TEMPERATURE TREND BIASES IN GRIDDED CLIMATE PRODUCTS AND THE SNOTEL NETWORK

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ABSTRACT

In the mountainous western U.S., temperatures from high-resolution gridded climate products are often used to assess climate impacts on local hydrology and ecosystem processes. However, there has been little formal analysis on the ability of these products to accurately capture temporal variability and trends in climate. Here, we summarize and expand upon recent assessments of trend biases in the widely used PRISM and Daymet data products (Oyler et al., 2014, 2015). Throughout the western U.S., we find that PRISM and Daymet contain systematic cold and warm trend biases. Most notably, we show that the products have propagated an extreme warm bias from the SNOTEL station network across large areas of mountainous terrain. (KEYWORDS: PRISM, Daymet, SNOTEL, temperature trends, inhomogeneities)

INTRODUCTION

Accurate and reliable temperature data in the mountainous regions of the western U.S. are critical for assessing climate change impacts on local hydrology, and ecosystem processes and services. However, temperature observations are limited to single station locations and outputs from global climate models and atmospheric reanalyses cannot capture local topoclimatic variability. As a result, there is an increased reliance on high-resolution gridded climate datasets, particularly the PRISM and Daymet data products (Thornton et al., 1997; Daly et al., 2008). Both products input single point station observations and, using topoclimatic factors from a digital elevation model, statistically interpolate daily and monthly temperatures. The growing use and importance of PRISM and Daymet resides in the fact that their grids are produced at resolutions from 800-m to 4-km, resolutions that better match the scales of local topoclimatic factors and related environmental processes.

While there have been detailed analyses of the ability of PRISM and Daymet to capture important spatial variations in topoclimatic temperature (Daly et al., 2008), there has been less focus on their ability to capture temporal variations and trends. In other words, are these products accurately representing both inter-annual and inter-decadal variations in climate, and long term climate trends? Accurate temporal depictions of historical climate are essential for attributing climate change impacts and for understanding the climatic sensitivity of various environmental processes.

It is well-known that many station temperature records contain non-climatic temperature variations produced by changes in instrumentation, station siting, or observation protocols (Trewin, 2010). Because these artificial changes, termed inhomogeneities, can affect interpretations of temperature trends and, at worst, lead to erroneous conclusions, there is a rich statistical and climate literature on homogenization—the statistical identification and correction of inhomogeneities (Peterson et al., 1998; Reeves et al., 2007; Menne and Williams, 2009). Most global gridded temperature datasets, which are specifically designed for analyzing climate variability and trends at continental and global scales, use station observations that have been rigorously homogenized (e.g. CRUTEM4; *Jones et al.*, 2012). In contrast, PRISM and Daymet do not homogenize input station data. This is an important and underappreciated distinction between the different types of gridded climate products.

In the western U.S., the SNOTEL station network is one of the most important inputs to PRISM and Daymet. In many regions, SNOTEL provides the only longer-term continuous temperature observations we have at higher elevations and remote mountainous locations. Despite SNOTEL's importance in PRISM and Daymet and for mountain climate research, its main purpose is operational hydrometeorological monitoring and forecasting. As such, the U.S. Department of Agriculture Natural Resources Conservation Service (USDA NRCS) has issued cautionary reports on using SNOTEL temperature observations in a climatic context (Julander et al., 2007). In fact, SNOTEL is one of the few U.S. station networks for which we do not have good understanding of the homogeneity

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of its observation record. We do not know if any inhomogeneities within the SNOTEL temperature record are simply random (i.e.—station specific) or systematic across the network. While random inhomogeneities can be significant for local analyses, they are often less an issue at larger regional observation aggregations because artificial temperature increases and decreases from station-to-station will tend to cancel each other out (Easterling and Peterson, 1995). Systematic inhomogeneities are a more significant issue since they produce an artificial directional change across an entire region and, without knowledge of the station changes that occurred, can be very difficult to discern from natural climate changes.

In this context, we recently conducted a detailed homogeneity assessment of the SNOTEL temperature record (Oyler et al., 2015). Here, we summarize the results of this assessment. We first discuss the types of inhomogeneities that are apparent across the SNOTEL network. We finish with a discussion of how PRISM and Daymet have been affected by inhomogeneities from both SNOTEL and other station networks (Oyler et al., 2014, 2015).

