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Key Points:

- Different inference paths for climate effects on snow have different outcomes
- Season average P and T predict April 1 SWE and snow residence time well
- Snowpack sensitivity to climate greater than previously thought in some areas

Supporting Information:

- Auxillary material for snow sensitivity

Correspondence to:
C. H. Luce,
cluce@fs.fed.us

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Sensitivity of snowpack storage to precipitation and temperature using spatial and temporal analog models

Charles H. Luce[1], Viviana Lopez-Burgos[1], and Zachary Holden[2]

[1]U.S. Forest Service Research and Development, Rocky Mountain Research Station, Boise, Idaho, USA, [2]U.S. Forest Service Region 1, Missoula, Montana, USA

Abstract Empirical sensitivity analyses are important for evaluation of the effects of a changing climate on water resources and ecosystems. Although mechanistic models are commonly applied for evaluation of climate effects for snowmelt, empirical relationships provide a first-order validation of the various postulates required for their implementation. Previous studies of empirical sensitivity for April 1 snow water equivalent (SWE) in the western United States were developed by regressing interannual variations in SWE to winter precipitation and temperature. This offers a temporal analog for climate change, positing that a warmer future looks like warmer years. Spatial analogs are used to hypothesize that a warmer future may look like warmer places, and are frequently applied alternatives for complex processes, or states/metrics that show little interannual variability (e.g., forest cover). We contrast spatial and temporal analogs for sensitivity of April 1 SWE and the mean residence time of snow (SRT) using data from 524 Snowpack Telemetry (SNOTEL) stations across the western U.S. We built relatively strong models using spatial analogs to relate temperature and precipitation climatology to snowpack climatology (April 1 SWE, $R^2=0.87$, and SRT, $R^2=0.81$). Although the poorest temporal analog relationships were in areas showing the highest sensitivity to warming, spatial analog models showed consistent performance throughout the range of temperature and precipitation. Generally, slopes from the spatial relationships showed greater thermal sensitivity than the temporal analogs, and high elevation stations showed greater vulnerability using a spatial analog than shown in previous modeling and sensitivity studies. The spatial analog models provide a simple perspective to evaluate potential futures and may be useful in further evaluation of snowpack with warming.

1. Introduction

One of the more critical sensitivities affecting the water resources and ecology of western U.S. mountains is changes in snowpack storage of water [*Barnett et al*., 2008; *Holden et al*., 2012; *McKelvey et al*., 2011; *Westerling et al*., 2006]. Storage has two dimensions, how much water is held, and how long it is held. The Snow Water Equivalent (SWE) on 1 April is a commonly applied metric describing the depth of stored water for the spring and summer runoff season, as it is a metric with a long record of measurement at many sites [e.g., *Mote*, 2003; *Regonda et al*., 2005]. Storage time metrics are less well developed for snowpacks because there are a limited number of stations with relatively short records (e.g., Snowpack Telemetry stations, SNOTEL) where such measurements can be made [*Clow*, 2010; *Serreze et al*., 1999]. The timing of streamflow has been applied as a related metric [e.g., *Cayan et al*., 2001; *Stewart et al*., 2005], and similar metrics of timing have been applied for center of melt timing [*Clow*, 2010] and the center of mass of SWE [*Kapnick and Hall*, 2012]. Hydrologists commonly apply the idea of mean residence time with respect to water in soil or other reservoirs [e.g., *Kirchner*, 2009; *McGuire et al*., 2005; *McNamara et al*., 2011; *Soulsby et al*., 2009]; however, the metric has not been applied to snowpacks despite the advantage of snow's comparatively short-tailed (and finite) residence time distribution. There has been substantial discussion of trends and sensitivity of April 1 SWE as well as future projections [*Casola et al*., 2009; *Hamlet et al*., 2005; *Mote*, 2003, 2006]. Although there has been discussion of trends of timing aspects of snowmelt [*Cayan et al*., 2001; *Clow*, 2010; *Kapnick and Hall*, 2012; *Stewart et al*., 2005], quantitative evaluation of the sensitivity of timing to seasonal precipitation and temperature metrics has been limited [*Hamlet et al*., 2005; *Stewart et al*., 2005].

Three primary sources of information have informed our understanding of the potential impacts of climate change on water resources and ecology: temporal analogs, spatial analogs, and simulation models.

Temporal analogs show the sensitivity of processes to shifts in climate by reasoning that warmer futures look like warmer years or warmer days do now [*Mohseni et al*., 1998; *Mote*, 2006; *Sankarasubramanian et al*., 2001; *Sawicz et al*., 2011]. Temporal analogs are usually constructed using time series, say interannual data, of weather data regressed against outcomes of interest, for example April 1 SWE.

Spatial analogs rely on a logic that a warmer future may look like warmer places do now; they are sometimes called "space-for-time" substitutions. Spatial analogs are constructed by regressing climatological averages of weather data against outcomes of interest, for example species presence-absence data. In the absence of longtime-series of fluxes or states, spatial analogs are commonly used to develop models of sensitivity to climate [e.g., *Tchebakova et al*., 1994; *Vose et al*., 2012; *Wenger et al*., 2011]. With respect to snow, this would look like examining how average April 1 SWE changed from place-to-place as a function of the climate of those locations.

Mechanistic simulation models are applied when there is concern that climate futures may not look like any temporal or spatial analogs available to us now or in the recent past, and that the empiricism inherent in them may break down under altered climates [*Williams and Jackson*, 2007]. Though there may be substantial reliance on simulation models for relatively simple processes like snowmelt [*Casola et al*., 2009; *Elsner et al*., 2010; *Hamlet et al*., 2005; *Minder*, 2010; *Sproles et al*., 2013], there is still some need for calibration and model improvement. Even in the relatively low parameter-dimensionality of physically based snowmelt models, some suppositions must be made that may not be practical to simulate from first principles and common weather data but that could lead to substantial divergence in estimates [e.g., *Dai*, 2008; *Marks et al*., 2013; *Rutter et al*., 2009]. Among these are estimating the phase, solid versus liquid, of precipitation during a given event, and not the least of the uncertainties is temporal downscaling from a "2°C warmer" climate to the distributions of temperatures on wet versus dry days in particular months. Ultimately, simulation models do what modelers tell them to do, and having empirical analogs to inform, guide, and validate sensitivity estimates is valuable for constraining modeling choices.

Empirical evaluation of snowpack sensitivity to climate has used temporal analogs, for example through regression of interannual variability of April 1 SWE to interannual variability in precipitation and temperature [*Mote*, 2006]. These empirical correlations and temporal trend analyses have been contrasted with simulation models like the Variable Infiltration Capacity (VIC) model [*Liang et al*., 1994] to show similar qualitative expectations from independent lines of reasoning [e.g., *Casola et al*., 2009; *Elsner et al*., 2010; *Hamlet et al*., 2005; *Mote et al*., 2005].

Some uncertainties remain from these analyses. One of the findings regarding snowpack sensitivity to climate in this context is that temporal model fits may not be the strongest in the locations with the seemingly most vulnerable snowpacks [*Casola et al*., 2009; *Mote*, 2006]. In addition, some higher elevation locations show increased April 1 SWE with increasing temperature (even when precipitation is specified as constant) [*Hamlet et al*., 2005; *Mote*, 2006]. An important caveat regarding these studies, one expressed by their authors, is that in both simulation model experiments and empirical analyses, temperature, and precipitation inputs were derived from predominantly low elevation stations, sometimes far from the actual SWE observations [*Hamlet et al*., 2005; *Mote*, 2006]. This required simplifying assumptions about how those inputs vary across space and with elevation [*Minder*, 2010], and unfortunately, interannual variations in high elevation weather are not always well captured by nearby low elevation stations [e.g., *Dettinger et al*., 2004; *Luce et al*., 2013]. Validations of snowmelt timing simulations compared to streamflow data show pronounced bias [*Wenger et al*., 2010], suggesting some need for further evaluation of timing sensitivity as well.

