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RESEARCH ARTICLE

Spatio-temporal snowmelt variability across the headwaters of the Southern Rocky Mountains

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Abstract Understanding the rate of snowmelt helps inform how water stored as snow will transform into streamflow. Data from 87 snow telemetry (SNOTEL) stations across the Southern Rocky Mountains were used to estimate spatio-temporal melt factors. Decreases in snow water equivalent were correlated to temperature at these monitoring stations for eight half-month periods from early March through late June. Time explained 70% of the variance in the computed snow melt factors. A residual linear correlation model was used to explain subsequent spatial variability. Longitude, slope, and land cover type explained further variance. For evergreen trees, canopy density was relevant to find enhanced melt rates; while for all other land cover types, denoted as non-evergreen, lower melt rates were found at high elevation, high latitude and north facing slopes, denoting that in cold environments melting is less effective than in milder sites. A change in the temperature sensor about mid-way through the time series (1990 to 2013) created a discontinuity in the temperature dataset. An adjustment to the time series yield larger computed melt factors.

Keywords melt, SWE, temperature, SNOTEL, temperature sensor change

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1 Introduction

The snowpack is an important water storage component; understanding the timing of snowmelt is crucial to determine changes in streamflow for snow dominated watersheds (Doesken and Judson, 1996). The amount of water in the snowpack (snow water equivalent or SWE) varies over the year as snow accumulates and then later melts. SWE also varies inter-annually based on winter precipitation amounts. The rate of melt varies as a function of the energy balance, which includes short wave and long wave radiation, sensible and latent heat fluxes, ground heat, and heat from precipitation, and total melt quantities are a function of net accumulation (U.S. Army Corps of Engineers, 1956).

Modeling snowmelt using the energy balance approach requires estimates of all the energy components (Ohmura, 2001), which is typically difficult to obtain at many locations. As such, a temperature-index approach is often used. This method relates melt factors with temperature and has been explored for over a century (Horton, 1915). It has been used extensively to estimate snowmelt (e.g., U.S. Army Corps of Engineers, 1956) and streamflow, such as with the Snowmelt Runoff Model (SRM, Martinec et al., 2008). There have been various evaluations of the advantages and disadvantages of each approach (temperature index versus energy balance) (e.g., He et al., 2011; Kumar et al., 2013; Valéry et al., 2014). This current paper explores the temperature-index approach across the Southern Rocky Mountains using station observations.

The linear slope between snowmelt and temperature yields a melt factor, but this melt factor varies over time (Linsley, 1943; U.S. Army Corps of Engineers, 1956;

Rango and Martinec, 1995; Anderson, 2006). The temporal variation is a function of a variety of factors including the progressively lower cold content of snowpacks and the increasing incoming short wave radiation as the melt season progresses, and changes in snow surface albedo, in some cases due to melt water at the surface. Estimates of net (short and long wave) radiation have been added to the temperature-index approach to contend with melt factor changes over time (Rango and Martinec, 1995; Brubaker et al., 1996). However, short and long wave radiation data are not readily available.

Temperature is among the most commonly measured meteorological variables. However, measurements tend to be limited in snow covered environments, such as at higher elevation mid-latitude regions. Yet, daily snowmelt measurements necessary to compute melt factors have historically been very limited and are for sites with very specific characteristics. Often melt factors are calibrated in a hydrological model and not based on measurements (e.g., Leavesley, 1989; Zeinivand and De Smedt, 2009, Omani et al., 2016). Temperature-index models need enhancement to bridge the gap between restricted data availability and increasing demand for high resolution estimates (Hock, 2003).

Therefore, this paper explores the temporal and spatial variability in melt factors based on multi-year, daily snowmelt and temperature measurements collected by the Natural Resources Conservation Service (NRCS) at the automated snowpack telemetry (SNOTEL) stations (Natural Resources Conservation Service, 2016a). However, there is an inconsistency among the SNOTEL temperature data due to sensor changes occurring from 2004 to 2006 across the study domain (Julander et al., 2007). This change has been shown to cause an artificial amplification of warming trends (Oyler et al., 2015). An adjusted temperature time series could improve the consistency of the dataset (e.g., Ma et al., 2016). To evaluate bias due to this sensor change, concurrent sensors (pre- and post-change) were operated at a number of sites in Idaho (stated in Oyler et al., 2015 and presented by Morrisey, 2015). This bias adjustment was used to adjust the temperature time series prior to the sensor change. Therefore, the unadjusted and adjusted time series can be used to compute the melt factor and the implication of this sensor change can be demonstrated.

