the end of the century (Chambers & Pellant, 2008; Klos et al., 2014). We defined the Great Basin region based on the hydrologic unit code Region 16 adapted from (Seaber, Kapinos, & Knapp, 1987) defined by the United States Geological Survey (Figure 1).

2.2 | Ephemeral snow mapping and derivation of environmental variables

We used MODIS/Terra Snow Cover Daily L3 Global 500 m (MOD10A) gridded data and a Normalized Difference Snow Index with parameters outlined in Hall, Salomonson, and Riggs (2006) to find fractional snow-covered data. We then used an object-based approach in the spatial and temporal domain with an algorithm made in Google Earth Engine, which is described in the study Petersky and Harpold (2018) and adapted from Thompson and Lees (2014), to account for the effects of cloud cover and build a reliable daily estimate of snow cover. Using this method, we generate daily snow cover, the maximum consecutive duration for each snow-covered event, classify snow-covered events as seasonal or ephemeral, and create an SSM that was used to quantify a MODIS pixel's tendency to have ephemeral or seasonal snow (<60 or ≥ 60 days of consecutive snow cover):

$$SSM = \frac{Days_{Seasonal} - Days_{Ephemeral}}{Days_{Total}}. \quad (1)$$

The SSM classifies each day where seasonal snow is present as +1 and each day with ephemeral snow present as −1, and then averages these values to create 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. The SSM can distinguish between long snow-covered periods that have ephemeral shoulder seasons in the spring and fall (values near +1) from ephemeral snowpacks that never fully develop (values <−0.5) (Petersky & Harpold, 2018). Additionally, we averaged the values of the SSM for each year in order to estimate the tendency of each MODIS pixel to contain a seasonal or an ephemeral snow event.

We obtained winter precipitation, downward shortwave radiation, and temperature for each year during 2001–2015 from 4-km Gridded Surface Meteorological data (Abatzoglou, 2012). 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 and eastness using the following equations:

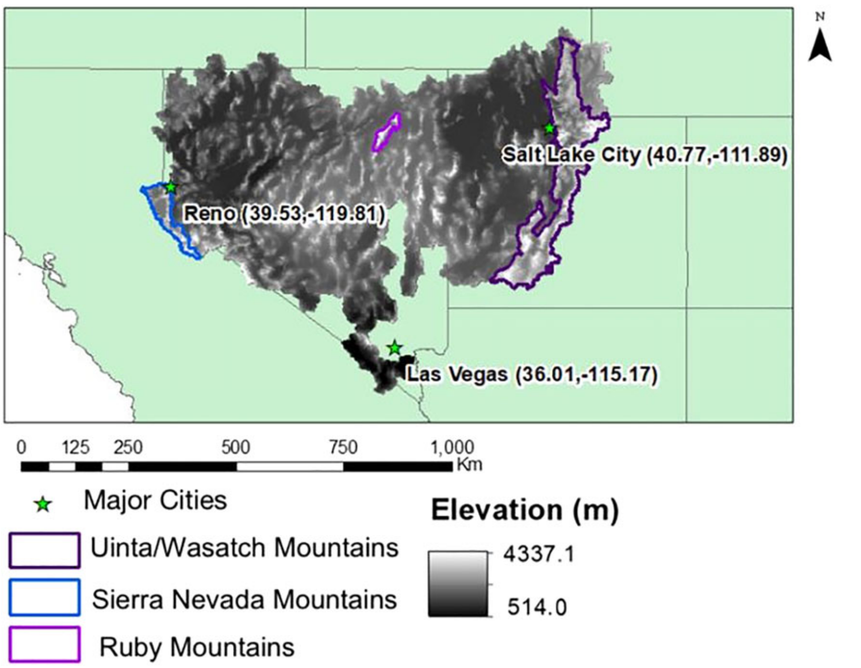

FIGURE 1 Map of the Great Basin region, United States as defined by the United States Geological Survey hydrologic unit code Region 16 along with major cities and mountain ranges. The Sierra Nevada, Ruby, and Wasatch/Uinta mountain ranges are highlighted

$$Northness = \cos\left(\frac{aspect^*\pi}{180}\right), \quad (2)$$

$$Eastness = \sin\left(\frac{aspect^*\pi}{180}\right). \quad (3)$$

We then rescaled the aspect, eastness and northness rasters to the same 500-m resolution as the MODIS imagery using bilinear sampling.

2.3 | Random forest modelling

RF modelling uses decision tree learning to build a robust predictive model, rank variable importance, and find and visualize bivariate interactions (Breiman, 2001). The model also provides an importance estimate for each predictor variable. In this project, we used the two topographic variables (eastness and northness) and three climatic variables (average winter precipitation, average winter temperature, and average winter downward shortwave radiation) from Abatzoglou (2012) as predictors for our RF model. For this analysis, "winter" was defined as December 1 to April 1. The response variable for this model was the average maximum consecutive snow duration in days. 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 elevation. We used 500-m elevation bins, with the first bin containing elevations under 1,500 m and the last bin containing elevations above 3,000 m. To reduce substantial computational requirements, 5,000 samples per year were randomly sampled across five 500-m elevation strata, for a total of 75,000 samples (4% of study area). We repeated the sampling process 10 times in order to check for consistency. Because there were no statistical differences, we randomly chose one model out of the 10 to be the final sampling protocol and used this final model to make predictions across the entire dataset.

2.4 | RF model performance, validation, and prediction

The RF model was validated using root mean square error (RMSE) to compare predictions with observed data. We also calculated RMSE on an independent sample not used to build the model. We used a Nash Sutcliffe efficiency (NSE; Nash & Sutcliffe, 1970) to determine the effectiveness of the RF model's fit compared with the mean of the observed data.

We then ran four additional sets of RF models. Two of those models raised the average winter temperature by +2 and + 4°C while using average precipitation. Two of the models raised temperature by +2 and + 4°C and also reduced average winter precipitation by 25%. We chose these temperature thresholds because they fall within the predicted temperature increases in the Great Basin by the end of the 21st century (Chambers & Pellant, 2008) and because the 2°C is the minimum temperature increase outlined in the 2015 Paris agreement (Klos et al., 2014; Rhodes, 2016). We chose to reduce the precipitation by 25% because it is comparable with the coefficient of variation, a representation of interannual variability, for average winter precipitation from 2001 to 2015 of 0.32 over the study domain. The results of these models were compared with the original data set to determine if each MOD10A pixel 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 interannually (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 U.S. Environmental Protection Agency 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 U.S. Environmental Protection Agency L3 classification (Omernik, 1987; Figure 6).