The reasoning behind spatial analogs has been one of the underpinnings for a movement toward observatory networks for ecological and hydrological sciences [e.g., *Schimel et al*., 2007]. While quantitative spatial analogs have been applied to model the sensitivity of ecological systems [e.g., *Monserud et al*., 1993; *Wenger et al*., 2013], they have not been applied for snowpacks. Considering just the simple utility of being able to compare snowpack sensitivity to ecological sensitivity in some settings, there is value in contrasting spatial and temporal analogs for modeling snowpack sensitivity to climate variations. The potential for improving sensitivity estimates in locations where the temporal analog performs poorly is another justification for exploring the spatial alternative, as is the potential to test more complex model formulations with a larger sample size. There are certainly conceptual challenges to applying spatially referenced sensitivities when temporal ones are available. One potential worry is that stations in different geographic locations do not

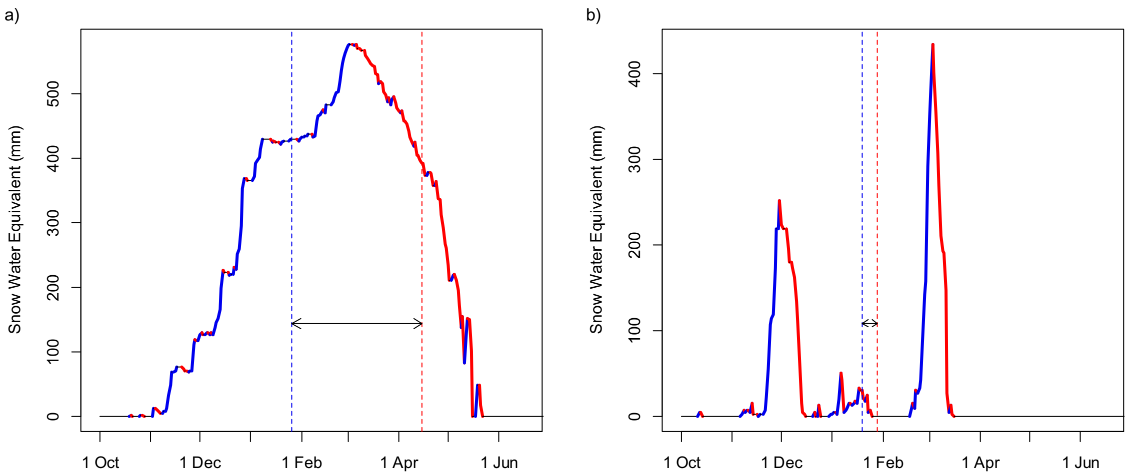

Figure 1. Example traces of snow water equivalent (SWE) for water year 2007 contrasting places with short-snow and long-snow residence times. The plots show two stations in Oregon at (a) 1645 m elevation and (b) 950 m elevation. Blue indicates days when accumulation occurs, while red indicates days of melt, and black is a day with no change. The blue vertical-dashed line is the center of timing (first moment) of accumulation; the red vertical-dashed line is the center of timing of melt; and the arrow indicates the difference between them, the mean snow residence time (SRT). SRT is 79 days for (a) and 9.6 days for (b).

necessarily share similar weather sequences, variations in the jet stream path, and seasonal timing of storms, and solar azimuth angles in spring could conceptually overwhelm any signal due to simple metrics of winter climate. While such issues might cloud interpretation of poor-fitting models, they only represent sources of residual variance when models have strong relationships. Resolving these questions would support ongoing design and investment in observatory networks.

We address several of these issues through examination of SNOw TELemetry (SNOTEL) network records, where daily precipitation, temperature, and snow water equivalent data are collected at each location. We have four objectives: (1) reexamine the temporal analog sensitivities using stations where weather information and snowpack information are collected in the same location, (2) consider the sensitivity of snowpack mean residence time as a metric of storage duration, (3) develop and test spatial analog models to further explore climatic sensitivity, and (4) contrast the temporal and spatial analog approaches for these sites with relatively rich information.

2. Methods

2.1. Data

Daily precipitation, temperature, and snow water equivalent data were obtained from the U.S. Department of Agriculture's Natural Resources Conservation Service SNOw TELemetry (SNOTEL) sites (http://www.wcc.nrcs.usda.gov/snow/). We used all stations in western United States (excluding Alaska) with data between Water Years 1991–2011, which comprised 524 stations. These stations were spread across the 11 western states plus one station in extreme western South Dakota. Although some stations have data extending into the early 1980s, we used a later period to allow inclusion of more stations. April 1 SWE was taken directly from the SNOTEL record each year.

Mean snow residence time (SRT) was estimated as the difference between the center of timing of snow accumulation (CT_{acc}) and the center of timing of melt (CT_{melt}) each year (Figure 1). Snow accumulation for each day was taken as any positive increment in SWE, and melt was taken as any decrement in SWE. They were calculated as:

$$CT_{\mathrm{acc}} = \frac{\sum t_i acc_i}{\sum acc_i} \tag{1}$$

$$CT_{\mathrm{melt}} = \frac{\sum t_i melt_i}{\sum melt_i} \tag{2}$$

where t_i is the number of days passed since 1 October, acc_i is the increase in SWE on day *i* and $melt_i$ is the decrease in snow on day *i*, following the approach of *Stewart et al*. [2005]. CT_{acc} and CT_{melt} are the depth weighted mean dates of accumulation and melt, respectively. The difference in the mean accumulation and mean melt dates is the mean residence time, SRT

$$\mathrm{SRT} = CT_{\mathrm{melt}} - CT_{\mathrm{acc}} \tag{3}$$

Data from the California Department of Water Resources (CADWR) snow sensor station network were also examined, but we did not use them because of differences in protocol for temperature and SWE measurements between the CADWR and SNOTEL networks and among stations within the CADWR network. Although differences were slight, even seemingly minor differences in selection or placement of instruments can lead to inconsistencies when comparing among stations (see supporting information).

2.2. Temporal Analog Analysis

The temporal analog analysis parallels that of *Mote* [2006] in applying multiple linear regression to find a model that estimates the dependent variable (April 1 SWE or SRT) for each year at a site using the precipitation and temperature from each year. We found the parameters for the least squares fit to the following equations at each site

$$\mathrm{Apr1SWE}(t) = \mathrm{a_{Pa}Prcp}(t) + \mathrm{a_{Ta}T_{min}}(t) + \varepsilon_{\mathrm{a}}(t) \tag{4}$$

$$\mathrm{SRT}(t) = \mathrm{a_{Pr}Prcp}(t) + \mathrm{a_{Tr}T_{min}}(t) + \varepsilon_{\mathrm{r}}(t), \tag{5}$$

where Prcp(*t*) is the annual time series of total November through March precipitation taken from the precipitation gage at each site, and $T_{min}(t)$ is the annual time series of the November through March average of the daily minimum temperature. We used the daily minimum temperature because the correlations were stronger using that metric than when using T_{avg}. a_{Pa} and a_{Ta} are the regression coefficients for precipitation and minimum temperature for predicting April 1 SWE, and a_{Pr} and a_{Tr} are the regression coefficients for SRT. ε is the residual at year *t*. Data were assessed for normality and were not obviously skewed.

Standardized beta coefficients were also obtained to determine the relative effect of the independent variables on the dependent variable:

$$\beta_{Pa} = \mathrm{a_{Pa}} \cdot \frac{sd(Prcp)}{sd(Apr1SWE)} \tag{6a}$$

$$\beta_{Ta} = \mathrm{a_{Ta}} \cdot \frac{sd(Tmin)}{sd(Apr1SWE)} \tag{6b}$$

$$\beta_{Pr} = \mathrm{a_{Pr}} \cdot \frac{sd(Prcp)}{sd(SRT)} \tag{6c}$$

$$\beta_{Tr} = \mathrm{a_{Tr}} \cdot \frac{sd(Tmin)}{sd(SRT)} \tag{6d}$$

where *sd* denotes standard deviation.

