Estimating Continuous-Coverage Instantaneous Precipitation Rates Using Remotely Sensed and Ground-Based Measurements

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ABSTRACT

This study demonstrates a method of temporally and spatially scaling precipitation rates at low probability of precipitation-rate exceedance levels (e.g., 0.1%) from coarser-resolution global datasets to near-instantaneous localized rain gauge precipitation rates. In particular, the 8-km-, 1-h-resolution Climate Prediction Center Morphing (CMORPH) dataset was scaled to 1-min localized rates using the Automated Surface Observing Station (ASOS) rain gauge data. Maps of these scaled precipitation rates show overall patterns and magnitudes that are nearly identical to the lower-spatial-resolution rain gauge maps yet retain the much higher resolution of the original remotely sensed global dataset, which is particularly important over regions of complex geography and sparse surface observing stations. To scale the CMORPH data, temporal and spatial conversion factor arrays were calculated by comparing precipitation rates at different temporal (ASOS 1-min and 1-h) and spatial (ASOS 1-h and CMORPH 1-h) resolutions. These temporal and spatial conversion factors were found to vary by probability level, season, and climatological region. Meteorological implications of these variations are discussed.

1. Introduction and literature review

Accurate estimates of the probability of extreme localized precipitation rates over a short period of time are of importance for many different applications, including flood warning and mitigation (e.g., Mogil et al. 1978), flood insurance estimates (e.g., Changnon and Changnon 1989) and atmospheric attenuation of radio communications (e.g., Crane 1980). Other applications use cumulative distribution functions (CDFs) of precipitation rate to determine the climatological range of raindrop size distributions for a given region (e.g., Karasawa and Matsudo 1991; Tattelman et al. 1995) and for applications such as material modeling for high-speed projectiles (e.g., missiles or helicopter blades) through precipitation.

Since the advent of weather satellites, remote sensing has allowed for global estimates of precipitation characteristics (Griffith et al. 1978). Remotely sensed estimates of precipitation rate are typically derived from measurements that are averaged in space and time. The Global Precipitation Climatology Project product, for example, has daily, 1° global coverage since 1979 (Adler et al. 2003). Recent improvements in retrieval techniques have resulted in several high-resolution datasets [e.g., the Climate Prediction Center Morphing (CMORPH) technique and Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)]. Both CMORPH (Joyce et al. 2004) and PERSIANN (Hong et al. 2004) provide global coverage over ±60° latitude. PERSIANN is offered at a nominal resolution of 4 km and 30 min, and CMORPH is available at a nominal resolution of 8 km and 30 min. Both retrievals estimate precipitation from a combination of passive microwave and infrared and rely on temporal and spatial averaging to reduce sampling errors; thus, the representative time scale of these measurements is on the order of an hour at best.

To estimate the frequency of occurrence of the most intense rainfall rates and their spatial distribution, one can statistically relate the satellite-based precipitation
rates of lower-temporal-resolution rates to near-instantaneous precipitation rates. Karasawa and Matsudo (1991) presented a technique using surface rain gauge measurements to calculate the ratio of 1-min to 1-h precipitation rates at the 0.01% probability of precipitation-rate exceedance ($P_c$) level for seven locations in Japan. This ratio was then applied to hourly observations from over 1300 automated stations used to obtain a 1-min rainfall-rate “climatology” for all of Japan for different $P_c$ levels. Several other researchers have calculated the relationship between the precipitation rates observed at varying time scales ranging from 10 s to 1 h (e.g., Watson et al. 1981; Ajayi and Ofoche 1984; Lee et al. 2000). These studies were limited in geographic extent and the range of $P_c$ values explored, however.

