AN ASSESSMENT OF DIFFERENCES IN GRIDDED PRECIPITATION DATASETS IN COMPLEX TERRAIN

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ABSTRACT

Hydrologic modeling and other geophysical applications are sensitive to precipitation forcing data quality, and there are known challenges in spatially distributing gauge-based precipitation over complex terrain. We conduct a comparison of six high-resolution, daily and monthly gridded precipitation datasets over the Western United States. We compare the long-term average spatial patterns, and interannual variability of water-year total precipitation, as well as multi-year trends in precipitation across the datasets. We find that the greatest absolute differences among datasets occur in high-elevation areas and in the maritime mountain ranges of the Western United States, while the greatest percent differences among datasets relative to annual total precipitation occur in arid and rain-shadowed areas. Differences between datasets in some high-elevation areas may exceed 200 mm yr^{-1} on average, and relative differences range from 5-60% across the Western United States. (KEYWORDS: orographic precipitation, precipitation uncertainty, hydrologic modeling, distributed datasets)

INTRODUCTION

The use of spatially distributed precipitation data has grown as distributed hydrologic, ecological and land surface models – which generally require distributed precipitation as an input – have made advances in resolution and process representation. In the extensive mountainous terrain of the Western United States, observation of precipitation is largely limited to in situ precipitation gauges. As a result, it is necessary to generate distributed estimates of precipitation based on measurements made at the point (gauge) scale. Many observational studies have demonstrated that topography can produce large differences in precipitation over small spatial scales, and these differences are apparent for both short and climatological timescales (Roe, 2005). Precipitation gauge networks are sparser in high-elevation mountainous areas (e.g., Lundquist et al., 2003) due to limited access and infrastructure, and gauges often suffer undercatch errors in snow-dominated and windy areas.

For datasets covering the mountainous Western United States, distributed precipitation information is typically generated via spatial interpolation of gauge observations, with a correction for elevation given the role of orographic enhancement in precipitation (Cosgrove et al., 2003; Lundquist et al., 2015; Newman et al., 2015; Livneh et al., 2015; Hamlet and Lettenmaier, 2005). Because of complex orographic effects on precipitation, it is useful to include a long-term, empirical climatology of precipitation when applying a topographic correction. The Parameter Regression on Independent Slopes Model (Daly et al., 2008; 2002) provides 30-year spatial precipitation climatologies at 800 m resolution over the continental United States. The spatial PRISM climatologies are used in other datasets to represent the relationship between precipitation at the gauge and that over the surrounding terrain.

Due to the challenges in estimating precipitation over complex terrain, multiple studies have demonstrated uncertainty or biases in the estimates of precipitation in gridded datasets (e.g., Gutmann et al., 2012) . Systematic evaluation of differences among gridded precipitation datasets would help make users aware of the implications for choosing one dataset over another, and for understanding the magnitudes of the uncertainty associated with the

Paper presented Western Snow Conference 2016
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NOTE: As of June 2016, a longer version of this manuscript is also is in review for the *Journal of Hydrology*'s special issue on precipitation.

precipitation estimates. At this time there is no "ground truth" for distributed precipitation in complex terrain beyond the often sparse gauge measurements. However, we can assess the sensitivity of estimated precipitation to the choices in the methodology used to generate the datasets, simply by comparing them with one another in data-sparse areas where they are likely to diverge.

DATA

We compare six publicly available gridded precipitation datasets over the Western United States, both against one another and against observations of streamflow and SWE. The six datasets are Hamlet et al. (2010), hereafter H10, which extends an earlier dataset (Hamlet and Lettenmaier, 2005); Livneh et al., (2015), hereafter L15; PRISM 2.5 arc-minute (~4 km) monthly data, hereafter PRISM-M, NLDAS-2 (Cosgrove et al., 2003); Newman et al., (2015), hereafter N15; and Daymet (Thornton et al., 1997). See Lundquist et al. (2015, their Table 1) and Newman et al (2015, their Table 1) for information about the gridded datasets. We chose these datasets because they are publicly available, have sufficient spatial and temporal resolution to capture precipitation in the complex terrain of the Western United States, and represent several independent efforts to distribute precipitation across complex terrain from gauge observations.