2.5 | Vegetation data sets

We selected 14 vegetation types from the LANDFIRE gridded data set (Figure A.3; Table A.1) based on both their prevalence in the region and to capture the range of vegetation types across elevation. We then determined the percent change in extent from seasonal to ephemeral snow for each vegetation type. We used the 10th percentile of maximum consecutive snow duration and SSM from 2001 to 2015, which included the 2015 record drought year in most of the Great Basin, as the baseline for identifying unprecedented snow ephemerality in each 500-m pixel under 2 and 4°C warming and drying scenarios.

3 | 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 SSM of less than −0.5 (i.e., always ephemeral). Conversely, about 8.8% of the basin had an SSM of greater than 0.5 or was always seasonal (Figure 3). The rest of the basin, about 37%, varied between ephemeral and seasonal depending on the year (Figure 3). As shown by Petersky and Harpold (2018), ephemeral snow was more prevalent in the low elevations of Central Nevada and Utah whereas seasonal snow was greatest in the Sierra, Ruby, and Wasatch/Uinta mountain ranges (Figures 1–3). The proportions of ephemeral snow varied depending on the year, with drier years having greater ephemeral snow extents than wet years (Figure 2).

The RF model had a RMSE of 29.0 days for the stratified random sample and 16.6 days for the entire Great Basin data set. The NSE for the stratified random sample was 0.76, and the NSE for the entire Great Basin data set was 0.79. For areas under 1,500 m in the stratified random sample, the RMSE was 15.2 days; for areas between 1,500 and 2,000 m, the RMSE was 21.4 days; for areas between 2,000 and 2,500 m, it was 30.9 days; for areas between 2,500 m and 3,000 m, it was 38.2 days, and for areas above 3,000 m, it was

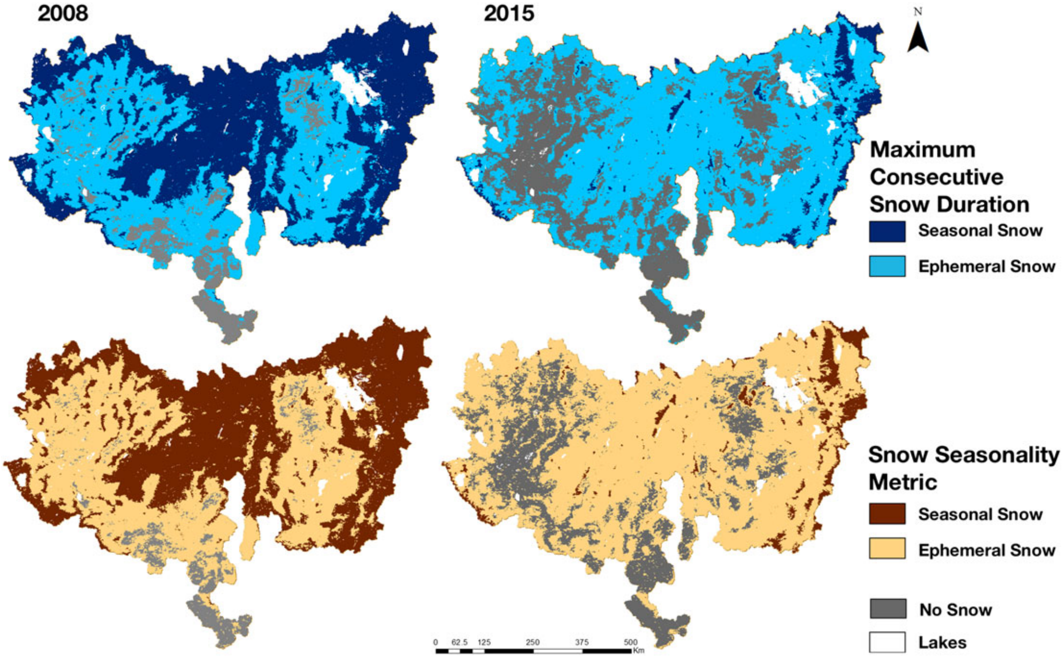

FIGURE 2 Maximum consecutive snow durations (top) and snow seasonality metrics (bottom) in the Great Basin in a wet year (2008) and a dry year (2015). The 60-day threshold in (a) is adapted from (Sturm et al., 1995). Seasonal snow is maximum consecutive snow duration >60 Days and SSM >0. Ephemeral snow is maximum consecutive snow duration $\leq$ 60 Days and SSM < 0. No snow is snow seasonality metrics = 0

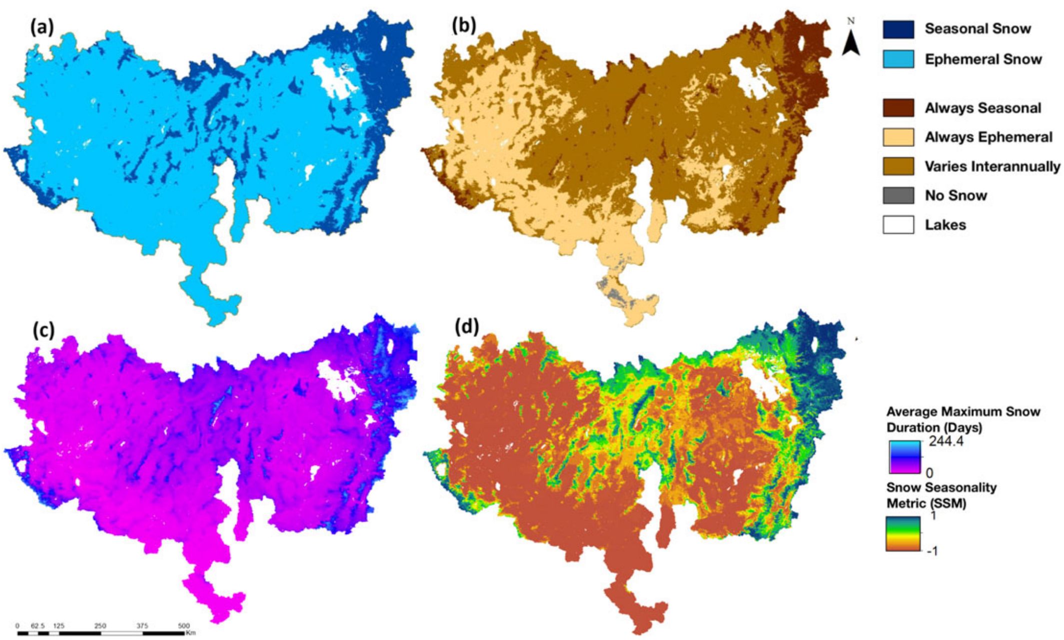

FIGURE 3 (a) Categorized maximum consecutive snow durations, (b) categorized snow seasonality metric (SSM) values, (c) maximum consecutive snow durations as a gradient, and (d) SSM values as a gradient in the Great Basin from water years 2001–2015. Seasonal snow is average maximum consecutive snow duration $\geq$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