The shape of a CDF of precipitation rates is strongly a function of the collection period, but it is also a function of the collection area. That is, data of differing horizontal resolution (e.g., rain gauge vs 8-km CMORPH) will have inherent differences related to scale. Scale dependence of the CDF can provide information on the type of precipitation endemic to a region; for example, CDFs of regions characterized by more showery precipitation will have different scale dependence than those dominated by larger-scale precipitating systems. Segal (1986) found that the relationship between CDFs of precipitation intensity varied by climatological region across Canada. The scale dependence of CDFs has been explored in recent studies (Zhou et al. 2008; Yilmaz et al. 2005; Sohn et al. 2010), but only as a means of evaluating satellite retrievals with rain gauge data. The primary focus of these studies was to compare the mean precipitation rate obtained at varying scales rather than comparing the full CDFs of precipitation rate at varying scales.

Numerous hydrological studies (e.g., Lovejoy and Mandelbrot 1985; Rahman et al. 2009; Tao and Barros 2010) have used spatial downscaling techniques to derive high-resolution precipitation rates from satellite data (e.g., from the Tropical Rainfall Measuring Mission) for streamflow modeling. These studies typically downscaled satellite data with resolutions on the order of 1 h and 25 km to much finer resolutions, such as those of radar data (~1 km and ~5 min), using techniques such as autoregressive and fractal downscaling (Ferraris et al. 2003). The focus of these studies was on statistically representing the spatial distribution of precipitation intensities for a particular event for streamflow modeling, and they were less concerned with understanding the probability of occurrence of a precipitation rate.

Whereas previous studies have typically only calculated conversion factors from climatological data from only a handful of climate areas and/or for only a discrete number of exceedance probabilities, this study demonstrates a technique for scaling CDFs of satellite-derived precipitation intensity to be more representative of ground-based, localized, near-instantaneous measurements available from a network of rapid-sampling rain gauges. These scaled satellite-based CDFs can be used to assess the likelihood of extreme events without gaps in data coverage inherent in a rain gauge network. The regional and seasonal variations in the temporal and spatial conversion factors are discussed in context with their meteorological implications.

2. Data and processing

The two datasets used in this study are the 1-min rainfall rates from the U.S. Automated Surface Observing Station (ASOS) rain gauge network (NWS 1998) and the hourly satellite-derived precipitation dataset from CMORPH (Joyce et al. 2004).

a. ASOS dataset

The first ASOS stations were deployed in September of 1992. Since that time, the number of stations has increased to 942 (NWS 1998), and they are located throughout the United States (Fig. 1). ASOS stations provide measurements every minute of temperature, dewpoint, pressure, wind direction and speed, precipitation accumulation, sky condition, and visibility. Precipitation is measured using a heated tipping-bucket rain gauge. For the purpose of this study, precipitation rates $R$ were calculated from the 0.254-mm-, 1-min-resolution ASOS rates following the method of Mandep and Hassan (2008) in which $R = B_t/\Delta t$ for the minutes before a tip occurred and $R = B_t/\Delta t + B_t(N_t - 1)$ for the minutes in which one or more tips occurred. Here, $B_t$ is the gauge resolution (0.01 in. = 0.254 mm), $N_t$ is the number of tips in the previous minute, and $\Delta t$ is the number of minutes between tips. All 942 ASOS stations provide liquid equivalent precipitation accumulation amounts every minute, and most (908) provide precipitation type (rain, snow, ice pellets, etc.) from the commercial Light Emitting Diode Weather Identifier (LEDWI) sensor. Only those stations providing precipitation type were processed for this analysis, because the precipitation type was used as a quality-control (QC) parameter to verify the occurrence of precipitation. For more details on ASOS data collection and processing, see the ASOS user’s guide (NWS 1998).