2.3. Spatial Analog Analysis

For the spatial analogs, we examined nonlinear response surfaces of snow climatology (April 1 SWE and SRT) to precipitation and temperature climatology. We used local polynomial regression of the average response variable at each site to average winter temperature and precipitation at each site. This model does not represent the temporal variation at sites, but differences in climates across sites.

Analyzing climatic differences among 524 stations allowed for consideration of more complex functional relationships between temperature, precipitation, and the dependent variables than was appropriate with time series of 21 years or less. Using short-time series in the temporal analog, it is difficult to identify significant interaction terms, for instance, or allow for nonlinear responses in temperature or precipitation. There was no theoretical expectation of the functional form of the relationship, other than considering the potential importance of an interaction term between temperature and precipitation. Such an interaction term would suggest that one would have less snow as a result of either warm temperatures *or* low precipitation, and that colder temperatures *and* greater precipitation are required for deeper snowpacks. This would also be intuitive in the case of the interannual analysis, but it is often difficult to identify significant interaction terms from short, noisy time series.

Without specific knowledge of the functional form, but also without the need to explicitly find parameters for that form, we applied a local fit algorithm to describe the shape of the surface. We used the locfit package [*Loader*, 1999] in R to plot a smooth surface through the data. Local regression finds a fit for the data points that resembles the unknown function $\mu(x_i)$, which describes the relationship between y (e.g., April 1 SWE or SRT) and x (Temperature and Precipitation).

$$y_i = \mu(x_i) + \epsilon_i \tag{7}$$

It does so by locally fitting a polynomial model of degree 2 to each pair of observations (x_i and y_i) by way of approximation (using Taylor's theorem) to data from observation pairs that are inside a user defined window. These neighborhood observations are weighted by a proximity function, the observations with the most similar independent variable values are more important. We specified the model in R as, for example:

$$\mathrm{locfit}(\mathrm{swe} \sim \mathrm{lp}(\mathrm{Tavg}, \mathrm{Precip}, \mathrm{nn}=0.8, \;\; \mathrm{scale}=\mathrm{T})) \tag{8}$$

where nn is a user defined bandwidth (with values 0 to 1) that controls the smoothness of the fit and states how many observation pairs (nearest neighbors) will be used for the approximation. Bandwidth selection was initially guided by a generalized cross validation, which indicated optimal bandwidths at nn=0.65 for April 1 SWE and nn=0.6 for SRT, though with relatively flat response. Stronger smoothing was applied to remove visually obvious local variations that were physically unrealistic, yielding a more monotonic relationship, at a slight expense for the overall goodness of fit (see below). We used nn=0.8 for both April 1 SWE and SRT, which means the approximation used the closest 80% of observation pairs to point x_i,y_i.

For the spatial analog approach, our two explanatory variables (x's) were total November through March precipitation and the average November through March daily average temperature. In this case, the daily average temperatures gave a better fit than did the minimum temperatures used in the temporal analog models described above. November-March precipitation and average daily temperature were averaged over the years with complete data at each station. Temporal coverage ranged from 8 to 21 years, with 50% of the stations having 18 or more years of complete data, and 95% having 13 or more years. Our dependent variables were SRT and April 1 SWE. We also examined fits to CT_{melt} and CT_{acc} individually to better understand results for SRT.

We assessed the fit between the smoothed/fitted surface and the observed data using the Nash-Sutcliffe model efficiency coefficient:

$$R^2 = 1 - \frac{V_r}{V} \tag{9}$$

Where V_r is the mean square error, and V is the variance of the response variable.

We also used locfit to identify the partial derivatives with respect to each explanatory variable. These partial derivatives of the smoothed surface are a measure of the local sensitivity to precipitation and temperature:

$$Sensitivity\ \ to\ \ Precipitation = \frac{\partial Response\ \ Variable}{\partial Precipitation} \tag{10a}$$

$$Sensitivity\ \ to\ \ Tavg = \frac{\partial Response\ \ Variable}{\partial Tavg} \tag{10b}$$

Bandwidths for derivatives must commonly be set higher than for the original variable [*Newell and Einbeck*, 2007], and we used nn=0.9 for the April 1 SWE temperature derivative and nn=1 for all other derivatives.

Besides identifying the local slopes, we further offer an example of how the spatial analog model could be applied to estimate the change in the response variable if the average temperature were to rise 3°C, accounting for potential nonlinearities in sensitivity. This hypothetic temperature rise is based on *Dettinger* [2013] and *Solomon et al.* [2007]. We estimated the changed snowpack by first evaluating the empirical response surface for P and T_{avg}, and then evaluating the same surface with P unchanged and T_{avg} + 3°C, and taking the difference. Negative estimated future values were set to zero, since all response variables were positive

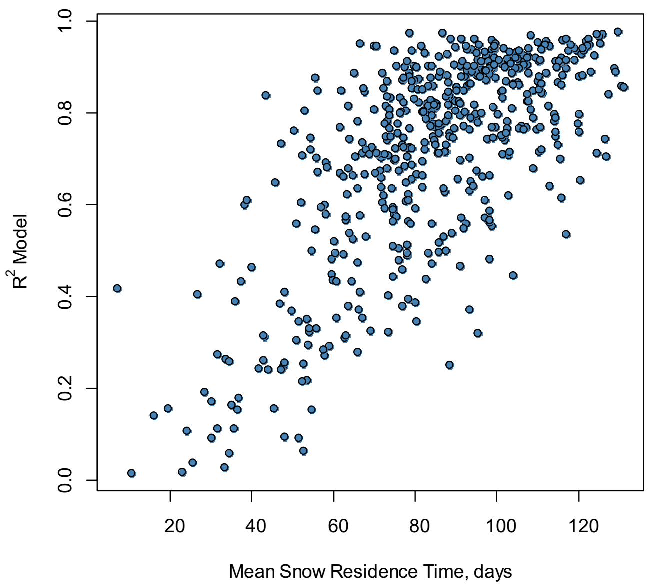

Figure 2. Relationship of at-a-station (temporal analog) regression quality to the station's mean snow residence time (SRT).

valued. We did not show an equivalent map for precipitation change, because it is estimated to be substantially uncertain across this region [*IPCC*, 2013]; precipitation is not well modeled by GCMs [*Blöschl and Montanari*, 2010], and there are substantial unresolved uncertainties for future precipitation in the mountains of the western United States [*Luce et al.*, 2013]. While these are not actual deterrents to making the computations, it might add confusion, and our intention is just to show a simple example that could be compared to similar analyses of change in temperature. Clearly more site-specific estimates of temperature change could be applied at each station.

3. Results

3.1. Temporal Analog

The overall goodness of fit (R^2) of the temporal analog models varies substantially across stations, from 0.015 to 0.98, although 75% of the stations have an R^2 greater than 0.6. Ninety-three percent of the p values for the models were less than 0.1. The R^2 of each station's temporal analog fit is strongly related to the square of the precipitation correlation with SWE (ρ_P^2) at that site (R^2=0.87, $p < 1 \times 10^{-15}$) while the correlation with temperature had no bearing on the overall quality of the model at each site (R^2=0.001, $p = 0.42$). Elevation is a relatively weak predictor of model quality (R^2= 0.27, $p < 1 \times 10^{-15}$); stations with poorer quality fits tend to be at lower elevations. Winter-averaged minimum temperatures have a slightly better relationship ($R^2 = 0.32$, $p < 1 \times 10^{-15}$), and again stations with poorer quality fits tend to be the warmer stations. This can be interpreted to say that what are broadly perceived to be the most vulnerable snowpacks are the ones with the poorest temporal analog fits. SRT was a reasonably strong predictor of the quality of fit ($R^2 = 0.50$, $p < 1 \times 10^{-15}$, Figure 2) offering a little further insight. One interpretation is that the season long temperature and precipitation averages may not be particularly informative of the year-to-year variations in April 1 SWE in places where the snowpack only lasts a few weeks and may nearly completely melt a few times each winter (see e.g., Figure 1b). If the effect of within-season timing of accumulation becomes a large source of variability in April 1 SWE, then the temporal analog will be poorer in places where snow accumulation and melt are shorter than seasonal scale. The number of years of complete data had an insubstantial influence on goodness of fit at each station (R^2=0.05, $p = 5 \times 10^{-8}$), and 71% of stations with less than 13 years of data had greater than average R^2 values.

