ARE TEMPERATURE-INDEX MODELS APPROPRIATE FOR ASSESSING CLIMATE CHANGE IMPACTS ON SNOWMELT?

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ABSTRACT

Robust projections of climate change impacts are critical for natural resource planning in snow-dominated watersheds. Numerous studies have applied temperature-index (TI) snow models using calibrated parameter sets from the historic period, and estimate climate change impacts by forcing TI snow models with different climate scenarios. However, this methodology is questionable because (1) it assumes stationarity in model parameters, (2) it assumes the climate change signal is embedded in temperature alone, and (3) it does not account for changes in the snowmelt energy balance in a warmer climate. Here we explore the relationships between TI melt factors and changes in climate to understand the reliability of TI models for quantifying climate change impacts on snow hydrology. We examine historic relationships between temperature and melt factors (derived from observations) at 510 SNOTEL sites across diverse hydroclimates. Results show that melt factors decrease with increasing mean annual temperature at 98.6% of the sites (76% with statistical significance), and decrease with declining peak SWE and earlier peak SWE timing at over 90% of the sites. The results imply that historically calibrated TI models will overestimate snowmelt rates when applied in a warmer climate, and therefore their usage in climate change studies is problematic. (KEYWORDS: temperature-index model, physically-based model, climate change, energy balance)

INTRODUCTION

Snowmelt runoff is a vital water resource for many human and ecological communities worldwide. Approximately one-sixth of the global population lives in snowmelt-dominated catchments where snowpack supplements reservoir storage (Barnett et al., 2005). Additionally, strong linkages exist between snowmelt and ecological processes in snow-dominated catchments, such as evapotranspiration, plant phenology and spatial distribution (e.g., Ford et al., 2013), and forest productivity and greening (Trujillo et al., 2012). Hence, there is significant concern about how climate change may alter the accumulation of seasonal snowpacks and the timing and rate of snowmelt, and how those changes will impact basin hydrology and ecology.

Numerical snow models provide a means for quantifying potential changes in snow hydrology due to shifts in climate or land cover. Two families of models are commonly employed to simulate snow accumulation and melt, including (1) conceptual temperature-index (TI) or degree-day models, and (2) physically-based energy balance (EB) models (Melloh, 1999). Despite continued progress in the physical understanding of snow hydrology, TI models remain widely used in research and operations (e.g., the National Weather Service River Forecasting Centers continue to use SNOW-17). This is due to their low data requirements (i.e., temperature and precipitation only) and comparable or (in some cases) better skill than more complex EB models when the TI models are carefully calibrated (Franz et al., 2008; Debele et al., 2009). The typical assumption of TI models is that snowmelt scales with air temperature (T_{air}) above some threshold value (T_{base}, typically 0°C) according to a melt factor (MF) parameter:

$$Melt = (T_{air} - T_{base}) \times MF \tag{1}$$

where MF may be either set as a constant, or may vary with factors such as snow density (Martinec et al., 2008), seasonality (Anderson, 1976), diurnal cycles (Tobin et al., 2013), forest cover (Jost et al., 2012), and topography (Shamir & Georgakakos, 2006). TI parameters such as MF are difficult to obtain a priori, as there is low correlation between TI parameters and site characteristics at the point scale (He et al., 2011). As a result, TI modeling studies often rely on local, historic calibration (assuming data are available) or literature values for model parameters.

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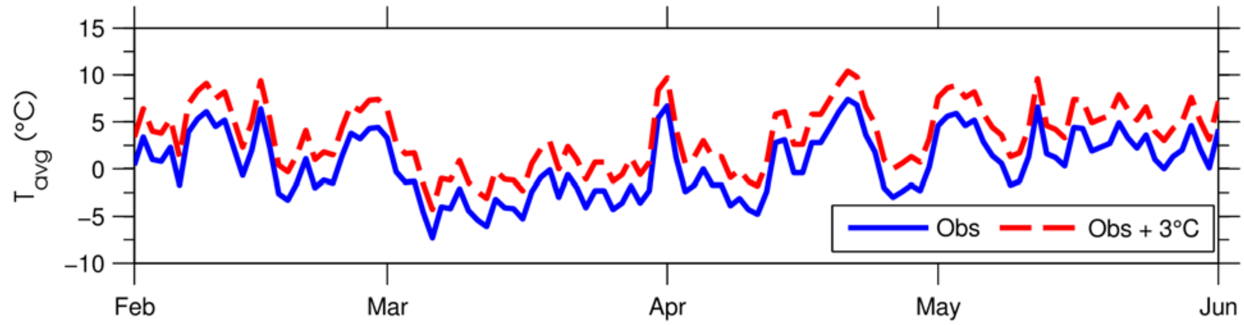

Figure 1. Example of a "ΔT" approach for simulating a climate warming of 3°C for average daily air temperatures at the Paradise (WA) SNOTEL site.