In this paper, the following four questions were addressed:

1) Can we estimate melt factor variability over time and space for ½ month periods across the Southern Rocky Mountains using SNOTEL data? 2) Can we explain the spatial and temporal melt factor variability based on terrain and land cover (type and density) across the entire domain? 3) Can we explain the spatial and temporal melt factor variability over individual headwater basins? and 4) What is the implication of a network-wide change in the temperature sensor configuration, specifically is there a systematic change in the melt factor?

2 Study area and data

The Southern Rocky Mountains span Southern Wyoming, Colorado, and Northern New Mexico of the Western U.S. The long-term NRCS SNOTEL stations across the study domain used by Fassnacht and Records (2015) were used in the analysis. The stations ranged in elevation from 2268 to 3536 meters (Fig. 1). These stations were established between 1979 and the mid-1980s to measure daily SWE and precipitation (Natural Resources Conservation Service, 2016b). In the late 1980s temperature sensors were added, and the 24-year time period of daily SWE and temperature data (wcc.nrcs.usda.gov) from 1990 through 2013 was extracted. The quality-controlled SWE data were obtained from Fassnacht and Records (2015). The concurrent temperature data were checked to remove outliers and other erroneous data (Avanzi et al., 2014).

An elevation dataset (ned.usgs.gov) was obtained from the U.S. Geological Survey (U.S. Geological Survey, 2016) and used to derive slope and aspect across the entire domain using the ArcGIS software (esri.com). Land cover and canopy density datasets (landcover.usgs.gov) were obtained for the study area from the National Land Cover Database (U.S. Geological Survey, 2016). The global position system (GPS) coordinates of each SNOTEL station, provided by the NRCS, were used to extract the slope, aspect, land cover type, and canopy density for each station at a 30-m resolution. These are the precise GPS coordinates, not the publicly available GPS coordinates from NRCS. These spatial data were obtained from Fassnacht and Records (2015). Land cover classification was simplified to evergreen when the NLCD was 42, and non-evergreen for all other NLCD land cover types, as evergreen was the only vegetation type to have above the snowpack foliage.

3 Methods

Snowmelt was calculated for each station during nine, half-month periods from early March through early July. For a specific half-month period, stations that experienced a daily decrease in SWE and had daily temperature measurements were used to calculate melt factor. This was calculated from the slope of daily average temperature versus daily decrease in SWE for all years of concurrent SWE and temperature measurement (e.g., Fig. 2) yielding a melt factor with units of millimetres per day per degree Celsius (mm/d/°C). The fit of the lines was not always strong (Fig. 2) since there are other drivers of melt besides temperature. The sample size for each half month period