METHODS

Given of the disparate spatial resolutions of the datasets, it is necessary to resample the datasets to a common grid in order to directly compare precipitation values. We aggregate each of the higher resolution datasets (H10, L15, PRISM-M and Daymet) to the coarser 1/8° grid of NLDAS-2 and N15. When resampling the high resolution datasets to the 1/8° grid, we calculate the average of the higher resolution cells within each coarser cell.

The six datasets have a temporal overlap which covers water years 1982-2006. For each water year and for each grid cell in the 1/8° domain covering the Western United States (defined here as areas in the United States from 32° to 49°N and 105° to 125°W), we converted daily (or hourly) datasets to water year totals by summing all times between 1 October of the previous year and 30 September.

We calculate the mean absolute difference (MAD) between a pair of datasets at a grid cell as:

$$MAD_{i,j} = \frac{1}{n}\sum_{k=1}^{n} \mathrm{abs}\left(P_{i,k} - P_{j.k}\right) \qquad [1]$$

where i, j indicates the difference between datasets i and j, k indicates the water year, n is the total number of water years, and $P_{i,k}$ and $P_{j.k}$ indicate the water-year total precipitation for datasets i and j, respectively, for water year k. We then calculate the mean relative difference (MRD) between a pair of datasets, which is defined as:

$$MRD_{i,j} = \frac{1}{n}\sum_{k=1}^{n} \left(\frac{\mathrm{abs}\left(P_{i,k} - P_{j.k}\right)}{\frac{1}{6}\sum_{m=1}^{6} P_{m,k}}\right) \qquad [2]$$

where m indicates the dataset and $P_{m,k}$ indicates the water-year total precipitation for that dataset and year. In other words, the MRD is the absolute difference between a pair of datasets for a given year and grid cell, divided by the six-dataset mean precipitation for that year and grid cell, and averaged over all water years.

RESULTS

In Figure 1 we present a comparison of the different dataset's estimates of water year total precipitation across the Western United States over 1982-2006. Figure 1 compares differences among the six datasets with one another both using the absolute and relative differences defined above. Panels above the diagonal in Figure 1 show MAD (eq. 1) for each comparison between pairs of datasets. Panels below the diagonal show MRD (eq. 2) between dataset pairs. Panels on the diagonal show the absolute difference anomaly for that dataset, defined as the difference between the average MAD for that dataset and the average MAD between the other datasets.

Taken together, the above-diagonal panels suggest that the highest absolute differences between the datasets occur in the maritime mountain ranges of the Western United States (Sierra Nevada, Coast Ranges and Cascades), with additional significant differences over the Rockies. Thus, (not surprisingly) the largest absolute differences occur in areas with higher mean precipitation, where methodological differences interpolation techniques