Broadly, precipitation seemed to be more influential than temperature on an interannual basis at the SNOTEL stations, and correlations between April 1 SWE and precipitation tended to be greater than those for temperature (Figure 3a). In addition, only 12% of the temperature coefficients had a p value less than 0.1 (suggesting that most were not statistically differentiable from 0), while 95% of the precipitation coefficients were significant ($p < 0.1$). Standardized beta coefficients are stronger for precipitation than temperature at a substantial majority of stations (Figure 3b), indicating that variations in April 1 SWE for the period of the SNOTEL records were dominated by variations in precipitation. There are a few stations where temperature was more influential, however. These few stations were in the lower half of the elevation distribution.

SRT integrates weather across longer time scales, building some expectation that the fits might be better. However, SRT fits were generally poorer with a mean R^2 of 0.44 and half of the values between 0.31 and

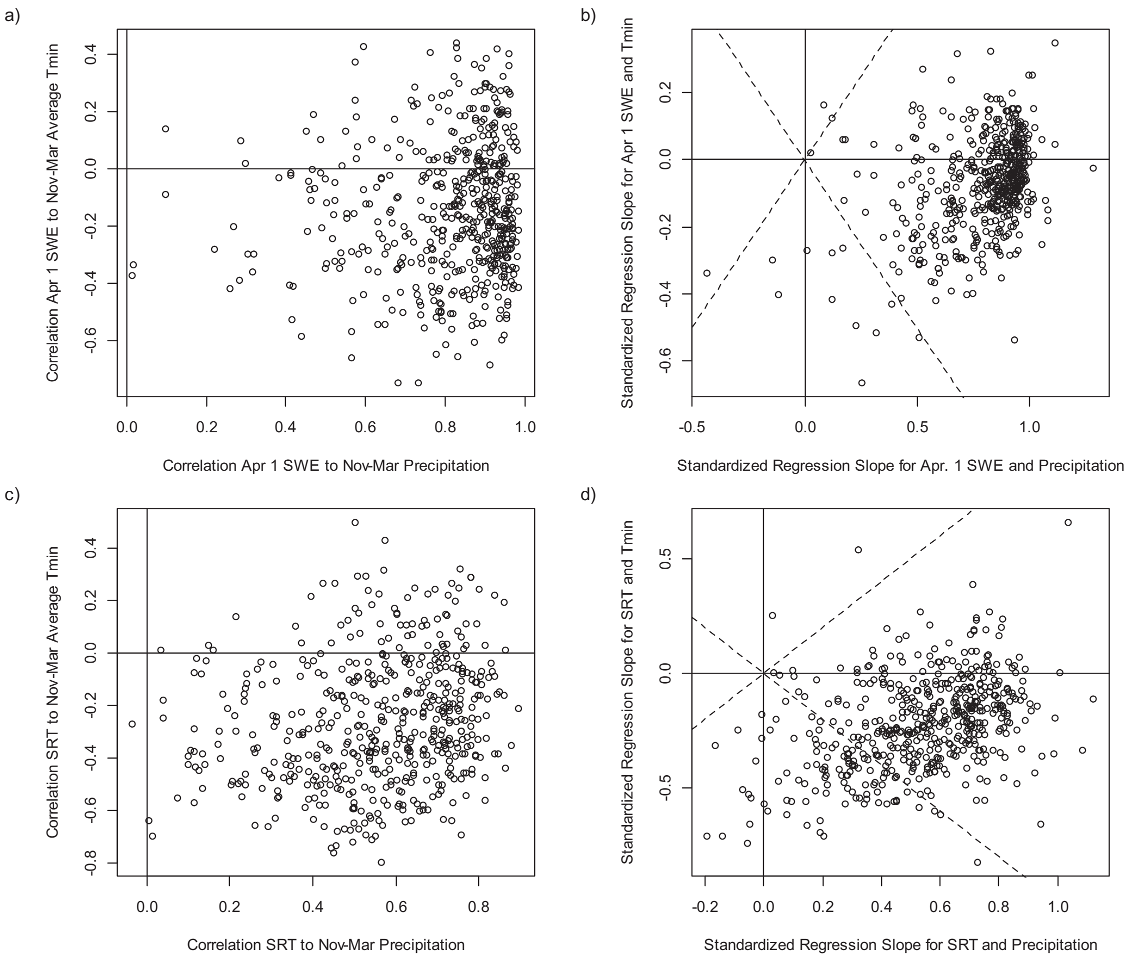

Figure 3. Correlations and standardized correlation coefficients for temporal analog models of (a and b) April 1 SWE and (c and d) mean snow residence time (SRT) at western U.S. SNOTEL stations. Dashed lines on standardized regression plots (b and d) are 1:1 lines showing where the relative influence of precipitation and temperature are equal.

0.57. Seventy-eight percent of the *p* values were less than 0.05. In contrast to the April 1 SWE fits, the precipitation correlations were not substantially and consistently greater than the temperature correlations, and the contributions of both the temperature and the precipitation correlations to the overall goodness of fit were more equal (Figures 3c and 3d). There was no relationship between the quality of fit for SRT and metrics like elevation or winter temperatures.

This study and that of *Mote* [2006] use different periods of record (1991–2011 versus 1960–2002), so it is difficult to quantitatively attribute differences between the two studies to methods. Nonetheless, the similarity of approach requires a brief comparison of findings. *Mote* [2006] used snow course records from the U.S. Natural Resources Conservation Service and offsite temperature and precipitation data from the U.S. Historical Climate Network, a subset of the National Weather Service's cooperative observer program, as well as a few stations from a Canadian counterpart. Fits for the interannual linear model of April 1 SWE appear somewhat improved in quality to those of *Mote* [2006] comparing Figure 3 therein to Figure 3a here. The mean correlation between April 1 SWE and precipitation is 0.82, and half of the values are between 0.76 and 0.93, higher than in *Mote* [2006], who reported a mean of 0.65 with half of the values between 0.53 and 0.81. The mean correlation with temperature was −0.15 with half of the values between −0.31 and 0.02. These temperature correlations are weaker than in *Mote* [2006], who reported a mean of −0.22 and half of the values between −0.36 and −0.10. Although some of these differences could be related to climate differences between the periods of analysis, the differences are also consistent with having collocated precipitation, temperature, and SWE data at SNOTEL stations and the fact that SNOTEL stations have a slightly higher elevation distribution than snow courses.

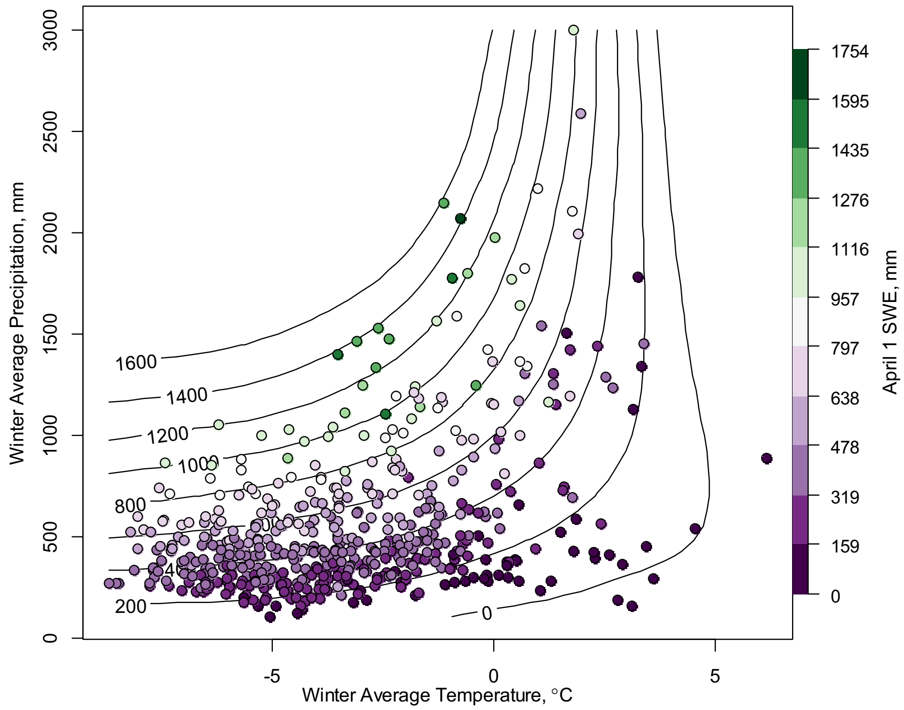

Figure 4. April 1 SWE (in color) as a function of winter average temperature and precipitation. Contours are a fitted surface using local polynomial regression. Units of contour levels are millimeter. Winter denotes November through March.