37.6 days. RMSE values were similar across vegetation types and varied between −4 and 15 days in maximum consecutive snow duration. The largest errors were observed for lodgepole Pine (average 15 days) and Engelmann Spruce (average 9 days; Figure A.4). These results give us confidence in applying the RF model to understand the effects of warming. The RF model indicated that winter temperature and precipitation were the most important climatic variables for predicting maximum consecutive snow duration and incoming net radiation was the most important topographic variable. Winter temperature was 33% more important than winter precipitation in predicting maximum consecutive snow duration (Figure 4).

The 2 and 4°C RF model warming experiments caused shifts from seasonal to ephemeral snowpacks and an overall increase in ephemerality. With an increase of 2°C in average winter temperature, areal

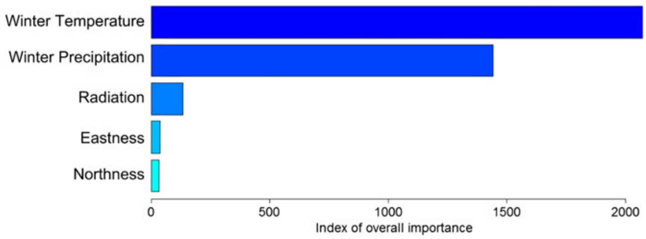

FIGURE 4 The index of overall importance of different predictor variables in the random forest model predicting the maximum consecutive snow duration. The index of overall importance is a normalized estimate of variable importance

seasonal snow extent in the Great Basin declined by 14.7% (8.8% of the Great Basin's historical extent is seasonal snow). The +4°C scenario caused a decline in seasonal snow extent of 47.8%. The +2°C and −25% precipitation scenario caused a seasonal snow extent decline of 25.0%. The +4°C and −25% precipitation caused a seasonal snow extent decline of 65.9% (Figure 5). The Sierra Nevada mountains (Figure 1) had an areal seasonal snow extent decline of 2.7% with the +2°C scenario, a seasonal snow decline of 9.1% with the +2°C and −25% precipitation scenario, a seasonal snow decline of 12.4% with the +4°C scenario, and a seasonal snow decline of 27.2% with the 4°C and −25% precipitation scenario (80.2% of the Sierra Nevada's historical extent was seasonal snow). The Wasatch–Uinta Mountains and Ruby Mountains saw larger declines in areal seasonal snow extent +4°C and −25% precipitation scenario of 33.6% and 34.2%, respectively (78.3% of the Wasatch/Uinta and 89.0% of the Ruby Mountain's historical extent was seasonal snow). The differential sensitivity across mountain ranges reflects variable effects from climate and topography.

Snow duration and SSM varied substantially among the different vegetation types and did not experience a monotonic increase at higher elevations (Figure 6). Saltbush-Greasewood, Sagebrush, and Blackbrush (average elevations 1,583–1,833 m) 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 1,950–2,299 m) 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 2,451–2,772 m) had historical average maximum snow durations above 120 days, and their median SSMs were above 0.5 (Figure 6).

Increasing winter temperature and decreasing precipitation led to declines in maximum consecutive snow duration across vegetation