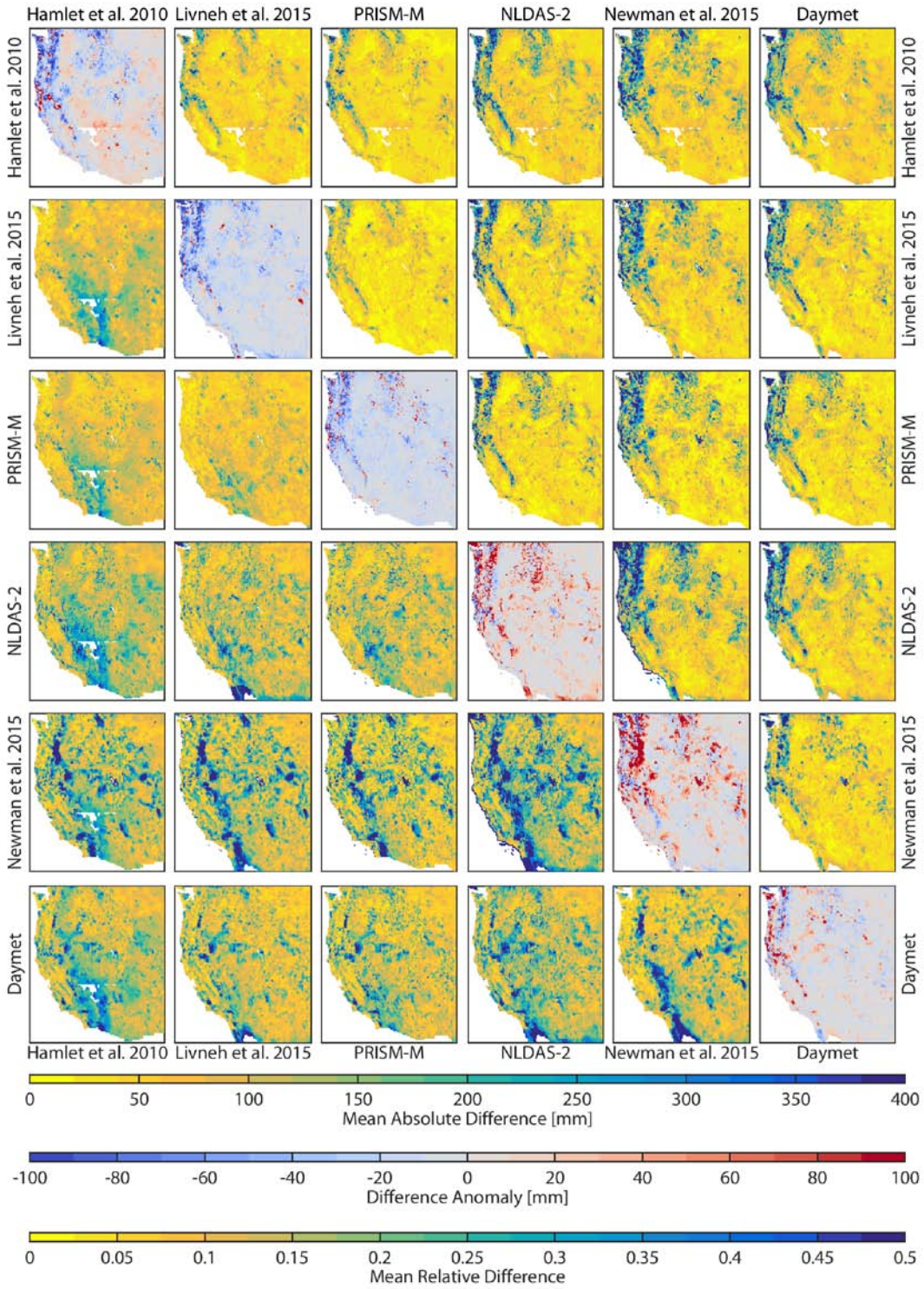

Figure 1. Comparison of yearly variability across datasets over water years 1982-2006 at 1/8° resolution.

can produce larger differences. These are predominantly higher-elevation and coastal regions. However, an examination of dataset pairs' differences show significant variation between pairs. The H10, L15 and PRISM-M precipitation totals tend to be more similar to one another than the NLDAS-2, N15 and Daymet totals are to other the datasets. For example, when the spatial distribution of MAD is sorted and percentiles are computed, the 95th percentile water-year total MAD between PRISM-M and L15 is 131 mm, while the 95th percentile absolute difference between NLDAS-2 and N15 is 375 mm. In particular, N15 has larger differences with other datasets along the eastern slope of the Cascade and Sierra Nevada ranges, while NLDAS-2 and Daymet have larger differences at the highest-elevation areas of these same ranges. Table 1 summarizes the 5th, 50th and 95th percentiles of MAD between all dataset pairs.