3.2. Spatial Analog and Contrast to Temporal Analog Results

3.2.1. April 1 SWE

The spatial analog for April 1 SWE on November–March precipitation and average temperature provided a strong fit (Nash-Sutcliffe $R^2=0.87$, RMSE=101 mm, Figure 4). The squared error at each station was unrelated to the number of years of record at the station ($R^2=0.004$, $p=0.14$). The curved contour lines show a strong interaction between precipitation and temperature in their effect on April 1 SWE, which is reinforced by the sensitivity plots (Figure 5) where temperature sensitivity is primarily a function of precipitation and precipitation sensitivity is predominantly a function of temperature. A simple linear model with an interaction term of the form:

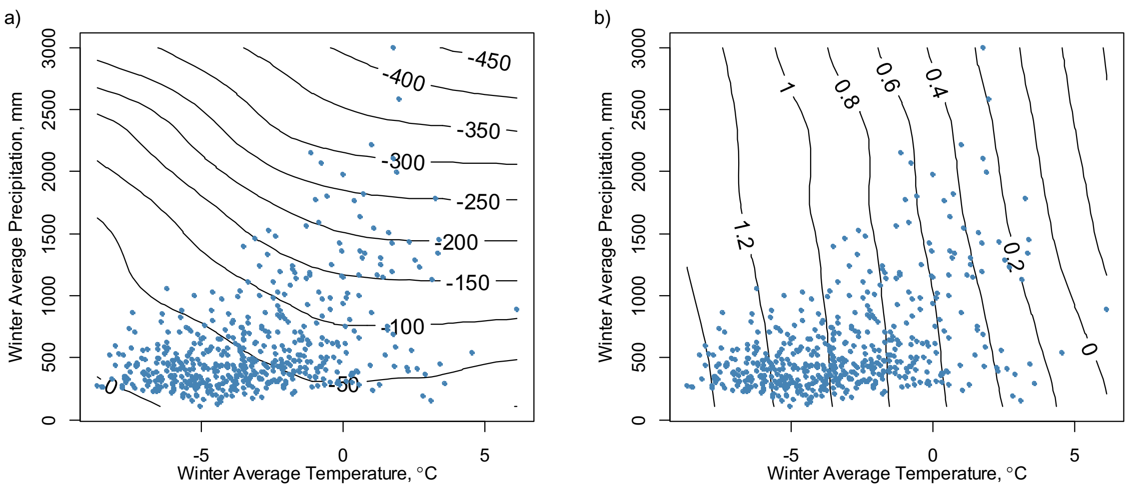

Figure 5. Spatial analog (a) temperature and (b) precipitation sensitivity of April 1 SWE as partial derivatives of the contours shown in Figure 4. Dots are for reference to show where the stations plot in T-P. Units on contour are mm/°C in (a) and mm-SWE/mm-P in (b). Winter denotes November through March.

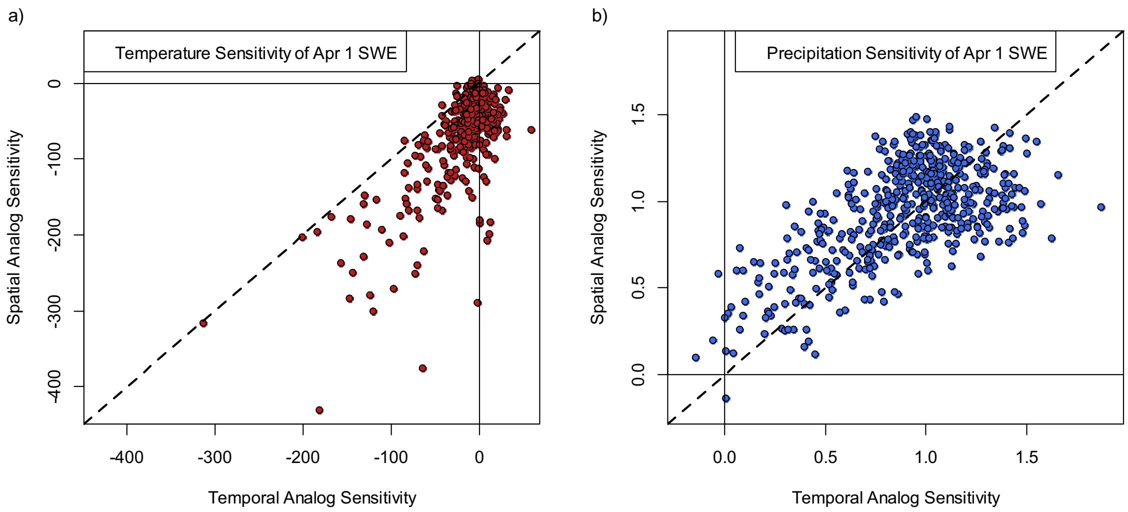

Figure 6. Comparison of (a) thermal and (b) precipitation sensitivity of April 1 SWE derived from temporal versus spatial analogs. Within each plot, axes have the same range, with lines drawn for 0 sensitivity and a dashed line showing where sensitivities are equal.

$$SWE = aTavg + bPrcp + c(Tavg\ x\ Prcp) + \epsilon_i \tag{11}$$

would yield an R^2 of 0.85, but would miss some of the nonlinearity in the local polynomial fit (other than that implied by the interaction itself). As might be expected from the general patterns noted in the analysis of temporal analogs and earlier analyses [*Mote*, 2006; *Mote et al.*, 2005], temperature sensitivity declines as precipitation sensitivity increases.

Differences between the spatial and temporal analog estimates of thermal sensitivity are substantial (Figure 6a). The mean temperature coefficient for the temporal analog was -14 mm/°C, while the mean partial derivative for the spatial analog was -58 mm/°C. While the temporal analog sometimes yielded physically

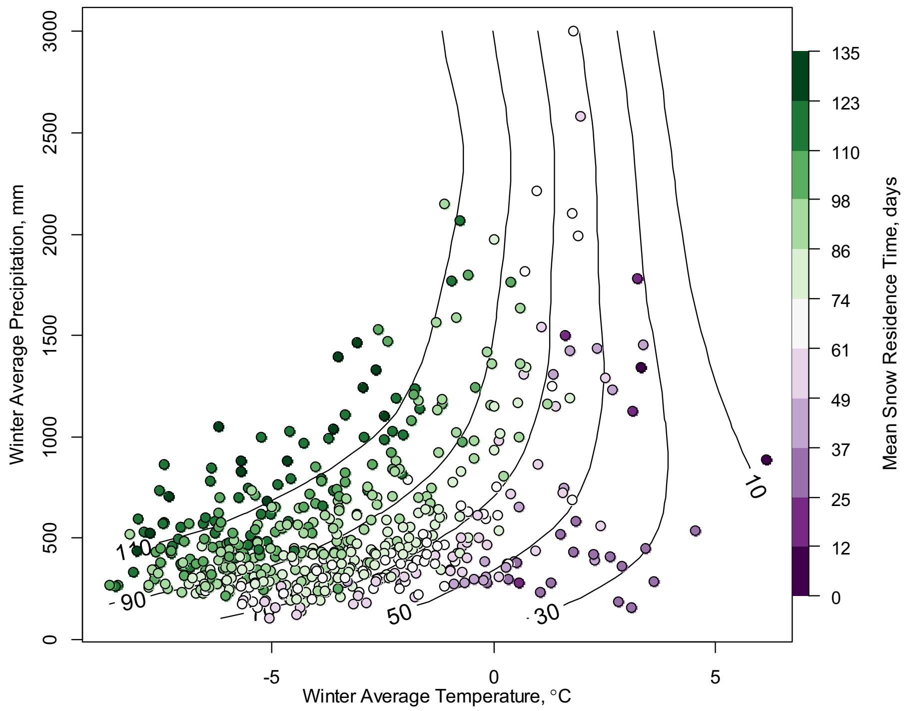

Figure 7. Mean snow residence time (SRT) as a function of winter average temperature and precipitation. Contours are a fitted surface using local polynomial regression. Units of contour levels are days. Winter denotes November through March.