SNOTEL HOMOGENETIY ASSESSMENT

To assess the homogeneity of the SNOTEL temperature record, we compared 1991 to 2012 annual SNOTEL minimum and maximum temperatures (Tmin, Tmax) to those of the homogenized U.S. Historical Climatology Network (USHCN). USHCN is the primary homogenized station database from the conterminous U.S. (Menne et al., 2009) and is often considered the "gold standard" for trend analyses. In the comparison, we first analyzed whether SNOTEL has any significant temporal patterns that are not found in USHCN. For each SNOTEL station, we changed its annual observations to annual anomalies (i.e. °C above/below normal) and then subtracted the average anomalies of neighboring USHCN stations. Anomaly difference series allow for easier identification of specific temporal differences, because the inter-annual variability common to both networks is removed. If there are no systematic differences, the anomaly difference series should vary randomly around zero. We also repeated the comparison after applying a standard homogenization algorithm (Menne and Williams, 2009) to the SNOTEL temperature record. If a significant temporal difference pattern is not removed after homogenization, we can have higher confidence that the difference is climate-driven and not the result of an inhomogeneity.

Using the methods described, we found that SNOTEL displayed significant temporal differences from USHCN over the 1991 to 2012 time period. Across all western U.S. states, SNOTEL had a distinctive +1.5 to +2.0°C jump in Tmin that was not seen in USHCN (Figure 1). This jump was removed after homogenization (Figure 1). In contrast, Tmax differences were more variable from state-to-state and generally not as distinctive as those for Tmax (Figure 2). Arizona even displayed a significant drop in Tmax relative to USHCN (Figure 2), the exact opposite pattern of Tmin (Figure 1).

The large and consistent increases in SNOTEL Tmin are concerning because of their affect on apparent temperature trends. From 1991 to 2012, the original SNOTEL Tmin observations display a +1.16°C decade^{-1} trend compared to just +0.106°C decade^{-1} after homogenization. This is an order of magnitude difference. Because the increases are step-like and removed after homogenization (Figure 1), it is highly likely that they are the result of a systematic inhomogeneity. Nonetheless, we are left with question of why there is such a different pattern for Tmax.

Based on discussions with NRCS, the most likely root cause of the Tmin increase is a sensor change. From the late 1990s up through the mid-2000s, a new extended range sensor was installed across the SNOTEL network to better capture extremely cold temperatures (Julander et al., 2007). At 4 stations in Idaho, the new and old sensor where co-located for various time periods from 1999 to 2001 by Phil Morrisey, hydrologist, USDA NRCS. These co-located observations suggest that the new sensor has a temperature-dependent bias relative to the old sensor (Figure 3a). Following a sine-like curve, colder temperatures are biased warm whereas warmer temperatures are biased cold (Figure 3a). This apparent temperature-dependent bias not only likely explains the large increases in Tmin, but also why Tmax had a different response. Based on the bias curve, typical Tmin temperatures at most SNOTEL stations are cold enough to maintain a positive bias throughout the year (Figure 3b). In contrast, for typical Tmax temperatures, the bias switches from positive in winter to negative in summer (Figure 3b). These counteracting seasonal biases likely lesson the impact on Tmax at the annual time step causing more moderate increases or decreases depending on a specific station's climate.