The raw ASOS data were obtained online (ftp://ftp.ncdc.noaa.gov/pub/data/asos-onemin/). The original
data format for ASOS stations varies somewhat from station to station and sometimes varies with time for individual stations. The first step in processing the raw ASOS dataset was to improve the data format and to create a continuous time series of the 1-min precipitation type and amounts for each station for the period of 1 January 2000–31 August 2008. Data were rejected in instances in which precipitation accumulation was indicated yet the precipitation type was “NP” (no precipitation), “missing,” or “other.” In addition, all precipitation rates that exceeded 0.20 in. (5.08 mm) min\(^{-1}\) were rejected, because these rare occurrences (occurring less than 0.001% of the time) are near the limit of what the ASOS tipping-bucket rain gauge is capable of accurately measuring (10 in. h\(^{-1}\) = 4.23 mm min\(^{-1}\); NWS 1998). These reports were also sometimes preceded and followed by null reports of precipitation, and they were considered suspect. Overall, less than 0.1% of all data were rejected, and no more than 0.6% were rejected for any individual station.

b. **CMORPH dataset**

Hourly, 8-km CMORPH precipitation-rate data were obtained from the National Oceanic and Atmospheric Administration Cooperative Institute for Climate and Satellites. The portion of the dataset used in this study spans the time period from 1 January 2003 to 31 August 2008. The CMORPH dataset was chosen because it had the highest correlations with rain gauges of any satellite-derived, high-resolution precipitation product with global coverage (Sapiano and Arkin 2009). The precipitation retrievals are based on passive microwave (from polar orbiting) and infrared (from geostationary) satellite instruments and thus span the entire globe between 60°S and 60°N. The dataset is explained in detail by Joyce et al. (2004).

The CMORPH data were quality controlled prior to creating the CDFs. The QC step included screening data records for localized anomalously high precipitation rates as well as for bad swaths. The first QC pass through the raw data was made to flag CMORPH images that contained large (~100 km wide and ~1000 km long) errant swaths in which the precipitation rate was nearly homogeneous with values of 1 mm h\(^{-1}\) or more (see Fig. 2). These errant swaths were found to occur in roughly 0.5% of the global images and would have had a deleterious effect on the CDFs, particularly those obtained in arid-to-semiarid regions. A second QC pass identified times and locations of grid points with precipitation rates that were more than 1.8 standard deviations greater than the 5-by-5 (40 km \(\times\) 40 km) area-average mean at a preliminarily calculated \(P_c\) level. Each flagged image was then individually visually inspected to determine if it needed to be removed from the dataset. The value of 1.8 standard deviations was chosen because it was the threshold that flagged most of the anomalous maxima yet did not increase the number of improperly flagged meteorological maxima beyond a level that could be reasonably individually inspected. Note that the CMORPH product has developed substantially over time. A reprocessing of the entire period of record is under way that will incorporate these improvements and should remove such artifacts as “bad swaths.”

3. **CMORPH and ASOS seasonal mean precipitation rates**

The 5-yr daily mean precipitation rates from ASOS and CMORPH are compared to assess the presence of
biases and errors in the datasets used in this study (Fig. 3). Overall, the general patterns evident in the two datasets are very similar. Prominent features detected by both datasets include the maximum mean precipitation rate in the Pacific Northwest and southeastern United States in December, January, and February (DJF) and in the Great Plains and along the Gulf Coast in June, July, and August (JJA). CMORPH appears to reproduce several other known precipitation maxima, such as that related to the North American monsoon over western Mexico in JJA (Adams and Comrie 1997) and the precipitation maximum over the Gulf Stream that is evident throughout the year (Carbone and Tuttle 2008). At the finer scale, CMORPH indicates several coastal-water regions that have much lighter precipitation rates [e.g., Florida in March, April, and May (MAM) and the New England coast and Great Lakes in JJA].