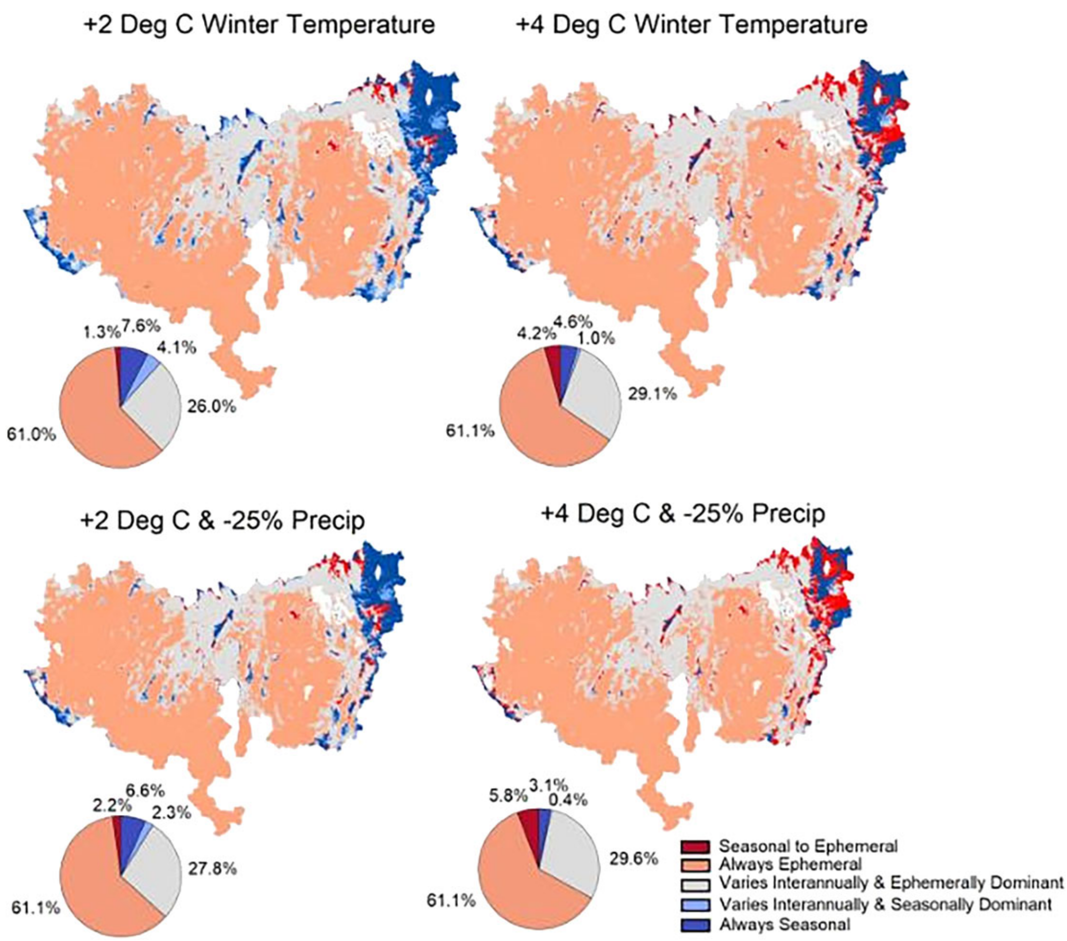

FIGURE 5 Where the snow seasonality (SSM) is always ephemeral (SSM <−0.5), always seasonal (SSM >0.5), shifted from seasonal to ephemeral (SSM >0.5 and predicted maximum snow duration <60), varied interannually and ephemerally dominant (−0.5 > SSM <0.5 and predicted maximum snow duration <60) and varied interannually and seasonally dominant (−0.5 < SSM <0.5 and predicted maximum snow duration ≥60) for a scenario with average winter temperature increased by +2°C (top left), +4°C (top right), +2°C and −25% precipitation (bottom left), and +4°C and −25% precipitation (bottom right). Pie charts represent the proportions of each category

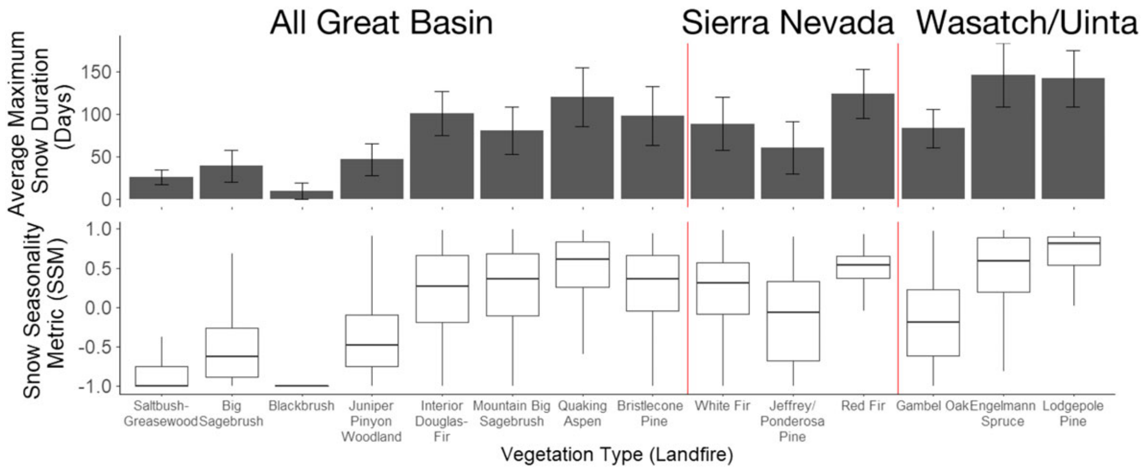

FIGURE 6 The historical average maximum consecutive snow durations (top) and snow seasonality metrics (bottom) for Great Basin vegetation types. Error bars on the top graph represent one standard deviation

types. Under a + 2°C scenario, none of the vegetation types showed declines that were below the 10th percentile historical minimum consecutive snow duration. Only red fir surpassed the historical shortest consecutive snow duration under a +2°C and −25% precipitation scenario. This reflects the severity of the 2015 drought in the region. Under a + 4°C warming scenario, big sagebrush, juniper-pinyon woodland, quaking aspen, bristlecone pine, red fir, and Gambel oak had declines consecutive snow duration beyond historical extremes. Using a scenario of +4°C and −25% precipitation, all vegetation types except Engelmann spruce had declines that surpassed the historical shortest consecutive snow duration (Figure 7). Overall, the greatest declines in maximum consecutive snow duration were for red fir (−61.1 days for +4°C and −76.4 days for +4°C and −25% precipitation scenarios), quaking aspen (−65.0 days for +4°C, and −76.0 days for +4°C −25% precipitation scenarios), and Gambel oak (−66.9 days for +4°C and −70.1 days for +4°C and −25% precipitation scenarios; Figure 7).

In addition to changes in maximum consecutive snow duration with warming, there are also changes to the percent of area covered by ephemeral snow (ephemeral snow extent) for each vegetation type and region. Red fir has decreases in seasonal snow extent of 3.5 and 35.3% for the +2°C and +4°C −25% precipitation scenarios, respectively (97.9% of Red fir's historical extent is seasonal; Figure 8). The large shifts in ephemeral snow extent for Red fir are due to widespread increases in snow ephemerality in the Sierra Nevada (Table 1). The two Sierra Nevada conifer vegetation types that occupy lower average elevations, White fir and Jeffrey/Ponderosa pine, have more modest decreases (between 3.8 and 28.3% for white fir and 2.3 and 15.8% for Jeffrey/Ponderosa pine, respectively; 84.1 and 55.0% of white fir and Jeffrey/Ponderosa pine's historical areal extents were seasonal; Figure 8). Vegetation types found throughout the lower elevations (e.g., pinyon-juniper, saltbush-greasewood, big sagebrush, and blackbrush) experience smaller shifts in ephemeral snow extent than mountain big sagebrush (which experienced decreases in seasonal snow areal extent between 9.2 and 42.0% and has a historical extent that is 75.3% seasonal) and the higher elevation forested vegetation types (Figure 8). This is due to the higher elevation vegetation types having greater historical seasonal extent, while the lower elevations have been historically ephemeral. The vegetation types that are mostly in the Wasatch/Uinta region (Gambel oak, Engelman spruce, and lodgepole pine) have lower percent changes in extent than comparable elevations or vegetation types from the Sierra Nevada region (Figure 8). Over the entire Great Basin, the three vegetation types that are the