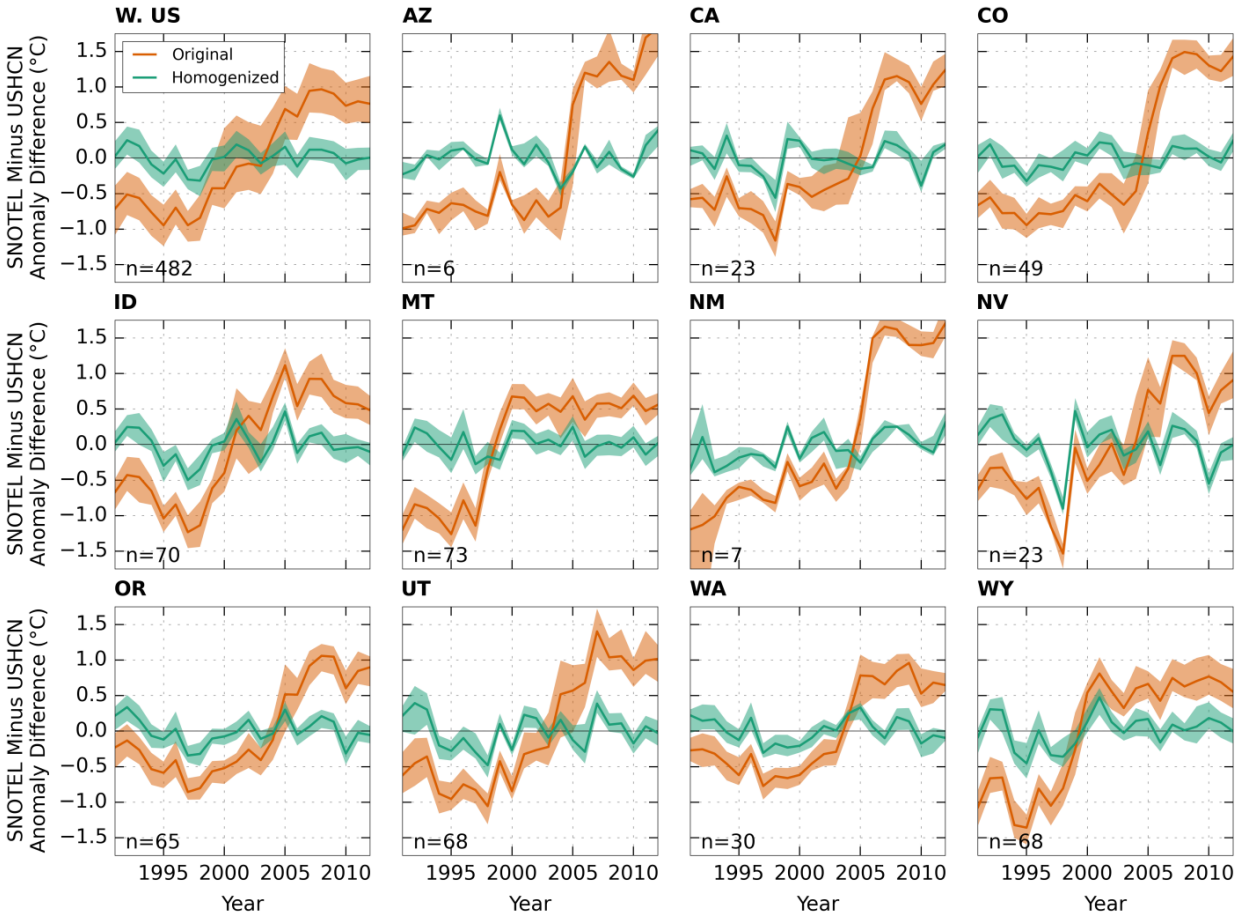

Figure 1. State-average differences in 1991–2012 annual minimum temperature (Tmin) anomalies between SNOTEL and USHCN stations. Differences are shown for both original and homogenized SNOTEL observations. Shaded areas are the interquartile range.

The SNOTEL sensor inhomogeneity is unique in two aspects. First, the overall magnitude of the Tmin bias is much higher than documented systematic inhomogeneities in other station networks. Second, the temperature-dependency of the bias makes it particularly troublesome. Many homogenization algorithms, including the one we used in this analysis, assume that an inhomogeneity will introduce a static and seasonally consistent bias (Menne and Williams, 2009). This likely makes it difficult for the homogenization algorithm to identify and fully correct for the sensor bias, especially on the seasonal time scale (Trewin, 2013).