Although the broadscale patterns in ASOS and CMORPH are similar, regional differences are evident and vary seasonally. The daily-mean precipitation rate was next calculated for ASOS and CMORPH by averaging all observations available in each 2.5° × 2.5° box shown in Fig. 1. The data for each grid box are plotted in Fig. 4, color coded by region. It is seen that CMORPH has a negative bias (lower values) for all regions in DJF and a positive bias (higher values) relative to ASOS for nearly all regions except the Northeast and Southeast in JJA and that the CMORPH precipitation estimates best match the ASOS gauge measurements in spring and autumn. The negative bias in DJF is a result of the challenge for passive microwave radiometers and infrared sensors to distinguish between snow and ice in clouds and at the surface, leading to an indeterminate precipitation-rate solution; on the other hand, the positive bias in JJA is due in part to the evaporation of rainfall between cloud base and the surface (e.g., Ebert et al. 2007). A plot of mean normalized bias (Fig. 4) indicates more clearly the CMORPH biases during JJA and DJF. Because conversion factors should remove biases between the datasets, it is also important to consider the mean scatter between the datasets, defined as the mean difference between the data points for each region and season, and a linear least squares fit to the data points. The mean scatter is highest for the north-central (NC) region during all but DJF, in the Southeast (SE) and south-central (SC) region during JJA, and in the Northeast (NE) and SE during MAM (Fig. 4). The scatter is indicative of random error in the measurements that likely is due, in part, to sampling errors and assumptions made in the satellite retrievals, and it should be considered when interpreting the results.

4. ASOS and CMORPH cumulative precipitation intensities

CDFs of the ASOS precipitation rates were generated by collecting observations in boxes defined by the 2.5° and 5° grids shown in Fig. 1. CDFs were created for accumulation periods of 1 min, 1 h, and 1 day to represent the probability of a given precipitation rate occurring over each grid box for a given season. CDFs were created by sorting the data for a given accumulation period from the ASOS stations within each grid square. The 1-min rainfall rates were stored for $P_r$ values ranging from 0.01% to 10% using 76 points on a logarithmic scale. Similar CDFs were created for the precipitation rates obtained for longer collection periods (hourly and daily). An example of CDFs for each season and collection period for a grid box in the SC region containing Dallas, Texas, (marked by a red X on Fig. 1) is shown in Fig. 5. Note that for the hourly and daily rates
the larger $5\times 5^\circ$ collection areas were used to extend the CDFs to the lower probability levels (indicated by the dotted segment of hourly and daily precipitation rates). As one would expect, precipitation rates associated with the least-frequent events ($P_e < 0.3\%$) decrease with increasing collection period. Figure 6 illustrates the relationship between precipitation rate and collection period for several $P_e$ levels for the Dallas grid point during JJA. For the most-extreme precipitation rates (i.e., $P_e < 0.1\%$), there is an inverse exponential relationship between the precipitation rate and collection period. That is, the more-extreme precipitation events are shorter in duration than the longer collection periods. This relationship becomes less pronounced for increasing $P_e$ levels. That is, as the event becomes more likely it becomes more temporally uniform. The most common events (i.e., $P_e \geq 0.3\%$) show very little relationship with collection period.

FIG. 3. ASOS and CMORPH daily mean precipitation rates for each season. Here, SON indicates September–November.
Fig. 4. ASOS-vs-CMORPH scatterplots of daily mean precipitation, averaged over all locations within each 2.5° × 2.5° grid cell. (bottom right) Mean scatter and mean normalized bias for ASOS and CMORPH data for each region and season.
FIG. 5. Example ASOS CDFs for each season for the SC grid point marked by a red X in Fig. 1. The solid line indicates 2.5° data, and the dashed line indicates 5° data.
The relationship between CDFs of two collection periods may be given by

\[ C_i(t_1, t_2) = \frac{CDF_{ASOS,i}(t_1)}{CDF_{ASOS,i}(t_2)}, \]

where \( C_i \), the temporal conversion factor, is defined as the ratio of the precipitation rates for two different accumulation periods (\( t_1 \) and \( t_2 \)) for every \( P_e \) level \( i \). For example, the temporal conversion factor from 1 min to 1 h at the 0.01% \( P_e \) level may be denoted as \( C_{0.01\%}(1 \text{ min}, 1 \text{ h}) \). Figure 7 shows \( C_i(1 \text{ min}, 1 \text{ h}) \) for different climate locations for each season. In general, the ratio ranges from 1.5 to 2.5 at a \( P_e \) of 0.01%, with the ratio decreasing relatively monotonically with \( P_e \) in all cases. The slope of each curve is indicative of the uniformity of the precipitation, with the steeper curves occurring in areas characterized by more transient precipitation systems. A more detailed description of the meteorological implications of the temporal conversion factor will be discussed in the following section.