Numerous studies have used TI models to project climate change impacts on snowmelt (e.g., Notaro et al., 2010; Rango, 1992; Miller et al., 2003; Semádeni-Davies, 1997), and in general, these types of applications calibrated the model on the historic period to project future conditions. However, this approach assumes (1) stationarity in the model calibration, and (2) changes in air temperature alone (via the common "ΔT" approach applied to historical records, Figure 1) account for all changes in the snow surface energy balance. Hence a key issue for TI models is whether the historic calibration of the melt factors is valid in a future, altered climate (and hence for an altered energy balance). For these modeling applications, Hock (2003) notes that "results must be interpreted with caution as the inherent assumption that degree-day factors remain constant under a different climate may not be true."

Calibrated TI snow models have historically demonstrated reasonable performance at the basin scale because the relative drivers of snowmelt in the energy balance tend to be similar from year to year. However, evidence suggests that when the energy balance is altered to a state beyond calibration or mean conditions, TI model performance becomes less reliable. A recent example of this limitation has emerged in the dust-on-snow events that have enhanced shortwave forcing (due to a lowering of the snow albedo) and accelerated snowmelt rates and melt timing in the Upper Colorado River Basin. Bryant et al. (2013) demonstrate that in years with above (below) average dust loading, the conceptual SAC-SMA / SNOW-17 model (Anderson, 1976; Burnash et al., 1974) used by the NWS River Forecasting Center tends to underestimate (overestimate) streamflow. In this example, the melt factors should have been increased with the dust-caused albedo decreases to account for greater snowmelt energy per degree-day (Hock, 2003). This demonstrates that changes in the energy balance can corrupt the calibration of conceptual models. We therefore expect that historically calibrated TI models are prone to yield biased snowmelt projections in climate change studies, as the contributions of different snowmelt change.

In this paper, we ask "Are temperature-index models appropriate for assessing climate change impacts on seasonal snowpack and snowmelt?" We hypothesize that historically calibrated TI models overestimate snowmelt in a warmer climate. We argue that only a few components of the energy balance (e.g., longwave, sensible heat) will see increases due to increased greenhouse gas concentrations in the atmosphere, but the TI approach scales all energy balance terms by changes in temperature, thereby leading to melt overestimation. As an initial test of this hypothesis, we analyze observational data from the NRCS SNOTEL network in order to determine how seasonal melt factors change with climate variables. Future work will attempt to place the results of this data analysis in the context of physical understanding.

OBSERVATIONAL SITES AND DATA

The observational analysis used data collected at snow pillow sites across the western USA from the NRCS SNOTEL network (Serreze et al., 1999). The SNOTEL data included daily observations of snow water equivalent (SWE) measured from snow pillows and mean daily air temperature (T_{air}). We initially considered the entire period of record (water years 1963-2012) and the 811 sites that were active as of water year (WY) 2012. We then conducted quality control on the daily data using maximum and minimum limits, and required that daily temperature did not deviate from the record daily mean at each site by more than 2.5 standard deviations. We further filtered the dataset by only retaining years with peak SWE of 100 mm or greater and required no more than 10 days of missing data in a valid year. To ensure multiple years of record (for sampling interannual variability), we required at least 15 years of complete data (i.e., meeting the aforementioned standards) in order to retain a station. The final number of stations available for the analysis was 510 sites (Figure 2). To make a serially complete dataset for these 510 sites, we filled missing data during valid years (i.e., no more than 10 missing days) using an empirical orthogonal function (EOF) technique (Henn et al., 2013) for air temperature, and temporal interpolation for missing SWE.