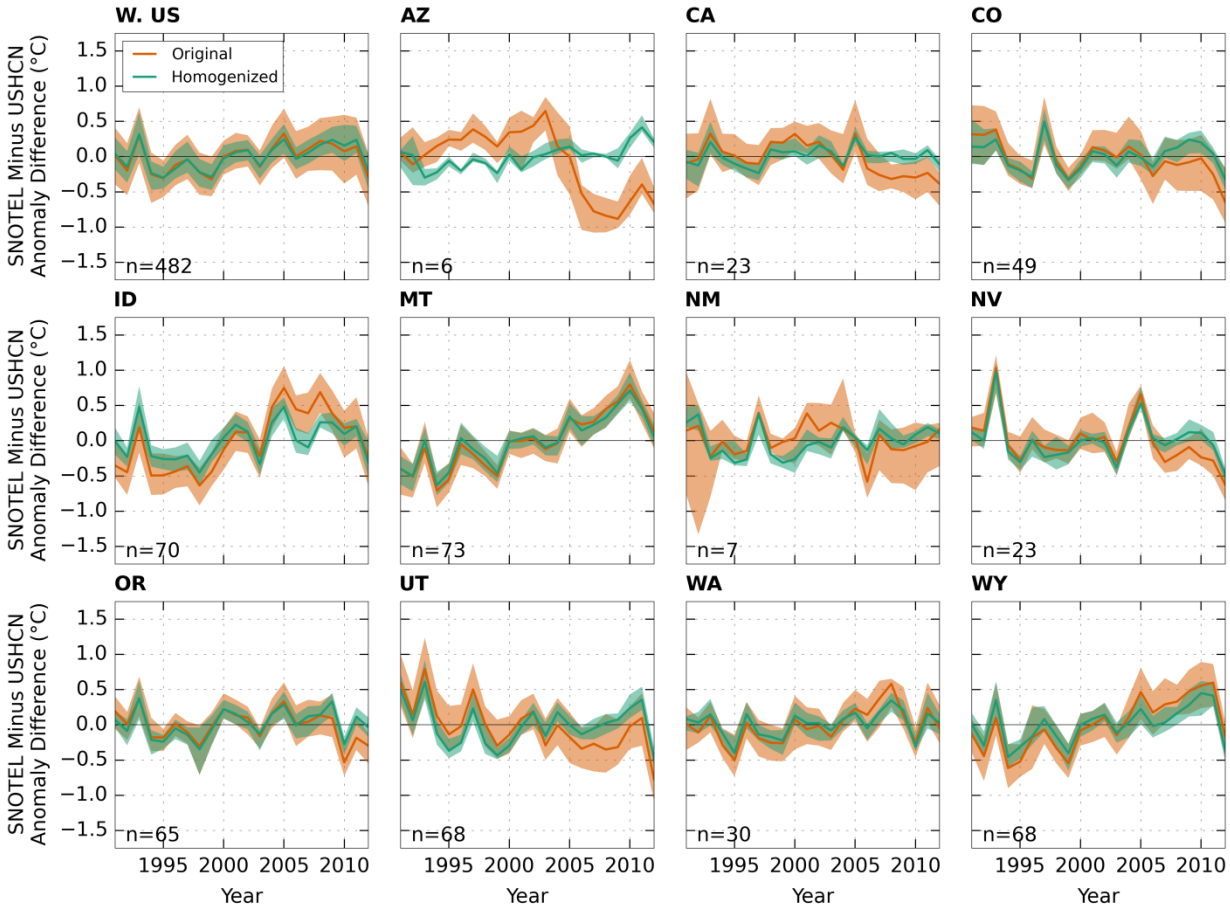

Figure 2. State-average differences in 1991–2012 annual maximum temperature (Tmax) anomalies between SNOTEL and USHCN stations. Differences are shown for both original and homogenized SNOTEL observations. Shaded areas are the interquartile range.