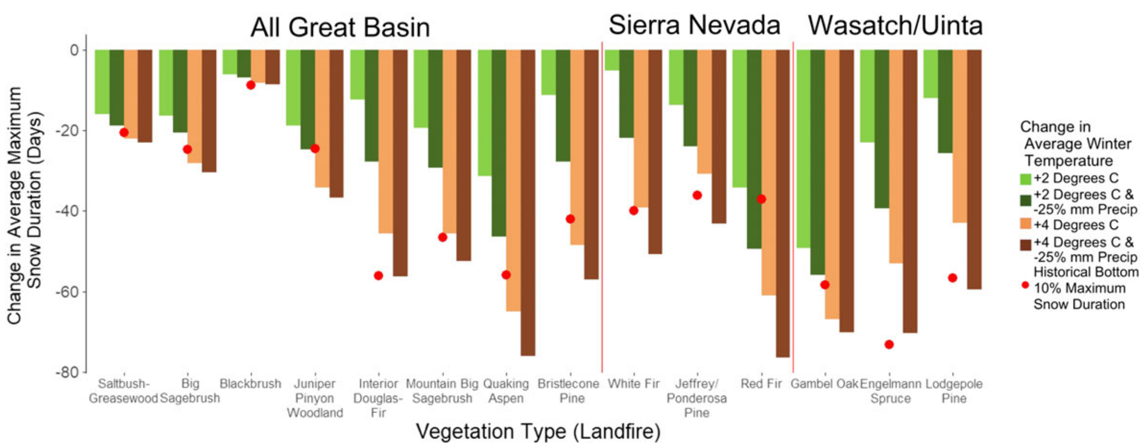

FIGURE 7 Changes in the historical average maximum consecutive snow durations and snow seasonality metrics for Great Basin vegetation types based 2 and 4°C warming scenarios combined with scenarios that reduced precipitation by 25%. Red lines denote each of the vegetation categories based on ecoregion

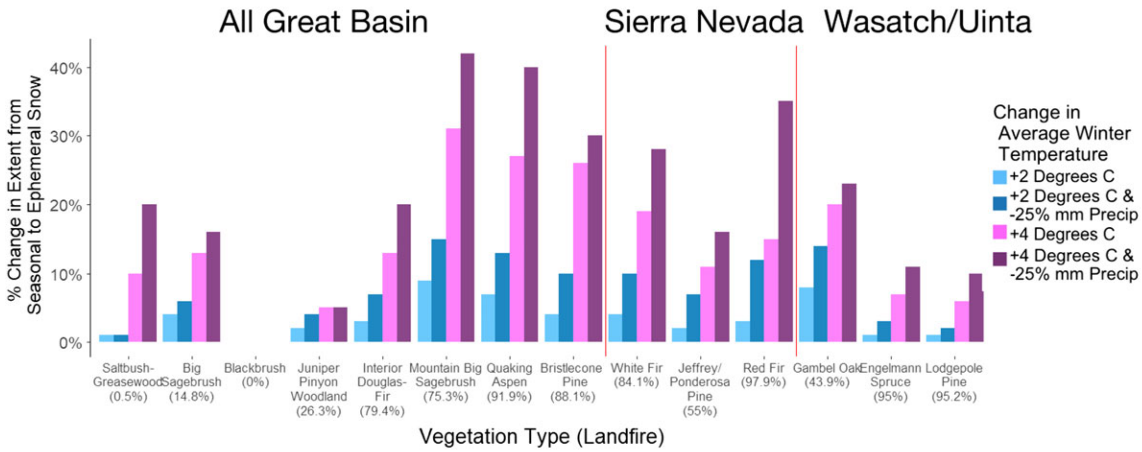

FIGURE 8 Percent decline in seasonal snow areal extent Great Basin vegetation types. Decline was measured as the percent shift from seasonal snow (SSM >0.5) to ephemeral snow (maximum snow duration <60) of the total areal extent of each vegetation type. Historical seasonal extents are in parenthesis below the vegetation types

TABLE 1 The minimum and maximum change in average maximum consecutive snow duration using scenarios of +2 and +4C and −25% precipitation by region

Vegetation category	% Change from seasonal to ephemeral with +2°C	Change from seasonal to ephemeral with 2°C and −25% precipitation	Change from seasonal to ephemeral with +4°C	Change from seasonal to ephemeral with 4°C and −25% precipitation
All Great Basin	(0.0, 7.0)	(0.0, 12.4)	(0.0, 25.0)	(0, 36.6)
Sierra Nevada	(1.2, 3.4)	(4.0, 12.0)	(5.9, 16.4)	(8.7, 34.6)
Wasatch/ Uinta	(0.6, 3.5)	(2.0, 6.0)	(5.9, 8.6)	(9.9, 10.8)

most at-risk of widespread transition to ephemeral snowpack are mountain big sagebrush, red fir, and quaking aspen.

4 | DISCUSSION

The Great Basin is well-suited for studying the effects of climate warming on snowpack ephemerality and has corresponding implications for diverse vegetation types spanning large elevational gradients. We found that the Great Basin is comprised of roughly 55% ephemeral and 9% seasonal snowpacks. Recent work by Petersky and Harpold (2018) demonstrates that ephemeral snowmelt is earlier, more episodic, and less intense than seasonal snowmelt in the Great Basin. Snowpacks below 1,500 m were nearly always ephemeral and above 2,500 m were a mix of ephemeral and seasonal (Petersky & Harpold, 2018). Aspect had a larger control on snowpack ephemerality for deeper snowpacks above 2,500 m, causing increased ephemerality on south facing slopes. A semi physically based model estimate from the SNOw Data Assimilation System, which had relatively poor agreement with MODIS derived snow cover, suggested the primary driver of snow season length was shifted to rain and a secondary driver was melted (Petersky & Harpold, 2018). However, the approach taken by Petersky and Harpold (2018) is not suitable for predicting climate sensitivity and relies on a model (i.e., Snow Data Assimilation System) with known limitations for shallow snowpacks. Consequently, our work fills an important knowledge gap needed to predict how climate affects snow ephemerality and its overlap with diverse vegetation types that are adapted to historic snow conditions.

Our approach demonstrates the utility of remote sensing and object-based processing in the temporal domain for detecting ephemeral snow and estimating snow ephemerality based on climate and topography. New tools and techniques are needed because current understanding of ephemeral snow is based upon few field observations, oversimplifications of shallow snowpack energetics, and remote sensing products that consistently underestimate snow ephemerality (Kelleners, Chandler, McNamara, Gribb, & Seyfried, 2010; McNamara et al., 2018; Kormos et al., 2014; Petersky & Harpold, 2018). Our RF approach, combined with an object-based method that accounts for missing data, was able to capture the <60-day threshold with high fidelity at all elevations (RMSE <16 days over study domain), despite larger error at higher elevations. The RF models avoid the inherent challenges in modelling the physics of shallow snowpacks, such as accounting for the increased importance of ground heat flux and rapidly changing cold content (Petersky & Harpold, 2018). Despite the limitations of interpreting complex statistical models, observed patterns resulted in meaningful inferences about the relationship between snow ephemerality and climate.