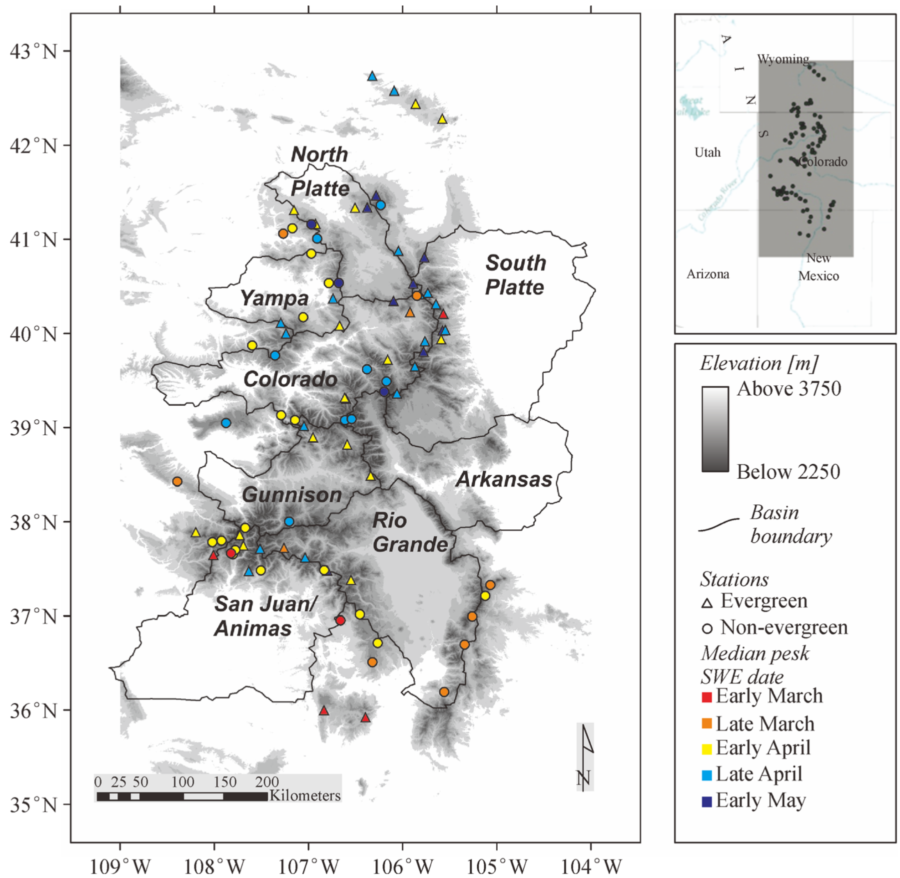

Fig. 1 Location of 87 SNOTEL stations across the Southern Rocky Mountains used to compute the half-month melt factors categorized by land cover type (evergreen or non-evergreen) and median date of peak SWE. The eight study headwater basins are shown.

was required to be greater than 20 days of concurrent melt and temperature measurements over the 24 years of record. Additionally, a minimum coefficient of determination (r^2) value for the fitted slope was required to be greater than 0.2 for the station to be included in the analysis. Possible outliers were identified as melt factors that were more than 2 times standard deviation greater than the mean, or that were less than 1.75 times less than the mean. This difference in acceptable standard deviations was used since the melt factors follow a log-normal distribution, based on observation of the distribution of the data.

Some difference in the computation of the melt factor may occur due to assumptions about the data used. Some studies only used temperature warmer than freezing and included negative melt and small amounts of melt, within the precision of the snow pillow (2.54 mm) (DeWalle et al., 2002; He et al., 2011). This study used daily mean temperatures colder than freezing temperatures (U.S. Army Corps of Engineers, 1956; Leavesley, 1989), but did not use negative melt or daily SWE decreases, i.e., melt of 2.54 mm.

The original temperature dataset was adjusted using a polynomial function fit to the Morrisey bias correction data, specifically all daily mean temperature data from the period prior to the sensor change were adjusted. Both the original and the adjusted dataset were used to estimate the melt factor for each station (e.g., Fig. 2). The resultant melt factors were then compared. This comparison addressed the fourth research question. The melt factors computed from the adjusted temperature were used for all subsequent analyses.

The spatio-temporal variability of melt factors was evaluated considering the time period and the independent terrain/canopy variables. These were location (latitude, longitude, and elevation), slope, northness (cosine of aspect times sine of slope (Fassnacht et al., 2012), canopy density, and land cover type as evergreen or non-evergreen. The independent variables were not cross-correlated, a maximum coefficient of determination (R^2) of 0.15 existed between latitude and elevation.

For the entire domain, time was the most important variable, and the best fit non-linear function was used to detrended all the station half-month melt factor data, yielding the residuals unexplained by the time variable. A sequential regression approach was then used where the residuals were correlated with subsequent terrain/canopy variables and further detrended. A split of the dataset by land cover type was considered if it improved the