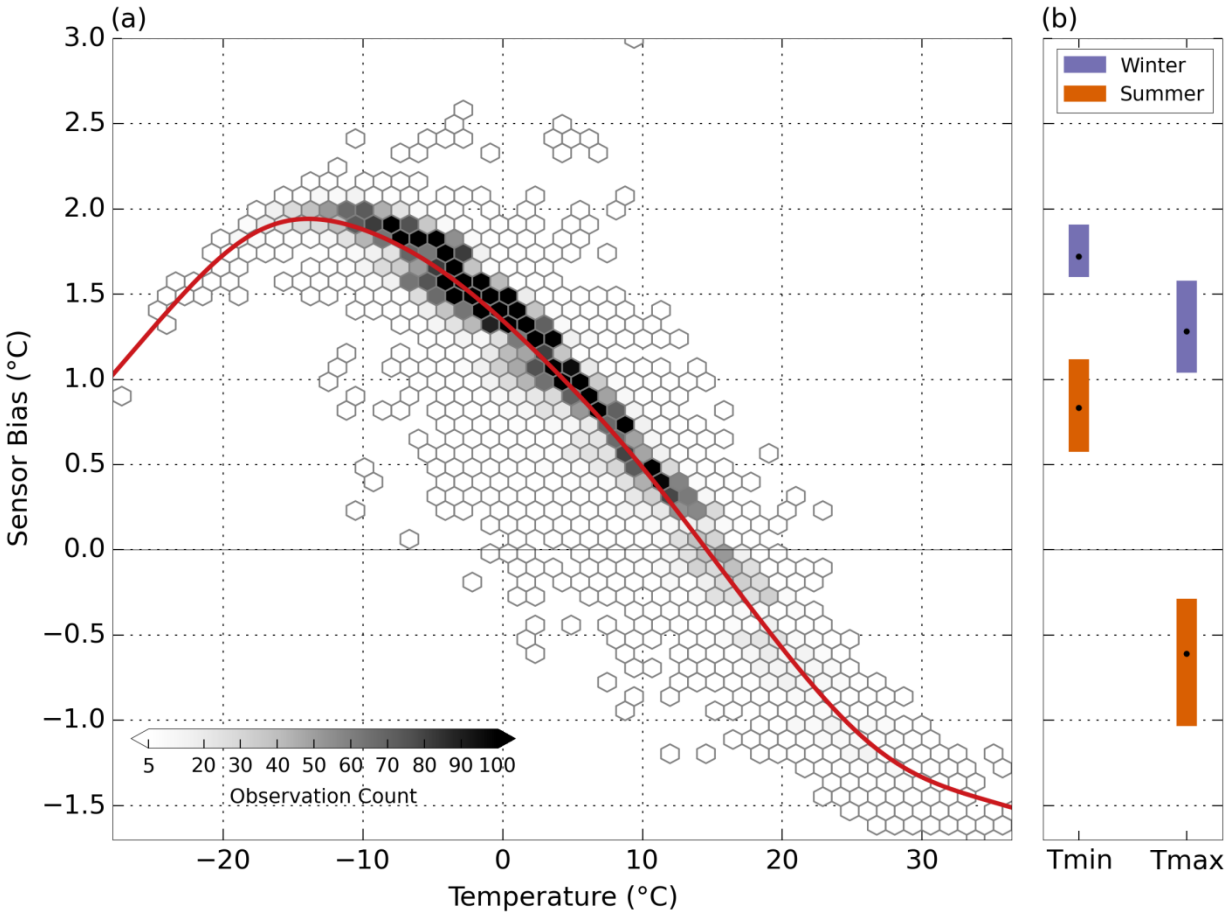

Figure 3. New SNOTEL sensor bias as a function of temperature. (a) New sensor bias relative to the old as measured by 3-hour and daily minimum and maximum co-located sensor observations (n=11 392) at 4 stations in Idaho over 1999-2001. Red line is a smooth GAM fit of the sensor bias as a function of temperature. Data courtesy of Phil Morrisey, hydrologist, USDA NRCS. (b) Estimated average sensor bias when model in (a) is applied to all Tmin and Tmax observations in winter (DJF) and summer (JJA) at SNOTEL stations across the western U.S. Dots are the average and colored bars are the interquartile range

INHOMOGENEITIES IN PRISM AND DAYMET

To examine the prevalence of inhomogeneities in PRISM and Daymet, we compare their western U.S. trends in annual temperature to both USHCN and the TopoWx data product. TopoWx is a relatively new high-resolution gridded climate dataset for the conterminous U.S. that homogenizes its input station observations (Oyler et al., 2014). Because Daymet is only available from 1980-2013, we perform the trend comparison over the 1981 to 2012 32-year time period.

Although all three gridded products display warming trends across most regions of the western U.S., inhomogeneities in PRISM and Daymet are readily apparent (Figure 4 and 5). Compared to TopoWx, PRISM and Daymet show dramatic increases in Tmin trends with elevation (Figure 6a). These increases are a direct result of the SNOTEL inhomogeneity (Oyler et al., 2015). At higher elevations, PRISM trends are 400% greater than USHCN and Daymet trends are more than 1000% greater. In comparison, higher elevation TopoWx Tmin trends are only 60% greater than USHCN, a statistically insignificant difference (Figure 6a). The extreme warming in Daymet even relative to PRISM is a result of differences in interpolation methods between the two products. PRISM simply propagates the SNOTEL inhomogeneity to higher elevation mountainous terrain whereas Daymet propagates and enhances it. Because of the less consistent nature of the SNOTEL inhomogeneity for Tmax (Figure 2), PRISM and Daymet Tmax trends at higher elevations are not as extreme (Figure 6b).