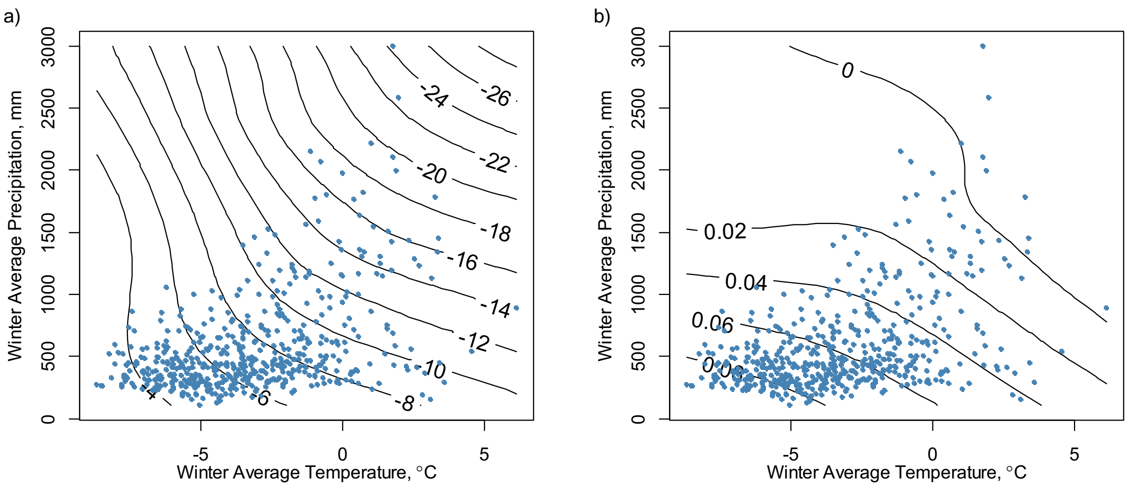

Figure 8. Spatial analog (a) temperature and (b) precipitation sensitivity of mean snow residence time (SRT) as partial derivatives of the contours shown in Figure 7. Dots are for reference to show where the stations plot in T-P. Units on contour on (a) are days/°C and on (b) are days/mm. Winter denotes November through March.

unreasonable positive coefficients, the spatial analog almost universally had negative coefficients. There were only three stations where the temporal analog predicts a greater thermal sensitivity than the spatial analog.

Differences in precipitation sensitivity for April 1 SWE are less pronounced, with no obvious bias and a slight degree of correlation (Figure 6b, $R^2=0.39$, $p<2.2\times10^{-16}$). The mean precipitation coefficient was 0.89 for the temporal analog and the mean partial derivative for the spatial analog was 0.94.

3.2.2. Snow Residence Time

The spatial analog fit for SRT is almost as good as that for the April 1 SWE (Nash-Sutcliffe $R^2=0.81$, RMSE=10.1 days, Figure 7). The squared error at each station was very weakly related to the number of years of record at the station ($R^2=0.019$, $p=0.002$). The fit of SRT shows interacting effects between precipitation and temperature similar to those for SWE, but with partial derivatives that are somewhat more sloped across the T-P plane than those of April 1 SWE (Figure 8). Warm-wet places show the greatest sensitivity to temperature change, and for a given precipitation level, warm places show greater temperature sensitivity. The precipitation partial derivatives have more of a joint sensitivity to T and P than do the precipitation partial derivatives of April 1 SWE.

As for April 1 SWE, the SRT thermal sensitivity estimated by spatial analog is generally greater, with a mean of −7.4 days/°C compared with −2.8 days/°C for the temporal analog. None of the spatial analog estimates

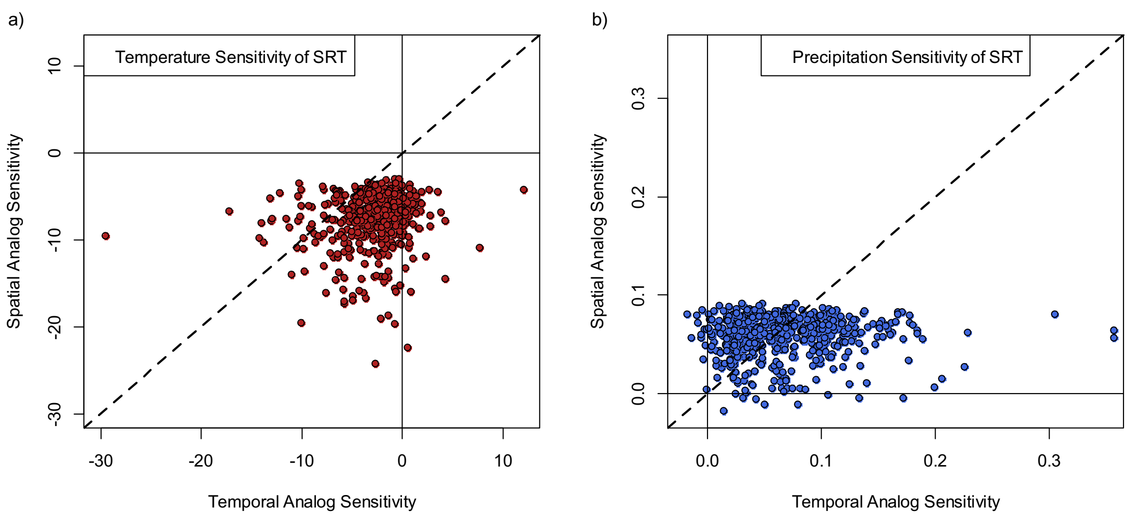

Figure 9. Comparison of (a) thermal and (b) precipitation sensitivity of mean snow residence time (SRT) derived from temporal versus spatial analogs. Within each plot, axes have the same range, with lines drawn for 0 sensitivity and a dashed line showing where sensitivities are equal.

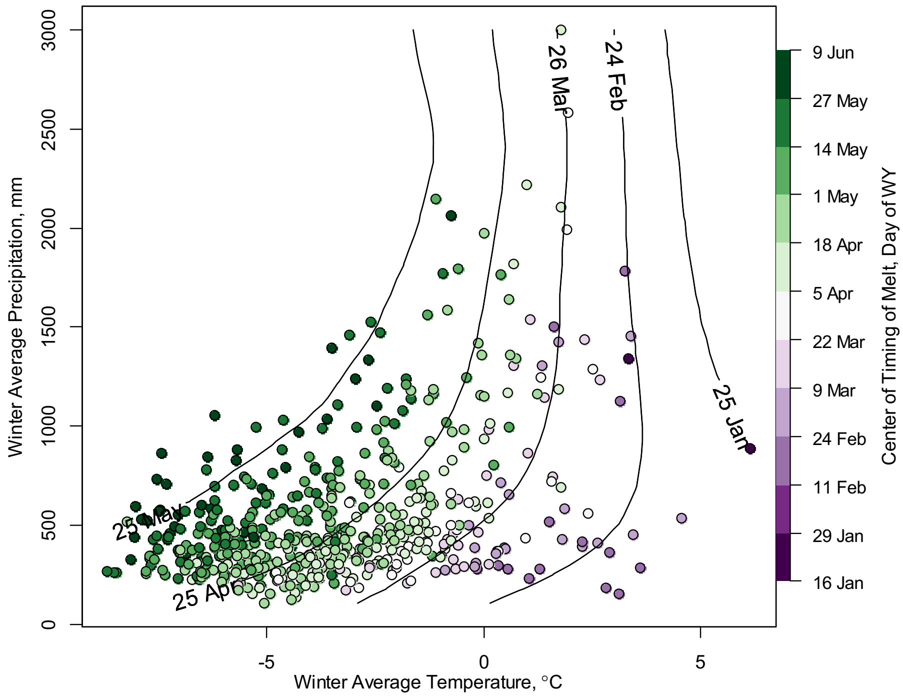

Figure 10. Center of timing of melt (CT_{melt}) as a function of winter average temperature and precipitation. Contours are a fitted surface using local polynomial regression. Contours are spaced 30 days apart. Winter denotes November through March.