Our approach would benefit from finer spatial resolution imagery than MODIS to reduce uncertainty related to topographical variation. For example, snow-covered duration modelled at 500-m scales was ground-truthed using field measurements from snow pillows that are only 3-m wide (Figures A.1 and A.2). Fractional snow-covered estimates could be improved using spectral mixing models, such as MODIS Snow-Covered Area and Grain size retrieval algorithm (Painter et al., 2009) but would not solve the need for an arbitrary threshold to define snow disappearance (Nolin, 2010; Painter et al., 2009).

Our RF model shows that snow ephemerality is sensitive to warming in ways accentuated by typical interannual variations in precipitation. The importance of winter precipitation (Figure 4) reflects the sensitivity of snow accumulation to shift from snow to rain and increased energy for snow ablation. The greater importance of temperature than precipitation (Figure 4) suggests that snow ephemerality can increase even in wet, warm years. Our RF models predict that the combination of +2 and +4°C and −25% precipitation would decrease the extent of seasonal snow by 4.2 and 5.8% (the historical areal extent is 9%), respectively. Not surprisingly, the increases in snow ephemerality would occur primarily at the lower extent of the seasonal snow zone (2,000–2,500 m) where temperatures are warmer, and precipitation is lower. This is consistent with the two primary temperature mediated causes of snow ephemerality: snow accumulation limited from a lack of snowfall and corresponding lower internal cold content that requires less energy to melt (Petersky & Harpold, 2018). Shifts from snow to rain and the corresponding impacts on snow accumulation will vary with elevation and temperature (Klos et al., 2014), along with other factors like humidity and storm characteristics (Harpold, Rajagopal, Crews, Winchell, & Schumer, 2017; Harpold, & Brooks, 2018). Increased ephemerality from sublimation would result in a net loss of water available to vegetation, although sublimation remains challenging to quantify at these larger scales (Petersky & Harpold, 2018; Sexstone et al., 2018). The combination of topographic (e.g., hypsometry) and climate characteristics make Sierra Nevada ecosystems more sensitive to increased snow ephemerality.

Our approach enables us to overlay snowpack ephemerality, and its sensitivity to climate, with vegetation distributions to identify three groups of vegetation types with different levels of risk for changing snowpacks. The first group is least at risk because they are already dominated by ephemeral snowpacks (i.e., saltbrush-greasewood, big sagebrush, blackbrush, Pinyon Juniper; Figure 6). As expected, the high degree of historical snow ephemerality limits increasing ephemerality from warming and drying (Figure 7). The second group that includes Douglas fir, Jeffrey/Ponderosa pine, and Gambel oak has historically received a mixture of ephemeral and seasonal snowpacks (Figure 6). Again, this group showed minimal change in snowpack ephemerality compared with historic extremes, with the slight exception of Gambel oak. The third group consists of sites that historically had consistent seasonal snow cover. This group can be divided into those vegetation types that did not experience more extreme ephemeral snowpack from warming and drying scenarios (i.e., white fir, Engelman spruce, and lodgepole pine) versus those types that are predicted to exceed historic extremes under climate change scenarios (i.e., quaking aspen, mountain big sagebrush, and red fir). Vegetation types that have historically not experienced ephemeral snowmelt may be challenged by a new hydrologic regime that is characterized by earlier and more episodic water inputs with less deep soil moisture recharge (Petersky & Harpold, 2018). Water inputs that come earlier in the year are challenging for vegetation to use for efficient photosynthesis (Stephenson, 1990; Tague & Peng, 2013), particularly for deciduous vegetation types (e.g., quaking aspen) that may not have leaves during parts of snowmelt. Earlier cessation of water inputs under ephemeral melt will lead to greater duration of soil water stress in areas without substantial summer rain or storage of excess snowmelt in the subsurface (Harpold, 2016).

The degree to which forest productivity and disturbance patterns will respond to increased snow ephemerality will depend on how the subsurface drains and stores water (Harpold, 2016; Klos et al., 2018; Tague & Peng, 2013) and how the ecophysiological adaptation of the local vegetation allows access to stored water and the carbon allocation strategies available for weathering longer periods of water limitation (Garcia et al., 2016). In general, vegetation phenology is expected to respond strongly to changing snow ephemerality and higher summer water demand, with the expectation of earlier greening and browning under earlier water inputs (Parida & Buermann, 2014; Scott-Denton et al., 2013). Vegetation with deeper roots can effectively increase plant available water by accessing subsurface storage, whereas shallow roots may be important for utilizing episodic snowmelt or rainfall that has limited infiltration depth (Fan, Miguez-Macho, Jobbágy, Jackson, & Otero-Casal, 2017; Klos et al., 2018; Petersky & Harpold, 2018; Small & McConnell, 2008). Evergreen coniferous trees may be particularly well adapted to climates with warm, rainy winters because they are capable of photosynthesis and nutrient uptake outside the active growing season and are often better able to regulate water loss during dry conditions in late summer (Kelly & Goulden, 2016; Waring & Franklin, 1979). However, conifer forests would need to effectively allocate carbon in the snowmelt season to have sufficient carbohydrates to weather water stress later in the season (Kelly & Goulden, 2016). For example, Knowles et al. (2018) showed that greater carbon uptake early in the season did not offset reduced carbon uptake caused by water stress late in the season, resulting in reduced net carbon uptake in a montane conifer forest in Colorado.

It is expected that many plant species will not be able to adapt to a new, more episodic hydrological regime, and greater summer water demand, resulting in increased plant mortality, reduced regeneration success, and the potential for species compositional shifts. For example, water stress during drought has been linked to increased mortality for white and red firs in the Sierra Nevada region (Das, Stephenson, Flint, Das, & Van Mantgem, 2013; Van Mantgem & Stephenson, 2007). In addition to tree growth and maintenance, drier conditions lead to increased susceptibility of evergreen forests to disturbance (Anderegg et al., 2015; Bales et al., 2011). Previous work suggests that smaller snow water inputs increase the chances of catastrophic fire (Westerling et al., 2006). These hydrologically induced changes are accentuated by increased atmospheric water demand and more extreme heat (Allen, Breshears, & McDowell, 2015). Increased water demand during periods of reduced water availability is likely to accentuate negative effects for vegetation during the hottest times of the growing season. We encourage field research that explicitly tests the sensitivity of plant species to ephemeral snow conditions, while accounting for ecophysiological adaptations and the role of local water storage in buffering the effects of increased snow ephemerality.