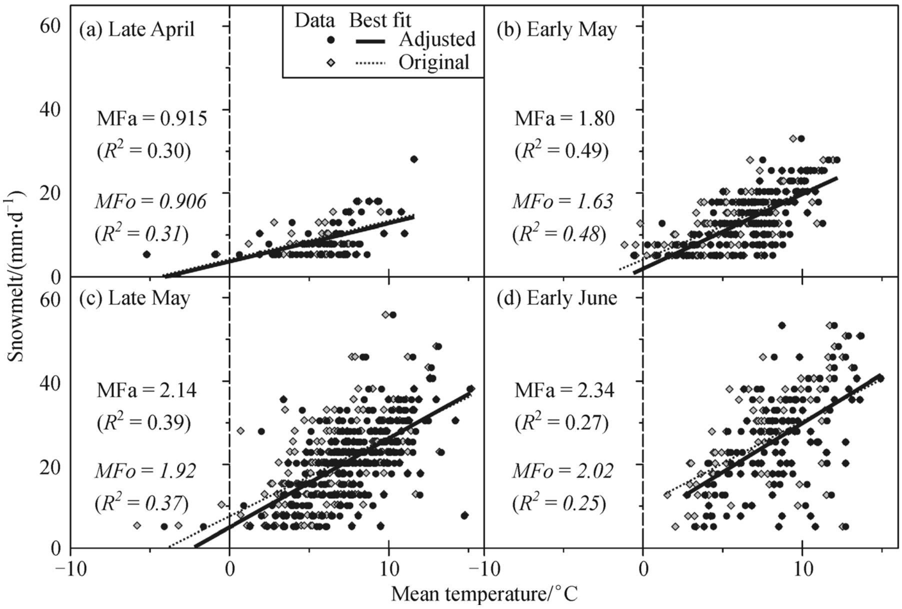

Fig. 2 Daily snowmelt measured as a decrease in SWE versus mean temperature daily four half-month for (a) late April through (d) early June at the Bear Lake (05J39S) SNOTEL station. Temperature is given as the original dataset (MFo in italics, *T* as light diamonds) overlain by the adjusted dataset (MFa, *T* as dark circles). The best fit line for each period and the two datasets is shown with slope and coefficient of determination (R^2 value). All relations are statistically significant at the $p < 0.05$ level.

correlation with terrain/canopy variables. This process continued until the improvement in R^2 value was smaller than 0.05 (Fassnacht et al., 2013). This showed the sequential explanation of variance by different terrain/canopy variables.

To investigate the correlation of terrain/canopy without time, a multi-variation linear regression was applied to each half-month period with at least eight computed melt factors. Each of the six variables independent variables was correlated to the melt factor, the most highly correlated variables were chosen to develop an equation. The coefficients in the linear equation were optimized by searching for the combination to maximize the R^2 and Nash-Sutcliffe coefficient of efficiency (Nash and Sutcliffe, 1970) values. This regression approach was used for the entire study domain and then for eight smaller headwater regions across the Southern Rocky Mountains (Fig. 1).

4 Results

From the best fit criteria, a variety of half-month periods could be computed for 87 of the 90 stations used by Fassnacht and Records (2015): 1) melt factors were not computed for three stations (Culebra #2, Columbine, and Red Mountain Pass), 2) only one half-month melt period was computed at six stations, and 3) melt factors for six half-month periods were computed at seven stations. An average of 3.6 melt periods was computed per station (40% of all the possible station melt-periods). Early May was the half-month period with the most computed melt factors at 69 stations (Fig. 3(a)). Since the melt factors could only be computed for one station during the early July period (Fig. 3(b)), this period was removed from further analysis. In total there were 312 station-periods of melt factors computed.

The melt factor increases as the winter progresses into the spring and the variability increases with time (Fig. 3(a) and Fig. 3(b)). A non-linear function with time can explain 70% variance in melt factor and but a limited amount of the remaining variance across the Southern Rocky Mountains is explained spatially (Fig. 4). Longitude is the most important spatial variable across the entire domain, after which the melt factor dataset is divided into evergreen and non-evergreen (Fig. 4). After the land cover split, 9% of the variance in the residuals is explained by slope for evergreen and 10% by elevation in non-evergreen (Fig. 4).

Across the entire domain for individual half-month periods, the spatial variability is not well explained by terrain/canopy variables. The multi-variate regressions did not fit well with Nash-Sutcliffe coefficient of efficiency (NSCE) values between 0.05 (late May) and 0.31 (early April), with an average of 0.18 (Fig. 5(a)). The R^2 values are similar to the NSCE, but the latter present the fit to the 1:1 line, which is more appropriate here (Legates and McCabe, 1999). Terrain and canopy explain much of the spatial variation in the melt factors for the Yampa, North Platte and Arkansas (Figs. 5(b), 5(c) and 5(i), respectively) with basin average NSCE values from 0.49 to 0.61. There