We used the SNOTEL network in the analysis because it represents the most spatially comprehensive dataset in the western USA. However, we note that the dataset has potential issues, such as common measurement errors over snow (e.g., radiative heating of temperature sensors, Huwald et al. (2009)), changes in surrounding land cover, and changes in snow pillow type (e.g., conversion from steel to hypalon pillows in the 1990s, Julander & Bricco (2006)). Assuming similar radiative errors of the temperature data from year to year, we did not expect this error to impact our trend analysis greatly. We also expected the snow pillow type to have only a minor impact, as 80% of the station-years were after 1995 and 97% were after 1990, and hence much of the snow data is from a single type of snow pillow (i.e., hypalon).

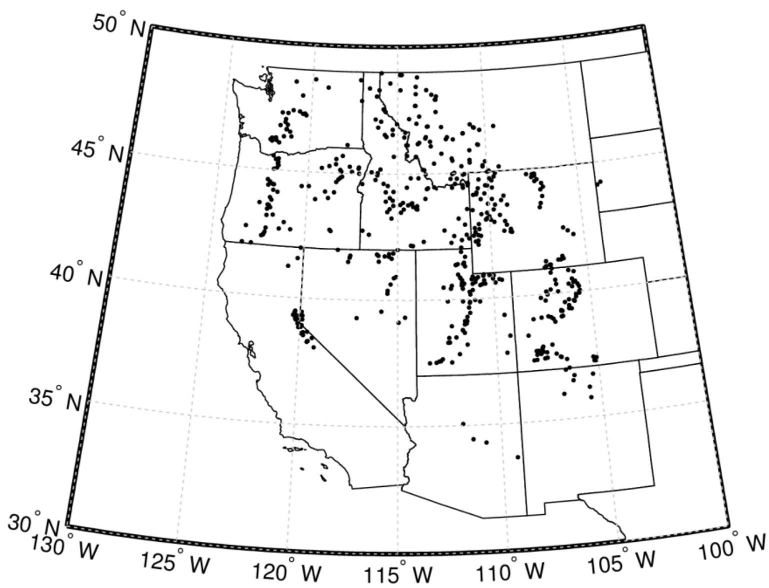

Figure 2. The 510 NRCS SNOTEL sites used in the observational analysis. No sites in Alaska were included.

METHODS

Using the SNOTEL observations, we computed seasonal (i.e., one per annual snowmelt season) melt factors and compared them to climate variables in order to understand how they vary with changes in annual snow conditions. At the point scale, melt factors (i.e., degree-day factors) can be calculated based on snowmelt and temperature data (DeWalle et al. 2002; Weiss & Wilson 1958). At each station-year, we derived melt factors from the snow pillow SWE observations and daily T_{air} data. We examined snow and temperature conditions only during the snowmelt season (i.e., from the latest date of peak SWE to the first snow-free date after peak SWE, Figure 3a). Daily snowmelt was assumed during any decreases in SWE. We assumed T_{base} was 0°C, and compared cumulative degree-days (T_{air}-T_{base}, taken only when $T_{air}>T_{base}$) to cumulative observed snowmelt over the snowmelt season (Figure 3b). The slope of the linear least-squares fit was taken as the seasonal melt factor for that station-year.

After calculating unique melt factors across all valid years at the 510 SNOTEL sites, we employed a simple correlation analysis to determine the direction and significance of their relationships with meteorological variables, snow variables and climate indices. At each site, we tested the relationship between the computed seasonal melt factors and seven variables. These included: (1) mean annual temperatures, (2) mean temperatures during the melt season, (3) mean temperatures during the entire snow season (accumulation and melt seasons), (4) peak SWE values, (5) peak SWE dates, (6) mean El-Niño Southern Oscillation (ENSO) indices, and (7) mean Pacific Decadal Oscillation (PDO) indices. Statistical significance was tested at the p=0.05 level using a Student's t-test.