5 | CONCLUSIONS

The snowpack of Great Basin will become more ephemeral under reasonable scenarios of future warming. The outsized importance of average winter temperature in predicting snow ephemerality in our RF model is consistent with snow-rain transitions and winter melt being the primary drivers of ephemeral snowpack in this region (Petersky & Harpold, 2018). Vegetation in the Great Basin is likely to be more sensitive to changes in precipitation phase from snow to rain (Klos et al., 2014) and increased winter ablation from warming temperatures (Harpold & Brooks, 2018). We classified Great Basin vegetation types in terms of expected sensitivity to increasing snow ephemerality: (a) low sensitivity due to historically ephemeral snow, (b) low sensitivity due to mix of seasonal and ephemeral snow, and (c) high sensitivity in areas that have not experienced ephemeral snow historically. In particular, forest vegetation types that are predicted to have unprecedented future snow ephemerality (i.e., quaking aspen, bristlecone pine, and red fir) are at risk for experiencing new hydrological regimes that stress existing vegetation. Our RF model predicts higher elevation montane Sierra Nevada forests, and red fir in particular, will experience snow ephemerality in excess of the extreme 2015 drought (Belmecheri, Babst, Wahl, Stahle, & Trouet, 2016). Shifts in vegetation structure and composition in response to new, more episodic melt regimes in semiarid regions like the Great Basin are likely to have cascading implications on large-scale water and carbon budgets and susceptibility to disturbance.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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APPENDIX A

Introduction

The following figures provide additional information about the ephemeral snow algorithm and modelled random forest ephemeral snow results across vegetation types. Figure A.1 shows how the measured number of ephemeral and seasonal snow events at snow telemetry 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 the distribution of vegetation types in the Great Basin. Figure A.4 shows histograms of residuals of measured and random forest modelled ephemeral snow for all vegetation species. Table A.1 shows average elevations, total area extents, average maximum consecutive snow durations, and average snow seasonality metrics across the Great Basin, United States from water years 2001–2015.

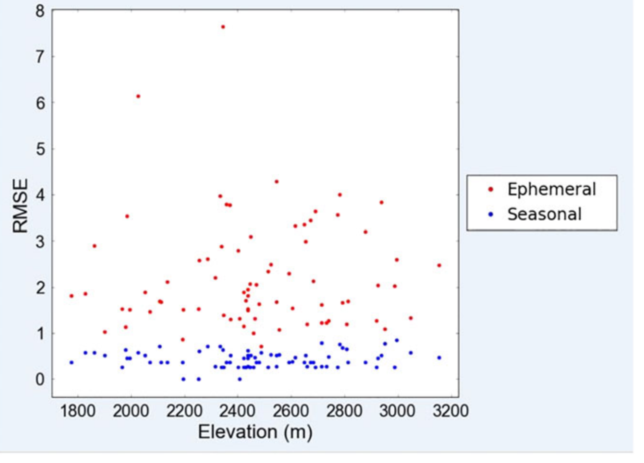

FIGURE A.1 Root mean square errors (RMSEs) between the number of observed ephemeral and seasonal snow events at snow telemetry stations and the number of ephemeral and seasonal snow events derived from the algorithm in Google Earth Engine in each 500-m moderate-resolution imaging spectroradiometer pixel corresponding to that station. Measured Snow Water Equivalent of 0.2 in. or greater was used to determine snow presence for snow telemetry sites

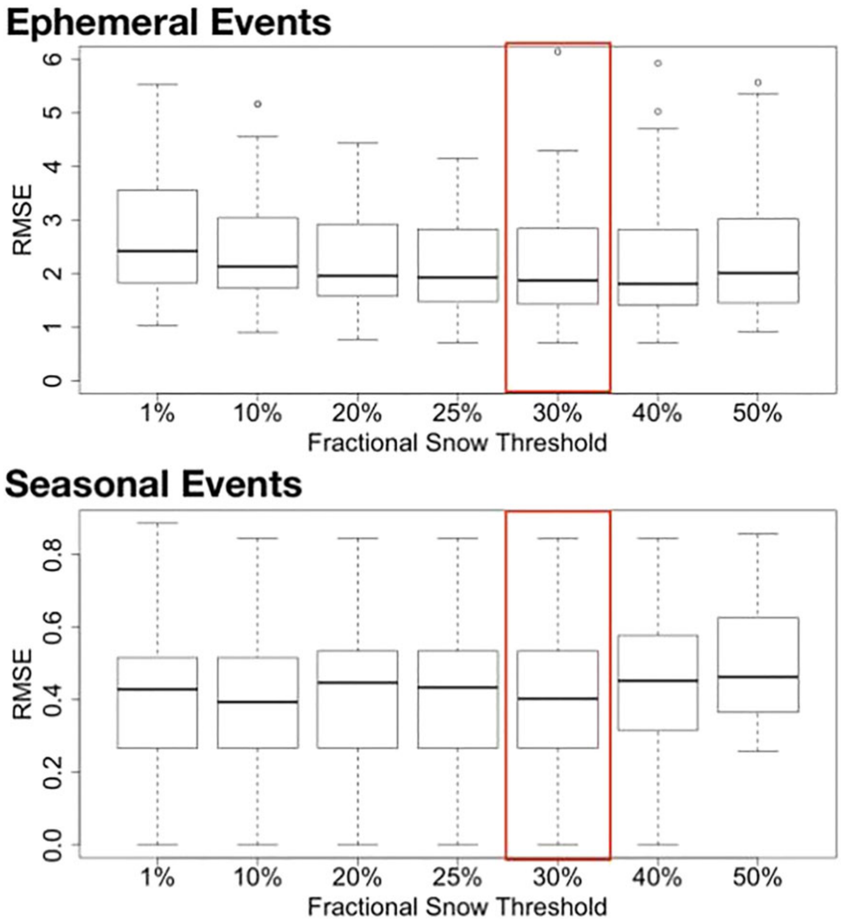

FIGURE A.2 Box plots depicting the root mean square errors (RMSEs) between the number of observed ephemeral and seasonal snow events at snow telemetry stations and the number of ephemeral and seasonal snow events derived from the algorithm in Google Earth Engine in each 500-m moderate-resolution imaging spectroradiometer pixel corresponding to that station at snow fractions of 1–50%. 30% (outlined in red) was the chosen snow fraction