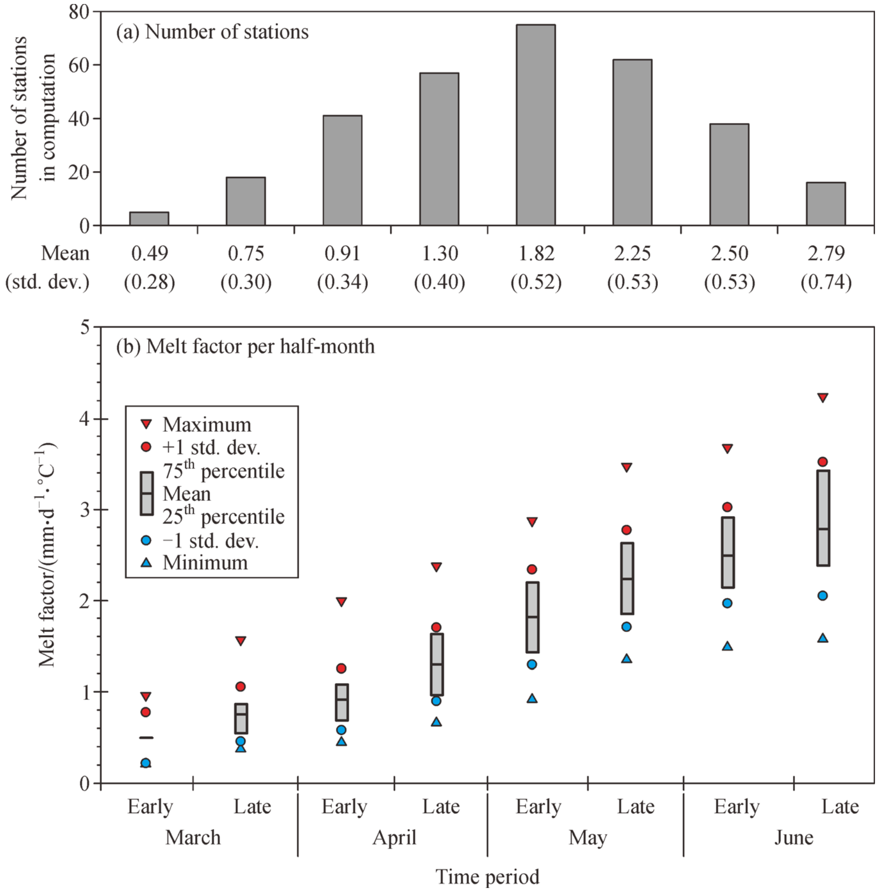

Fig. 3 Summary of (a) number of SNOTEL stations out of 87 during each of the eight half-month time periods from early March through late June that fit the snowmelt factor computation criteria, with the mean and standard deviation for each period, and (b) snowmelt factors as a function of time of year across the Southern Rocky Mountains. As there are only five station-periods for early March (Fig. 3), the 25th and 75th percentiles are not shown.

is a decent to good explanation for the Colorado, South Platte, and San Juan/Animas (Figs. 5(d), 5(f) and 5(g), respectively) with basin average NSCE values from 0.26 to 0.38. The spatial variation in the melt factors for early April over the Colorado and for late April over the Rio Grande were well explained by terrain/canopy, but the other periods were not (Fig. 5(d) and Fig. 5(h)).

Terrain and canopy variables do not explain much of the remaining variance across space (Fig. 4 and Fig. 5(a)). These terrain/canopy variables do explain much of the spatial variance for some of the individual basins (Fig. 1) but not for all (Fig. 5). For all basins, except the Gunnison, the NSCE and R^2 values are both greater than 0.5 for at least one half-month period. For the Yampa (Fig. 5(b)) and North Platte (Fig. 5(c)), the spatial variance for four half-month periods are well explained by the terrain/canopy variables. At temperatures colder than 15 Celsius the old temperature sensor had a cold bias, while at temperatures warmer than 15 degrees Celsius it had a warm bias (Morrisey, 2015). Melt temperatures were usually colder than 15 degrees Celsius and the adjusted temperatures were warmer than the original temperatures (Fig. 2). The computed melt factors were thus greater for the adjusted dataset (Fig. 2 and Fig. 6). The temperature bias is seen in the correlation between the two sets of melt factors. While the R^2 values are all greater than 0.98, the slope increases to 0.95 for late April and decreases to 0.84 in late June. Overall the melt factor computed from the original temperature data set is 92% of those computed from the adjusted temperature data (Fig. 6).

5 Discussion

The SNOTEL data can be used to estimate the melt factor (Fig. 3(b)) for most of the stations used by Fassnacht and Records (2015) and for different time periods (Fig. 3(a)). Beyond DeWalle et al. (2002) that focused on the Rio Grande region in the southern portion of this study domain (Fig. 1), SNOTEL data have not been directly used to estimate melt factors. This work provides an analysis of a dataset to confine acceptable values for calibration, etc. (e.g., He et al., 2011) and a possible means to extend results across space. This work can be extended to the