CDFs were also calculated for the hourly CMORPH dataset in the same way as with the ASOS dataset. To increase the number of points going into each CDF, however, the data were collected into 5 \times 5 gridpoint (0.36° \times 0.36°) squares so that the horizontal resolution of the final CDF grid was \( \sim 40 \text{ km} \), even though the effective resolution remained at 8 km. The larger collection area provides more data points by a multiplicative factor of 25, allowing determination of the precipitation rate to the 0.0003% \( P_e \) threshold for each season. An example CMORPH CDF plot for each season for Dallas in the SC region is shown in Fig. 8. Note that, although the hourly CMORPH CDFs are negatively biased relative to the hourly ASOS CDFs shown in Fig. 5, the shape and slope of the hourly curves are similar. Because the collection periods of the two datasets have been matched, the negative bias is assumed to be due to systematic errors in the measurements as well as differences in their representative spatial scales.

To convert the satellite-derived CMORPH CDFs of precipitation rate, which are hourly averages, to the 1-min localized rates, both temporal and spatial conversion factors must be used. First, the 1-min-to-1-h temporal conversion factors derived from the ASOS dataset were used to convert the hourly CMORPH precipitation rates to 1-min rates. Then, the spatial conversion factors were calculated by taking the ratio of the hourly ASOS and hourly CMORPH CDFs over the contiguous 48 United States, as follows:

\[ C_i(\text{gauge, 8 km}) = \frac{CDF_{ASOS,i}(1 \text{ h})}{CDF_{CMORPH,i}(1 \text{ h})}. \]

An example of the dependency of precipitation rate on effective resolution is shown for the SC region in Fig. 9 for JJA for several \( P_e \) levels. The ASOS gauge rates are indicated at 0 km, and the CMORPH rates are shown as area averages using box dimensions of 1, 3, 5, 7, and 9 grid points, resulting in effective resolutions of 8, 24, 40, 56, and 72 km. For the most-extreme events (e.g., \( P_e = 0.01\% \)), the precipitation rate decreases with increasing effective resolution. This indicates that the most-extreme precipitation events are typically small in area for this region during JJA. For the more-common events (e.g., \( P_e = 1\% \)), however, the relationship between precipitation rate and collection period is nearly constant, indicating that more-widespread stratiform precipitation is dominant for the more-common events. The spatial conversion factors needed to convert between the ASOS gauge dataset and the 8-km CMORPH dataset, \( C_i(\text{gauge, 8 km}) \), are shown in Fig. 10. Meteorological implications will be discussed in section 6.

5. Climatological variations in precipitation intensity

Regional and seasonal variations in the CDFs of precipitation intensity are assessed by creating maps of precipitation rates for multiple \( P_e \) levels using both ASOS and CMORPH data. The higher-temporal-resolution ASOS data allow for exploration of spatial and
seasonal patterns of near-instantaneous rain rates (Fig. 11). As one might expect, the most-extreme precipitation rates \( P_e = 0.01\% \) are confined to the southern states throughout much of the year. The heaviest rain generally occurs in JJA, when 1-min rates can exceed 100 mm h\(^{-1}\) along the Gulf Coast and over the central Great Plains. The lowest precipitation rates are generally found in the Intermountain West (IW), which has instantaneous rain rates of under 20 mm h\(^{-1}\) in all seasons except JJA. At the 0.1\% \( P_e \) level, similar patterns are seen, except that the maxima are weaker, and they are more confined to the Gulf Coast throughout much of the year. Also, at the 0.1\% level, a local maximum is evident along the West Coast in all but JJA. This maximum is most pronounced and extends farthest south in DJF, which coincides with California’s wet season. For the more-common precipitation events (1\%), the local maximum along the West Coast is most pronounced, with heaviest rates occurring in DJF. This is indicative of the much higher frequency of moderate precipitation in this region in winter. The location of the highest 1\%-likelihood rates shifts to the east in spring and summer and to the NE in autumn, coincident with the climatological maximum in the frequency of occurrence of coastal storms in this region (e.g., Whittaker and Horn 1984).