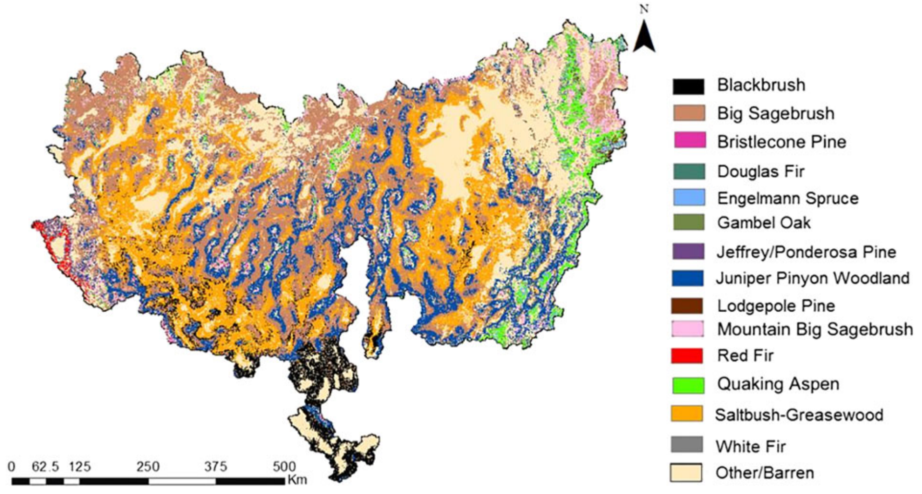

FIGURE A.3 Distribution of vegetation types from the LANDFIRE gridded data set in the Great Basin, United States

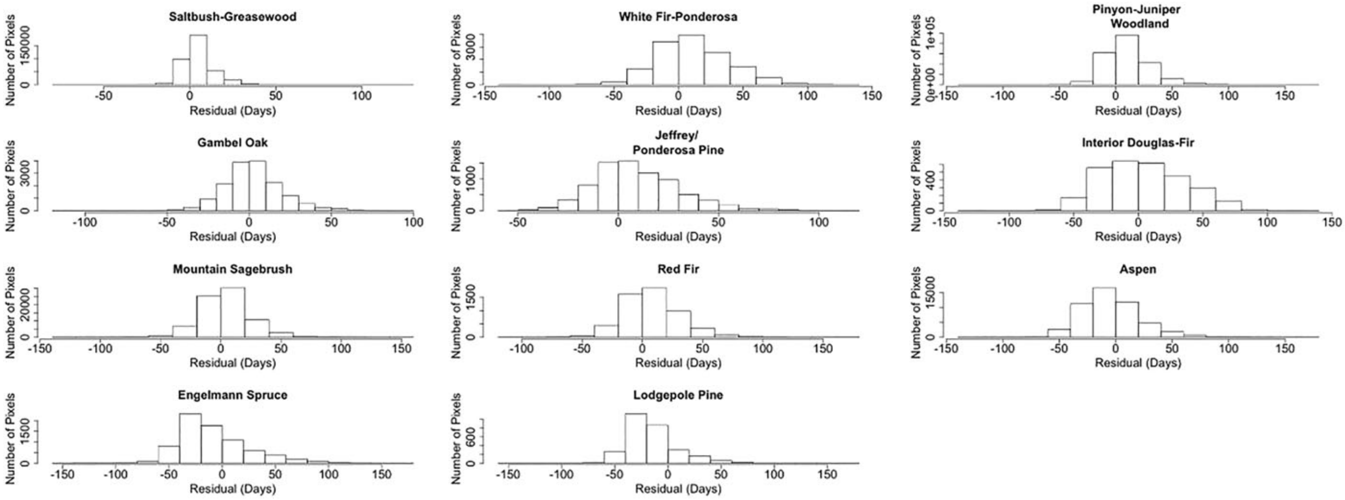

FIGURE A.4 Histogram of the residuals between the maximum consecutive snow duration measured using the Google Earth Engine algorithm and the maximum consecutive snow duration from the random forest model for each vegetation type (LANDFIRE)

TABLE A.1 Vegetation types (LANDFIRE), their average elevations, total area extents, average maximum consecutive snow durations, and average snow seasonality metrics across the Great Basin, United States from water years 2001–2015

Common name	Latin name	Average elevation (m)	Area (km^2)	Average maximum snow duration (days)	Average SSM
Saltbush greasewood	*Atriplex sp*. and *Sarcobatus vermiculatus*	1,583.2	339,820.2	26.1	−0.7
Sagebrush	*Artemisia tridentata tridentata* and *Artemesia tridentata wyomingensis*	1,796.9	485,971.2	39	−0.5
Blackbrush	*Coleogyne ramosissima*	1,832.9	74,852.1	9.4	−0.6
White fir	*Abies concolor*	1,950.0	12,616.2	89.1	0.2
Pinyon–juniper woodland	*Juniperus osteosperma* and *Pinus edulis*	2,003.8	20,6244.9	46.9	−0.4
Gambel oak	*Quercus gambelii*	2,006.0	11,571.3	83.5	−0.2
Jeffrey/Ponderosa pine	*Pinus jeffreyi* and *Pinus Ponderosa*	2,062	7,133.4	60.9	−0.2
Interior Douglas-fir	*Pseudotsuga menziesii var. glauca*	2,190.4	2,609.1	101	0.2
Mountain sagebrush	*A. tridentata vaseyana*	2,298.7	70,667.1	81.1	0.2
Red fir	*Abies magnifica*	2,450.9	4,995.9	124.5	0.5
Aspen	*Populus tremuloides*	2,522.9	45,166.5	120.8	0.5
Engelmann spruce	*Picea engelmannii*	2,727.8	6,715.8	146.6	0.5
Lodgepole pine	*Pinus contorta*	2,771.7	2,646.9	142.6	0.6
Bristlecone pine	*Pinus longaeva*	2,976.6	1,787.4	98.2	0.3

Note. SSM: snow seasonality metric.