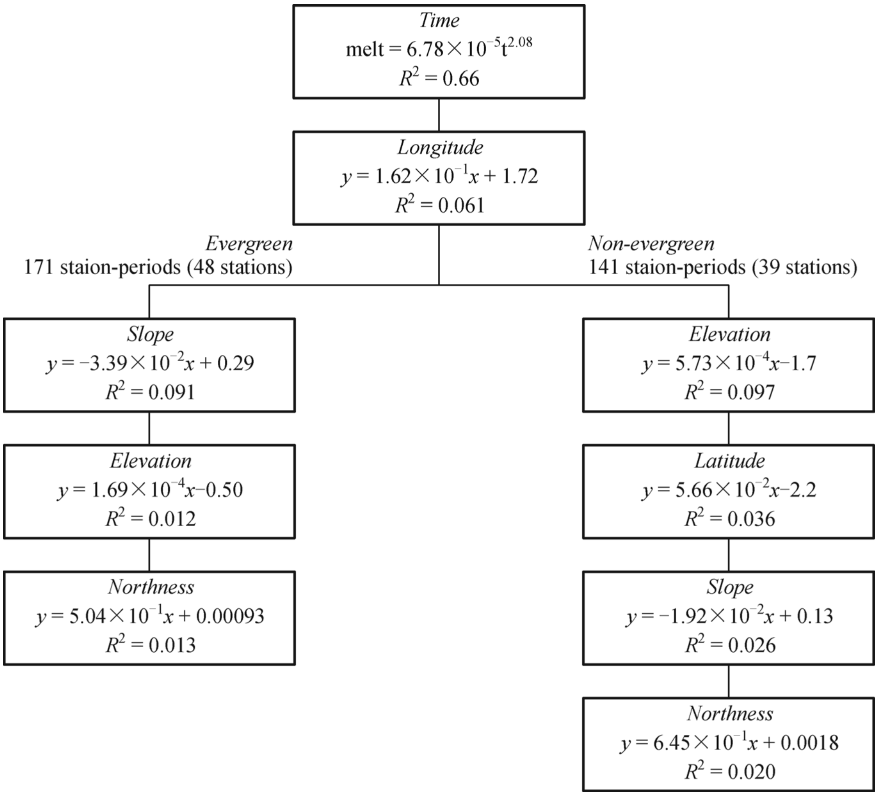

Fig. 4 Schematic of the sequence of the multi-step regression model to describe the correlation of melt factor with spatio-temporal variables (italicized). In each subsequent step, the residuals of the detrended values are correlated with a spatio-temporal variables; the dataset is divided into evergreen and non-evergreen land cover between the second and third steps. The equations and R^2 value explaining the variance for each successive step are given.

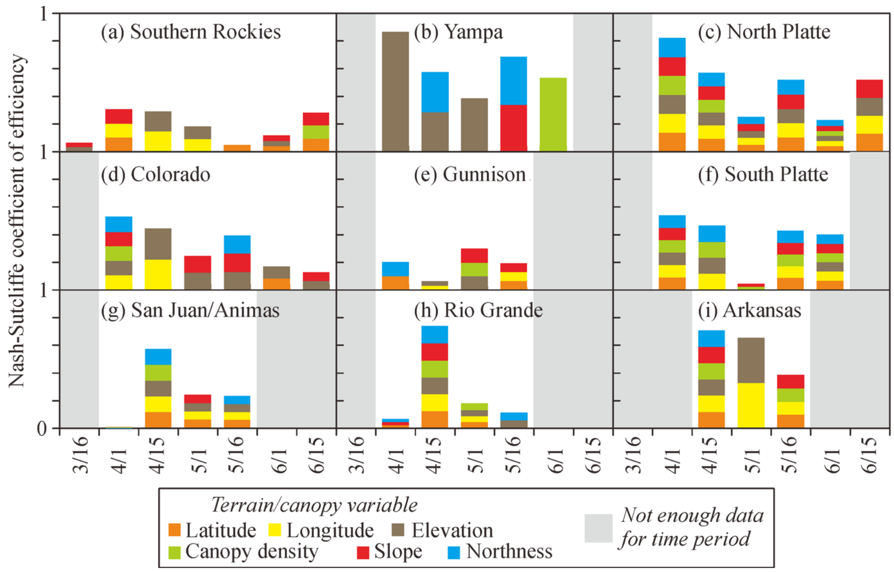

Fig. 5 Nash-Sutcliffe coefficient of efficiency (NSCE) and the specific terrain or canopy variables used in the multi-variate linear regressions over seven half-month periods (late March through late June) for (a) the entire study domain of the Southern Rocky Mountains, and (b) through (i) for the eight headwater regions in the area. Variables are shown when used in the regression. For example, for the Yampa River during early April (4/1), only elevation was used in the regression with a NSCE value of 0.87, whereas for the North Platte during the same period (4/1), all six variables were used in the regression with a NSCE value of 0.82. The grey bar indicates that melt factors were computed at too few (< 8) stations for the specific time period. All NSCE values were greater than zero, except during early April in the San Juan/Animas.