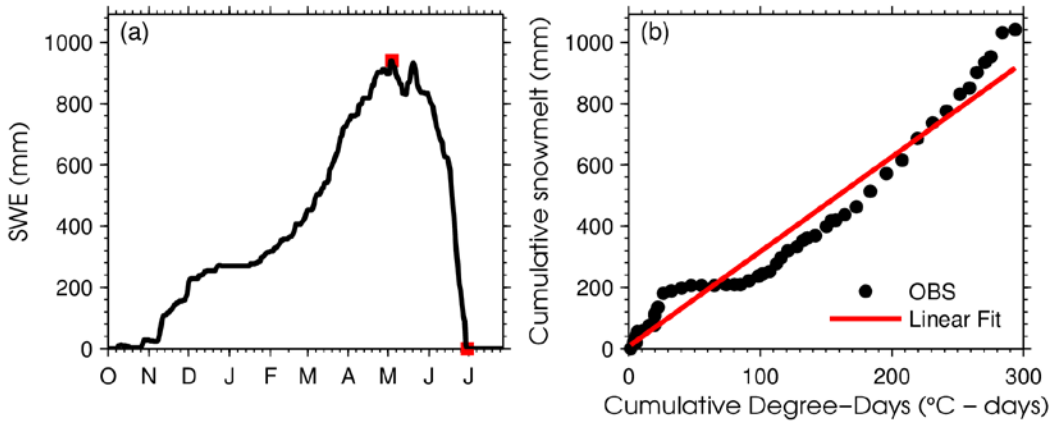

Figure 3. Method of calculating a seasonal melt factor from SNOTEL data. (a) Time series of observed SWE, with red squares indicating dates of peak SWE and snow disappearance (analysis constrained to period between these dates). (b) Cumalative snowmelt vs. cumulative degree-days at this site, with a linear fit shown. The slope of the linear fit (i.e., 3.1 mm $°C^{-1}$ day^{-1}) is the calculated seasonal melt factor during this particular station-year.

RESULTS

The computed melt factors had the most consistent relationship with mean annual air temperatures and peak SWE values (Figure 4). At 98.6% of the SNOTEL stations (503 out of 510), melt factors were negatively related to mean annual air temperature, with statistically significant relationships found at 76.3% of the stations (389 out of 510) (Figure 4). Only 1.4% of the stations (7 out of 510) had positive correlations between melt factors and mean annual air temperatures, and none of these positive correlations were statistically significant. Interestingly, significant negative correlations between the other temperatures (e.g., melt season temperature, snow season temperature) and melt factors were less frequent, suggesting factors other than temperature (e.g., precipitation) were important. None of the melt factor correlations showed a clear spatial coherency.

In contrast to mean annual air temperatures, peak SWE magnitudes were positively correlated with melt factors at 93.1% of sites (475 out of 510), with statistical significance at 57.3% of sites (Figure 4). Melt factors were negatively correlated with peak SWE values at only 6.9% of sites (35 out of 510), with no significant negative correlations. As with peak SWE magnitude, peak SWE timing was positively correlated with the computed melt factors at most sites (i.e., 91.2% of sites, 47.3% with statistical significance).

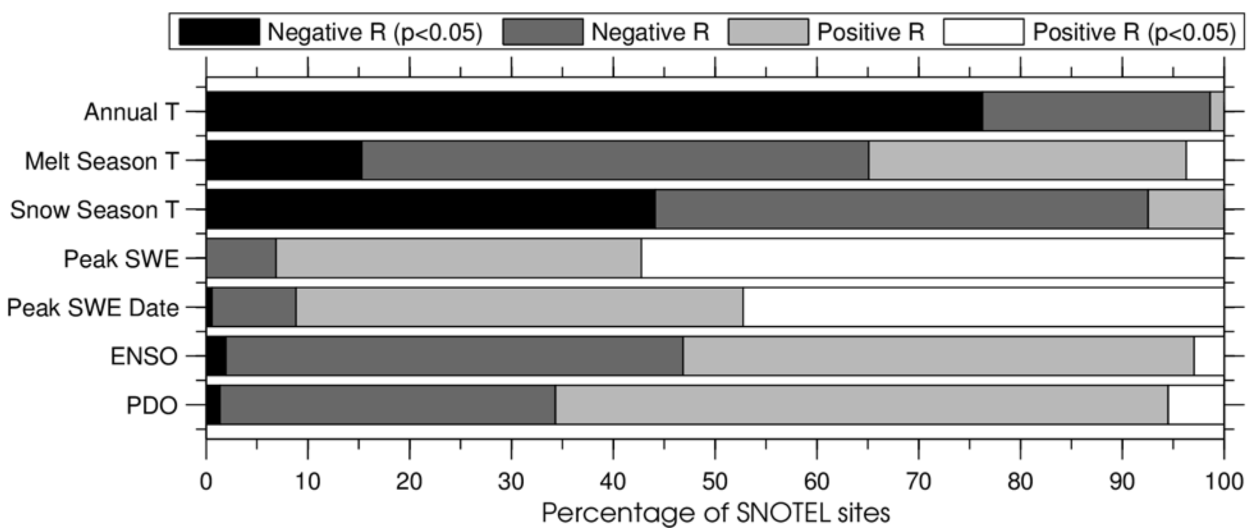

Figure 4. Frequency of the direction and statistical significance (5% level) of correlations between seasonal melt factors and seven climate/snow variables at 510 SNOTEL sites. For peak SWE date, the results indicate that later (earlier) peak SWE is generally correlated with higher (lower) melt factors.