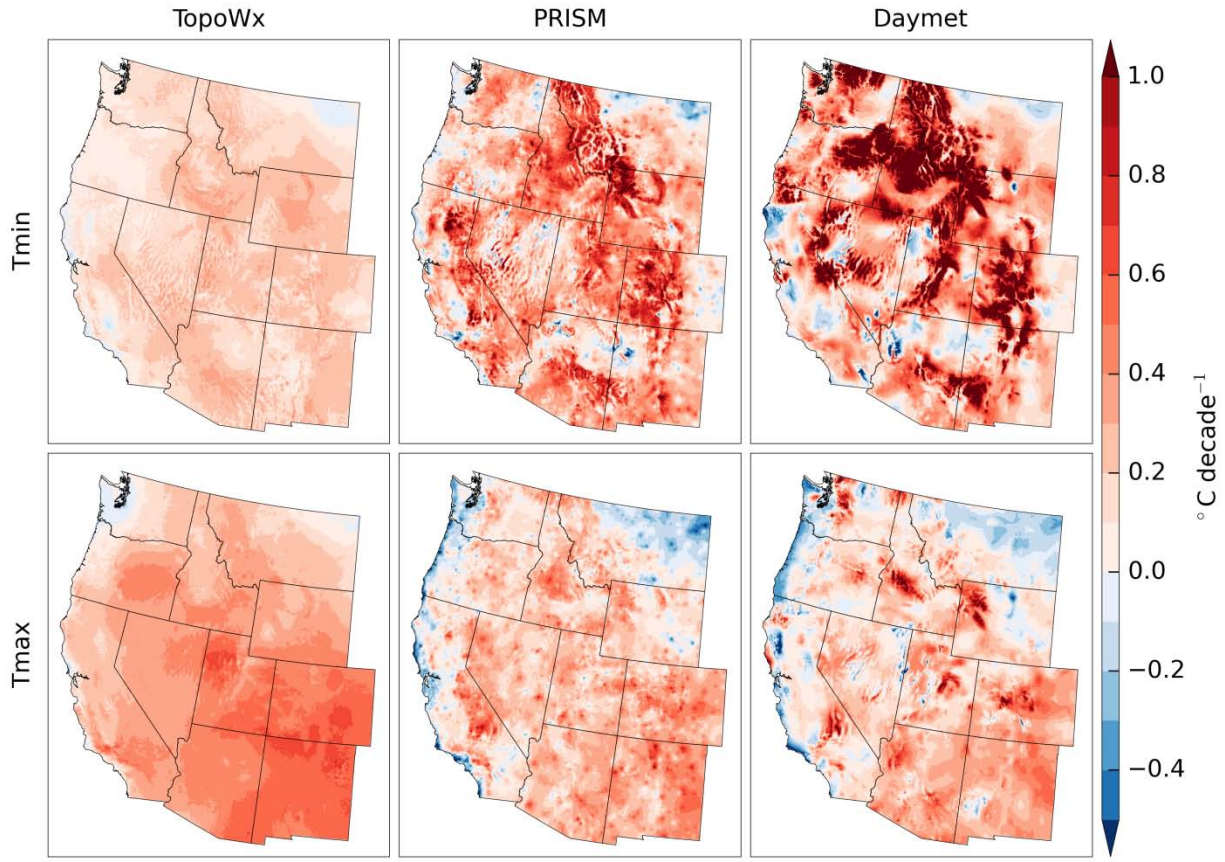

Figure 4. The 1981–2012 annual minimum and maximum temperature (Tmin, Tmax) trends for the western U.S. for the homogenized TopoWx data product, PRISM, and Daymet.

Systematic inhomogeneities from other networks are also evident within PRISM and Daymet. Across the western U.S., PRISM and Daymet Tmax trends are largely cooler than TopoWx (Figure 5). The aggregate Tmax trends for TopoWx and USHCN are +0.360°C decade^{-1} and +0.355°C decade^{-1}, respectively. In contrast, the PRISM Tmax trend is only +0.185°C decade^{-1} and the Daymet Tmax trend is only +0.166°C decade^{-1}. This difference is likely the result of a well-documented Tmax cold bias in NOAA's COOP network resulting from changes in time of observation, the network-wide conversion from liquid-in-glass thermometers to an electronic system, and the conversion of some stations to the Automated Surface Observation System (ASOS) (Menne et al., 2009).

Compared to TopoWx, PRISM and Daymet spatial patterns are also much more variable. Areas of extreme warming are interspersed with areas of extreme cooling (Figure 4 and 5). Unrealistic trend bull's-eyes are also apparent in PRISM Tmax (Figure 4 and 5). This is likely the combined result of both station-specific inhomogeneities and the limitations of the interpolation algorithm. Although some of this variability gets canceled out when trends are aggregated to the western U.S., local analyses could be significantly affected by such extreme and unrealistic spatial variations.

While the homogenized TopoWx trends are more spatially coherent across the western U.S. (Figure 4), two possible limitations should be noted. First, TopoWx trends still display a topographic spatial structure (Figure 4). More analysis is required to determine if these remaining spatial patterns are a result of the statistical models used for interpolation, remaining inhomogeneities, real climate variation, or a combination of all three. Second, homogenization does have the potential to remove unique climate variability at specific sites (Pielke et al., 2007). As a result, in some instance, trend spatial patterns could be over smoothed.