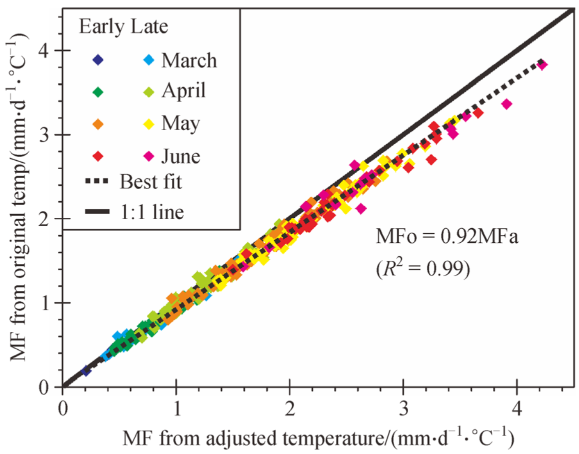

Fig. 6 Comparison of the melt factors (MF) computed using the original temperature dataset (MFo) versus the adjusted dataset (MFa) in the sequence of half-month periods. The best fit equation through the origin shows that the melt factors from the original temperature dataset are 92% of those compute from the adjusted temperature dataset.

Western U.S., including Alaska, to capitalize on the daily temporal resolution (Fassnacht et al., 2014) and the extent of the SNOTEL network (wcc.nrcs.usda.gov) and other areas were such SWE and temperature data exist (e.g., López-Moreno et al., 2010).

Melt factors increase as the snow season progresses from March through June (Fig. 3(b)) since incoming solar radiation increases, albedo may decrease due to enlarged rounding of grains and the increased presence of water at the surface, and incoming longwave radiation increases due warmer temperatures and the presence of more moisture in the air (Anderson, 2006). Moreover, as a snowpack approaches isothermal conditions, the effectiveness of energy inputs (including temperature) is greater for producing melting. Yet only temperature is used in the computation of melt factors. A temperature-based approach is thus reasonable (Ohmura, 2001; Hock, 2003), especially in areas with limited data availability (Lydon and Schulz, 1986). It should be noted that the correlation between SWE and temperature was often low (e.g., Fig. 2). Previous efforts have included net radiation (e.g., Rango and Martinec, 1995; Brubaker et al., 1996), but those data are not always available. Large individual quantities of melt (Cooley and Palmer, 1997; Fassnacht and Records, 2015) can occur on specific days that are much higher than what can be estimated from the melt factors presented herein (Fig. 3(b)) used with observed temperatures. However, such quantities are typically for specific days.

For the entire Southern Rocky Mountains, time explains two-thirds of the variance when the eight half-month periods from March through June are evaluated (Fig. 4). Across the Rio Grande, DeWalle et al. (2002) show a linear change in melt factor of 0.05 to 0.1 mm/d/°C per day depending upon the SNOTEL station. Herein, a non-linear increase in the melt factor is more appropriate than a linear increase (Fig. 4).

The melt factors derived from the SNOTEL stations across the Southern Rocky Mountains (Fig. 3) are similar to those found in the literature for this region. At a site in Central Colorado (Brumley), the calibrated model average late June melt factor was 1.18 mm/°C per 6 hours (He et al., 2011), and in this study the early June melt factor was 3.7 mm/d/°C (late June could not computed). In the Rio Grande, DeWalle et al. (2002) computed average melt factors from 2.9 (Wolf Creek) to 5.9 (Lily Pond) mm/d/°C. Here, the melt factors were similar to the lower values with an early June melt factor of 3.1 mm/d/°C at Wolf Creek. At four other SNOTEL station, the melt factors were lower (1.0 to 2.9 mm/d/°C for early April through early June) than those presented by DeWalle et al. (2002). The upper range of the DeWalle et al. (2002) is more similar to less continental environments (Linsley, 1943; U.S. Army Corps of Engineers, 1956). However, DeWalle et al. (2002) also showed 70% inter-annual variability in the average melt factor across the Rio Grande SNOTEL stations, due mostly to the timing of melt.