Correlations between the climate indices (i.e., ENSO, PDO) and melt factors were positive at the majority of sites (Figure 4). However, no more than 5.5% of the sites (28 out of 510) had statistically significant positive correlations, and even fewer sites had statistically significant negative correlations. Hence, ENSO and PDO were not strong predictors of computed seasonal melt factors at the SNOTEL sites.

DISCUSSION

The results of the observational analysis indicate that point-scale seasonal melt factors at SNOTEL sites are generally sensitive to variations in annual temperature and peak snow conditions within the historical record. With future increases in temperature due to climate change, we infer that using historically calibrated melt factors to project climate impacts on snow hydrology will result in overestimation of melt factors, and therefore, overestimation of snowmelt (Equation 1). Projections of regional precipitation change are less certain in climate studies, but nevertheless important, as increases in precipitation may yield greater peak SWE and later peak SWE timing, both of which are correlated with increased melt factors. However, increasing temperature may also decrease peak SWE and advance the timing of peak SWE to earlier in the season, thereby causing melt factors to decrease (Figure 4). Therefore, seasonal melt factors should decrease with climate change, unless these effects are offset or overwhelmed by increases in snowfall precipitation (as manifested in peak SWE). This uncertainty implies that historically calibrated conceptual TI models are not robust for projecting climate change impacts on snowmelt.

We note that the negative relationship between melt factors and mean temperatures found here at most SNOTEL sites was contrary to some previously reported trends in the literature. Based on modeling experiments, Braithwaite (1995) found that melt factors for snow increased with summer temperatures at two sites on the Greenland ice sheet, while MacDougall et al. (2011) found a slight increase in melt factors with respect to mean annual temperatures for a glaciated region in the Yukon. However, the conceptual logic of Hock (2003) was that melt factors decrease with decreasing elevation (hence, increasing temperature), which supports the SNOTEL results here. It was not clear why this inconsistency emerged, but we hypothesize that the discrepancy may be related to differences in the surface energy balance and the relationship between radiation and temperature in these contrasting areas of the cryosphere (seasonal snow vs. ice sheets and glaciers). Future work will utilize modeling experiments to better understand the physical controls on melt factors.

SYNTHESIS AND ONGOING WORK

An observational analysis at 510 SNOTEL sites provided evidence that melt factors exhibit sensitivity to climatic factors such as temperature and winter precipitation (through peak SWE magnitude and timing). Decreases in melt factors were seen in the observational analysis (Figure 4), implying that historical melt factors would tend to be too high in a warmer climate and cause exaggeration of climate impacts on snowmelt. These results provide compelling evidence that TI models that employ constant seasonal melt factors are not appropriate for quantifying climate impacts on snowmelt because historic relationships between temperature and snowmelt are not constant with respect to climate. We therefore conclude that either (1) advances must be made in the assignment of TI model parameters that would provide a means for accounting for systematic and physical changes in the snowmelt energy balance, or (2) energy balance models should be preferentially employed in climate impacts studies. Because there has been limited success in predicting TI model parameters with respect to site characteristics (He et al. 2011), we suggest that the more viable path forward lies with energy balance models.

The work presented here focused primarily on data analysis without investigating physical mechanisms that might explain why the melt factors tended to decrease with increasing climatological temperatures. Additionally, the presented analyses only focused on melt factors at the point scale over the seasonal time scale. Forthcoming work will examine how specific physical mechanisms affect conceptual melt factors in order to explain why melt factors vary with climate. Future work will also employ gridded output from different physical snow models at different spatial scales in order to analyze variations in coarse scale melt factors with climate change. Finally, the role of TI model complexity will be examined in future work. Specifically, the impact of using a time-variant melt factor (e.g., SNOW-17 changes the melt factor daily based on a sine curve with the minimum (maximum) value at the winter (summer) solstice) will be examined to determine whether refined specifications of the melt factor reduce the tendency for snowmelt overestimation in climate change studies. Other TI model enhancements, such as “cold content accounting” (e.g., Jost et al., 2012), also need to be examined to determine their impact on model robustness.

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