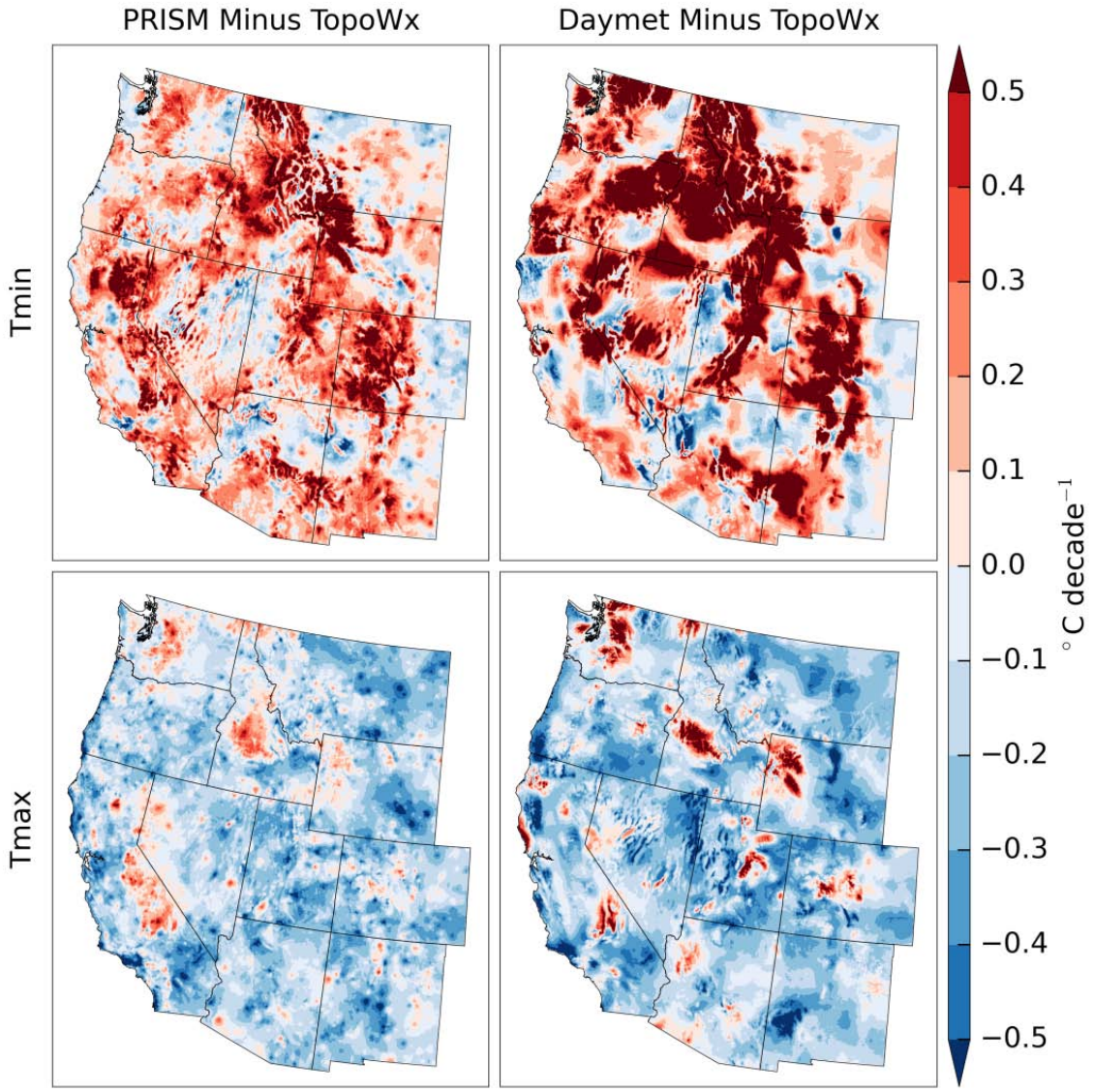

Figure 5. Differences in 1981–2012 annual minimum and maximum temperature (Tmin, Tmax) trends from Figure 4. First column is PRISM minus TopoWx. Second column is Daymet minus TopoWx.