show a positive sensitivity, while many of the temporal analogs do (Figure 9a). Although there is little difference in the mean precipitation sensitivity, 0.066 days/mm for the temporal analog and 0.058 days/mm for the spatial, there is no relationship between estimates from the two approaches (R^2=0.002, $p = 0.28$, Figure 9b).

The SRT at a station is strongly a function of CT_{melt} (R^2=0.9, slope=0.87 days/day, $p < 10^{-15}$), with a negligible contribution from variations in CT_{acc} (R^2=0.01, slope=0.28 days/day, $p = 0.026$). Although conceptually, the "accumulation season" is longer than the "melt season" for most seasonal snowpacks, the variance in CT_{acc} across SNOTEL sites is relatively small, with a standard deviation of just 8 days around a mean of 28 January (day of WY 120). A local fit surface using temperature and precipitation does not model the variability in CT of accumulation well, with a Nash-Sutcliffe R^2 of 0.26 and RMSE of 6.9 days. Elevation provides a slightly better estimate of CT of accumulation (R^2=0.35, $p < 10^{-15}$), although the slope is in the opposite direction of what might be expected if one were contemplating a strong effect of a later start to the accumulation season at lower elevations.

The CT_{mlt} has a variance of 25 days around a mean date of 22 April. The variability in CT_{mlt} can be reasonably well modeled with a local fit surface on temperature and precipitation (Nash-Sutcliffe R^2=0.78, RMSE = 12 days, Figure 10), with a pattern that appears primarily temperature related, with some precipitation contribution at colder temperatures. The fit of CT_{mlt} with elevation is poor (R^2=0.17, $p < 2.2 \times 10^{-16}$).

3.3. Comparison of Projected Responses to a Temperature Increase

Differences in performance and relative sensitivity of temporal and spatial analog models lead logically to the question of how the models might affect conclusions about the effects of projected warming on snow accumulation and melt. We examined differences in sensitivity of the spatial and temporal analog models to warming using a 3°C increase in winter temperature applied to each model. Although warming is not expected to be uniform across the western United States, applying a single temperature change to all sites allows comparisons of sensitivity more easily without confounding them with differences in exposure across sites.

Although the temporal analog only supports a linear application of the coefficient because the fit is a plane with no variations in temperature sensitivity, the spatial analog models have nonlinearities. We first checked whether the nonlinearities apparent in the spatial analogs were of consequence for a 3°C temperature change by comparing the amount of change estimated by a partial derivative versus that estimated by

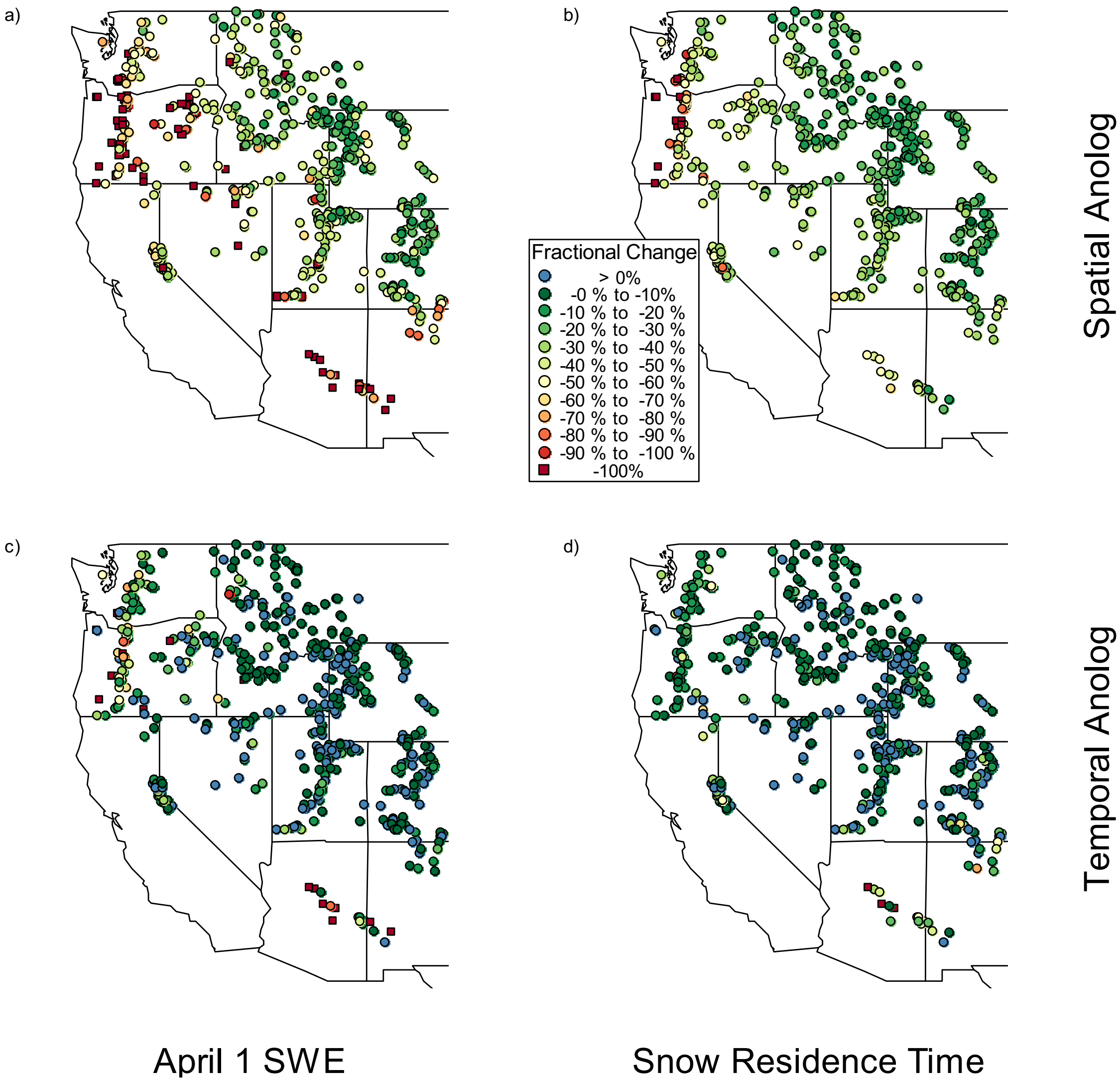

Figure 11. Comparison of fractional declines derived from spatial (a and b) versus temporal (c and d) analogs considering a 3°C increase in winter average temperature at each SNOTEL station. Left hand (a and c) maps are for April 1 SWE and right hand (b and d) maps are for mean snow residence time (SRT). Blue points denote projected increases.

directly calculating the difference in snow metrics between the observed T_{avg} and $T_{avg}+3°C$. Nonlinearities of response to temperature are modest but present, and the local sensitivity (from partial derivatives) generally underestimates the modeled change for a 3°C temperature increase by 21% for April 1 SWE and 10% for SRT. Differences tended to be more consistent and pronounced for less sensitive locations, with underestimates averaging 35% for April 1 SWE and 21% for SRT for the least sensitive half of the sites (as indicated by their partial derivatives). The nonlinear behavior is hinted at by Figure 5a, where there is temperature dependency of temperature sensitivity (the sensitivity contours have a slight slope through the blue points). Rather than using the partial derivatives to linearly estimate snowpack changes due to temperature changes, we used the local polynomial fits directly to incorporate the effect of these nonlinearities in maps of fractional decline using the spatial sensitivity (Figures 11a and 11b).