Most studies prior to 2015 used the original temperature time series. For example, DeWalle et al. (2002) used SNOTEL data from before the SNOTEL temperature sensor change, while others have used data across both time series (e.g., He et al., 2011). The adjustment used herein corrects a pre-sensor change time series that has a cold bias at temperatures colder than 15 degrees Celsius and that increases to about 2 degrees colder at a temperature of −15°C. There are thus different implications if only the pre-sensor change, post-sensor change or entire time series is used to estimate the melt factor. Herein, we show that melt factors would be larger when the time series is adjusted (Fig. 2 and Fig. 6).

There are other approaches to adjusting the SNOTEL temperature time series. Oyler et al. (2015) provided an adjustment using adjacent cooperative (COOP) weather stations that are part of the USHCN network (Menne et al., 2015). However, these COOP stations are mostly at lower elevation than the SNOTEL stations, and large differences can exist even in much more homogeneous terrain (Pielke et al., 2002; Fassnacht et al., 2016). In mountainous terrains, the spatial variability can be even more pronounced (Patterson, 2016).

There are limitations to extending the SNOTEL-derived melt factors beyond individual stations to locations between stations (He et al., 2011; Kumar et al., 2013). Using fine scale simulations over a small watershed (0.39 km^2), the temperature index approach was found to under-predict melt in open areas and over-predict melt in shaded areas (Kumar et al., 2013). At a much coarser resolution, specifically a dozen SNOTEL stations across the Western U.S., the variability in the late June melt factor was large and found to a sensitive hydrologic modeling parameter (He et al., 2011). However, the melt factors presented for the Southern Rockies are at a medium resolution of approximately 1 SNOTEL station every 2000 km^2. While the spatial distribution of the melt factors cannot be attributed to terrain/canopy variables across the entire domain (Fig. 4), across specific watersheds there is a strong correlation (Fig. 5). The seasonal variation in the melt factor is a non-linear function of time (Fig. 4). The NCSE would likely improve if the entire domain was separated into evergreen and non-evergreen; the analysis presented in Fig. 5 used all stations for the entire domain to be consistent with the analysis for the individual basins.

While a majority of the SNOTEL stations in this study (48 of 87) tend to be in evergreen land cover (Fig. 4) with an average canopy density of 70% (range from 23% to 92%), these stations are actually in small clearings in the forest (Meromy et al., 2013). Almost half of the remaining SNOTEL stations are in no or low-vegetation land cover (landcover.usgs.gov) with no canopy, but these also tend to be in the vicinity of forested areas to reduce wind effects on the snow pillow (Meromy et al., 2013). They also tend to be in locations where snow accumulated early and melts late (Daly et al., 2000).

The methods and results presented herein could be used with remotely sensed snow covered area (e.g., Richer et al., 2013) and SNOTEL data (e.g., Fassnacht et al., 2016) to model runoff (e.g., Dressler et al., 2006). The SNOTEL data could be combined with other data to expand melt factor computations to locations between SNOTEL stations (Sexstone and Fassnacht, 2014). The data could also be used to calibrate other models (e.g., Kampf and Richer, 2014). This work could also be expanded to a sub-daily time scale (e.g., Tobin et al., 2013; Webb et al., *in review*), but the sensitivity and precision of the snow pillow data (e.g., Johnson and Schaefer, 2002; Johnson and Marks, 2004) may preclude going to an hourly time step with the SNOTEL dataset. Similarly, snow lysimeter data (e.g., Dunne et al., 1976; Colbeck, 1979) could also be used to evaluate melt factors from SNOTEL stations, but such data are not as widely measured.

6 Conclusions

Computed snow melt factors varied exponentially as a function of time of year, ranging from 0.21 mm to 4.23 mm per day per degree Celsius across 87 stations in the Southern Rocky Mountains over eight half-month periods. Melt factors averaged 0.49 mm/d/°C in early March and reached a maximum average of 2.79 mm/d/°C in late June. Terrain and canopy variables could not be used to explain the spatial variability of melt factors across the entire domain, but were suitable to explain the spatial variability across five headwater basins (Yampa, North Platte, Colorado, South Platte, Arkansas). For three other basins (Gunnison, Rio Grande, San Juan/Animas), the variability in April melt factors was well correlated with terrain and canopy variables.

The SNOTEL temperature time series is discontinuous due to a sensor change. One method was applied to adjust this time series for the period prior to the change. This yielded a mean increase in the melt factor of 9%, range from 1.2% more in late April to 14.3% more in late June. This temperature time series discontinuity must be further evaluated.

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