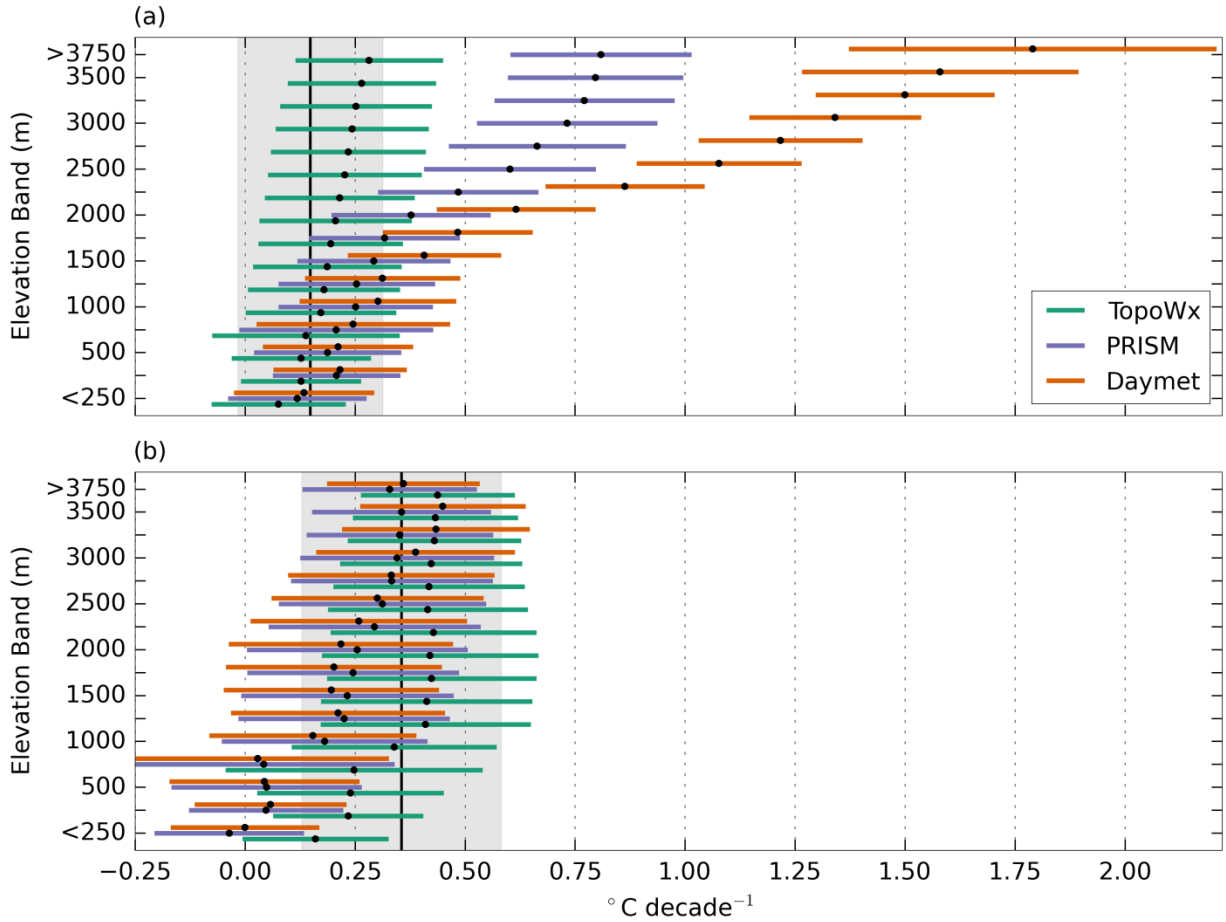

Figure 6. The 1981–2012 annual temperature trends for the western U.S. by elevation band for the homogenized TopoWx data product, PRISM, and Daymet. (a) Minimum temperature. (b) Maximum temperature. Dots and colored bars are composite trends and associated 95% confidence intervals of the different elevation bands. Vertical black line and light gray envelope represent the lower elevation USHCN western U.S. temperature trends and associated 95% confidence intervals.

CONCLUSIONS

The western U.S. has experienced a significant warming over the past 30 years, particularly in the Southwest (see TopoWx trends in Figure 4). However, the results of our analysis suggest that gridded climate products commonly used for climate impact analyses in the western U.S. are not robust to station inhomogeneities and are subsequently significantly biased. Due to SNOTEL inhomogeneities, PRISM and Daymet Tmin trends across mountainous higher elevation terrain have an extreme warm bias (Figure 4, 5, and 6a). In contrast, due to COOP station inhomogeneities, PRISM and Daymet Tmax trends have a moderate cold bias (Figure 5). PRISM and Daymet trends also have large spatial variability (Figure 4). Some of this variability could be real, but in many cases, trend spatial patterns appear unrealistic with pockets of extreme cooling interspersed with areas of extreme warming (Figure 4 and 5). Depending on the spatial and temporal scale of a specific climate analysis, these biases could have a substantial impact on climate attribution studies and possibly lead to erroneous conclusions. As a result, homogenized observations either in the form of a station record database (e.g. USHCN; Menne et al., 2009) or a gridded product (e.g. TopoWx; Oyler et al., 2014) should be used to ascertain trends.

Consistent with previous recommendations from NRCS (Julander et al., 2007), our analysis also suggests that SNOTEL temperature observations should be used with caution. The homogenization algorithm (Menne and Williams, 2009) we applied here and also in the TopoWx product is a good first step towards correcting the SNOTEL inhomogeneities. However, inhomogeneities likely remain, especially on a seasonal basis, due to the

strong temperature-dependency of the sensor bias (Figure 3). NRCS is currently investigating the cause of the sensor bias and will be conducting further controlled chamber and co-located sensor field experiments. The current hypothesis is that a suboptimal linear equation is being used to convert from thermistor resistances/voltages to temperature (Tony Tolsdorf, USDA NRCS). Once the root cause is determined, a transfer equation can likely be used to retroactively correct and better homogenize the SNOTEL temperature record.

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