When absolute differences for given water years are divided by the six-dataset mean total precipitation to estimate the differences as a fraction of average precipitation (Figure 1, below diagonal panels), different spatial patterns are observed. In contrast to MAD, MRD tends to be greatest in the rain shadows and deserts of the inter-mountain Western United States, while MRD is smallest in coastal lowlands and windward foothills of the maritime ranges. The percentiles of MRD for each dataset pair are also shown in Table 1; 95th-percentile MRD, largely found in arid and rain-shadowed areas (areas to the east of maritime mountain ranges), was between 0.18 and 0.61.

Table 2. 5th-50th-95th percentiles of mean absolute differences (above diagonal, mm) and mean relative differences (below diagonal) between datasets over 1982-2006.

Dataset	Hamlet et al. 2010	Livneh et al. 2015	PRISM-M	NLDAS-2	Newman et al. 2015	Daymet
Hamlet et al. 2010	-	21 - 47 - 146	19 - 39 - 159	25 - 56 - 234	24 - 62 - 283	27 - 58 - 211
Livneh et al. 2015	0.05 - 0.12 - 0.26	-	15 - 31 - 131	17 - 48 - 242	21 - 59 - 279	17 - 47 - 216
PRISM-M	0.05 - 0.11 - 0.24	0.04 - 0.08 - 0.18	-	17 - 43 - 233	14 - 50 - 299	18 - 44 - 236
NLDAS-2	0.07 - 0.15 - 0.33	0.06 - 0.12 - 0.33	0.05 - 0.11 - 0.29	-	23 - 70 - 375	21 - 59 - 260
Newman et al. 2015	0.06 - 0.15 - 0.43	0.06 - 0.14 - 0.47	0.04 - 0.12 - 0.45	0.07 - 0.18 - 0.61	-	20 - 48 - 225
Daymet	0.07 - 0.15 - 0.35	0.05 - 0.12 - 0.32	0.05 - 0.12 - 0.32	0.07 - 0.15 - 0.41	0.05 - 0.12 - 0.44	-

DISCUSSION AND SUMMARY

There are likely multiple reasons for the differences in the distributed precipitation estimates. The estimation of the local relationship between precipitation and elevation is subject to uncertainty, and precipitation estimates for high-elevation terrain are often extrapolations of precipitation-elevation relationships from lower-elevation stations. All of the datasets considered here assume locally linear relationships between precipitation and elevation that are derived from weighted least-squares regression. PRISM-M and L15 use the PRISM 1981-2010 climatology to establish the local topographic relationship with elevation; H10 uses the PRISM 1971-2000 climatology; N15 and Daymet conduct independent regressions of precipitation against elevation, but differ in how they weight stations with respect to their distance from the grid cell. The maps of absolute uncertainty in Figure 1 make it clear that differences between datasets increase with elevation.

There are also differences is in the climatological patterns between the PRISM-based and other datasets in how precipitation is distributed over the windward and leeward sides of mountain ranges. The PRISM climatological pattern is wetter on the windward slopes of the maritime Coast Ranges, Cascades and Olympics, and is drier on the leeward slopes. PRISM employs several methods to produce sharp gradients of precipitation in the interpolation of gauge data, which include more heavily weighting stations on the same topographic aspect as the grid cell and stations having similar distance to prevailing moisture sources as the grid cell (Daly et al. 2008, 2002). Another factor in the differences among datasets is the use of different precipitation gauge networks. PRISM, N15 and Daymet use SNOTEL precipitation in the interpolation, but the other datasets do not; N15 uses a bulk undercatch correction at the SNOTEL sites to try to account for undercatch, but Daymet does not.

In summary, we compare over the Western United States six distributed precipitation datasets that have temporal (daily or monthly) and spatial (1/8° or higher) resolution sufficient to capture patterns of precipitation in complex terrain. While there are no observations against which to evaluate the datasets' distributed precipitation, we examine the differences in their yearly variability in precipitation accumulations. Mean absolute and mean relative differences among the precipitation datasets' water year totals averaged 30-70 mm and 11-18% across the Western

United States, but the largest absolute differences of 100-200 mm or more were concentrated in high-elevation areas, while the largest relative differences of 18-61% were concentrated in arid areas and leeward rain shadows.

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