Using the spatial analog, estimated fractional changes in April 1 SWE with a 3°C warming are substantial at SNOTEL gages across the west (Figure 11a). The smallest decline was 9%, while some sites are expected to become snow free (100% reduction) on 1 April. The average decline projected across the SNOTEL sites is 46% with a median 40% decline. Coastal and southern mountains show the largest changes, with more modest declines predicted in interior mountains. Projected declines in SRT are not as severe, with an average decline of 33%, a median decline of 30% and a minimum decline of 8%. Fewer sites are expected to show nearly complete loss of seasonal snow (SRT declining 100%) than are expected to regularly see no snow on 1 April (Figure 11b). These patterns are consistent with the general findings of *Karl et al.* [1993] predicting decreased snow cover.

Contrasting the spatial analog change (top row in Figure 11) with the temporal analog change (bottom row) demonstrates substantial differences in estimated effects between the two approaches. The temporal analog model shows substantially lesser declines estimated for SWE and SRT using the temporal model, with average declines of 10% and 12% and median declines of 5% and 8%, respectively. With the temporal model, many stations (30% and 13% of stations, respectively) are projected to have increases despite specifying no increase in precipitation. In contrast the spatial model estimates no increases for either. Most of the stations projecting increases in the temporal analog model are at high elevations in the interior, but some of the stations with intermittent snow also show increases, likely due to uncertain temperature coefficients, which were largely (89% for April 1 SWE and 72% for SRT) not statistically different from 0 at $\alpha=0.1$. This finding suggests utility in comparison of model uncertainty in a similar set of maps, but the magnitude of differences in the expected values between approaches is itself important.

4. Discussion

Temporal model correlations estimated from local data at SNOTEL stations were generally greater than those presented by *Mote* [2006] where extrapolated weather data were used. Our fits also had substantially stronger correlation between precipitation and April 1 SWE. There are a few differences between the studies that could explain the differences, for example the period of record being different, a slightly higher elevation distribution for SNOTEL stations, or the difference between having and not-having collocated precipitation data. This final factor is related to the dynamic interplay between circulation patterns and terrain that moderate orographic precipitation and making projecting precipitation into mountains from low elevation stations difficult [*Colle*, 2004; *Dettinger et al*., 2004; *Luce et al*., 2013; *Yuter et al*., 2011]. Mean snow residence time distinguishes among stations with relatively poor and relatively strong fits of temporal sensitivity.

The models built in the context of a spatial analog provide a different picture of sensitivity than do the temporal analogs. Models of April 1 SWE and SRT based on climatological averages of P and T are relatively strong, so that spatial analogies of sensitivity to climatological warming seem reasonable. The spatial models, derived from SNOTEL stations distributed across a broad range of both T and P reveal expected interactions between T and P in generating snowpack. Deep and long-lived snowpacks are a function of both cold temperatures and high precipitation, so that shallow and short-lived snowpacks result from either low precipitation or warm temperatures. Thus, relatively wet warm locations where winter temperatures are near the rain-snow transition are more sensitive to even small increases in temperature than colder sites.

Thermal sensitivities derived from spatial differences are generally stronger than those derived from time series, and they also show very few positive sensitivities. A positive sensitivity, where there was more snow in warmer years, was more common among temporally derived sensitivities at cold stations, although only a few of the positive sensitivities were statistically significant. Such behavior has also been displayed for VIC simulations at higher elevations by *Hamlet et al*. [2005] even with precipitation fixed. The difference in thermal sensitivity is more pronounced for SRT than April 1 SWE. If some interannual variability is due to within-season timing of events (see Figure 1b), and this is not explained by T and P in the interannual models, the slope of the relationship is flatter than would be expected. The comparatively poor correlation coefficients on temporally derived thermal sensitivities highlight concerns about interpreting trends. For example, at a station such as the one illustrated in Figure 1b, a 2 week delay in the snow event would have resulted in a dramatically different April 1 SWE reading. When substantial noise in April 1 SWE is introduced that is related to the random timing of events, trends or correlations could appear as nonsignificant because of the timing-related noise. In contrast, the slower declines and rises in Figure 1a yield a situation that is less sensitive to snowfall event timing. To apply the spatial analog in this study, we first built a climatological model of differences in snowpack storage across locations. Similar work has been done for accumulation and snow cover duration [*Hantel and Hirtl-Wielke*, 2007; *Woods*, 2009]. Although the approach of *Woods* [2009] uses a subseasonal-scale simulation to develop and melt a snowpack, it uses climatological constructs affecting snow accumulation and melt, as opposed to actual time series. In that sense, this study supports the broad connection between season-scale precipitation and temperature climatology and both the depth and duration of snowpack storage found by *Woods* [2009]. A symmetric sensitivity of snow accumulation start and end to shifts in the dimensionless temperature proposed by *Woods* [2009] would help explain the small variance in CT_{acc} across the large diversity of sites and its relative insensitivity to temperature-related predictors. It may be that some variance could be explained by the differences in season-scale phase correlation of precipitation with temperature. The strength of the relationship between snowpack duration and both precipitation and temperature suggests that adding precipitation information to the model of *Hantel and Hirtl-Wielke* [2007] could improve its fit. The importance of CT_{mlt} to the overall SRT combined with the point that deeper snowpacks take longer to melt offers a mechanism for the importance of precipitation on snowpack duration.

Contrasting expected changes in April 1 SWE and SRT between the spatial and temporal analog approaches yielded much greater change projections using the spatial model than the temporal. Temperature coefficients for the temporal model were generally smaller and less certain than the precipitation coefficients for the temporal models, and the majority were not statistically significant, despite models that were mostly significant overall (considering variations in both T and P). It is possible that on an interannual basis, other factors besides November–March temperature and precipitation perturb SWE and SRT responses sufficiently to disrupt estimates of the temperature coefficient. The spatial analysis would suggest that chief among these might be interactions between temperature and precipitation, but unfortunately such a model is not well supported by the relatively short time series. This final result might suggest that temporal analogs are less trustworthy than generally accepted for purposes of projections, with a tendency to underestimate temperature effects. Comparison of both approaches to physically based snowpack modeling would have value for further understanding seasonal snow dynamics in a warmer world.

5. Conclusions

We contrasted two approaches to empirically determining sensitivity of snowpacks to climatic variations: one using variations from year-to-year at each station, and the other using variations in temporally averaged climate across stations. Our findings on temporally derived correlations were similar to previous studies [*Mote*, 2006], but with stronger model fits. The climatologically based spatial analog approach yielded stronger sensitivities of both April 1 SWE and SRT to variations in temperature and precipitation, and ultimately, greater projected changes. Sensitivities from the spatial analog were more consistently physically reasonable, in contrast to the time series approach, which gave unrealistic mean estimates of sensitivity in some locations, though we acknowledge that zero sensitivity was within the range of most temperature coefficient estimates from the temporal analogs.

Additionally, the spatial analog models captured the interaction between precipitation and temperature in forming snowpacks, where either warm conditions or low precipitation could yield a shallow, short-lived snowpack. Consequently, temperature sensitivity was highest in places that are already relatively warm, and warm snowpacks with high precipitation are likely to suffer some of the largest changes in snow storage as the climate warms. The spatial analog models also exhibited stronger sensitivity of cold, high elevation snowpacks to both temperature, and precipitation variations than previously noted. Given some of these differences, it is worthwhile to add the use of this simple climatological snowpack model in assessments of climate change impacts to water resources.

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