Hourly ASOS precipitation rates are easily derived from the 1-min data by summing over all 1-min observations within each hour for a given station. The resulting hourly precipitation-rate maps for three \( P_e \) levels are shown in Fig. 12. The spatial variations in the hourly averaged precipitation intensities are broadly similar to those obtained for the 1-min data, but there are several notable differences. The magnitudes of the hourly precipitation rates at \( P_e \) values of 0.01\% and 0.1\% are significantly less than the 1-min values (Fig. 11). This indicates that the highest rates are usually of very short duration. Note also that the local maximum at \( P_e = 0.01\% \) that was found along the West Coast using the 1-min data appears as being much weaker in the hourly

**Fig. 7.** ASOS 1-min-to-1-h temporal-conversion-factor arrays for each season and for the locations in each region marked by a red X in Fig. 1. Dashed lines show data from the 5\(^\circ\) x 5\(^\circ\) analysis, and solid lines show data from the finer 2.5\(^\circ\) x 2.5\(^\circ\) analysis.
ASOS rainfall rates. Smallest differences are seen when comparing at $P_e = 1\%$, indicating that these lighter precipitation rates are characteristic of longer-duration events.

The hourly ASOS rates may be compared with the hourly CMORPH rates shown in Fig. 13. Although spatial patterns of the precipitation rates associated with the three $P_e$ levels are similar in the two datasets, there are several important differences. First, the CMORPH rates tend to be lower than the ASOS rates for the most-extreme events ($P_e = 0.01\%$ and $0.1\%$), with largest negative biases evident in the NE in DJF. This enhanced wintertime bias may be explained by contamination of the satellite-based precipitation retrievals that is due to the presence of snow either in the column or on the ground (Joyce et al. 2004). The underestimation of the precipitation rates associated with the most-extreme events likely is due to intrinsic differences of the measurement techniques (e.g., size of sampling area) and can be corrected by using regionally dependent spatial conversion factors, as described above.

Although biases are evident in the CMORPH data, the benefit of the higher spatial resolution and comprehensive coverage is clearly evident. For example, CMORPH data indicate that there are maxima in precipitation rates over the Gulf Stream in all seasons (e.g., Minobe et al. 2008), as well as over the Sierra Madre in JJA, as has been reported in the literature (e.g., Hales 1972). The CMORPH data also show a clear local maximum in precipitation intensity over the central Great Plains in JJA and a local minimum over the Carolinas in September, October, and November—features that are not as obvious in the ASOS data.

6. Meteorological implications of temporal and spatial conversion factors

Temporal and spatial conversion factors were computed for the entire contiguous United States (CONUS) for all seasons using the hourly ASOS and hourly CMORPH datasets. The spatial variability and seasonal variability of these conversion factors are related to the characteristics of precipitation endemic to a particular region.

a. Temporal conversion factors

As discussed in section 4, the temporal conversion factor may be calculated as the ratio of precipitation rates at each $P_e$ level, determined over two different collection periods. The ASOS 1-min-to-1-h temporal conversion factors, $C_t(1 \text{ min}, 1 \text{ h})$, for each of the seven climatic locations marked by a red X in Fig. 1 are shown in Fig. 7. The values at the 0.01% $P_e$ level ($\sim 1.5$–2.5) are similar to those found by other studies. At a similar latitude in Europe, Watson et al. (1981) reported a mean $C_{0.01\%}(1 \text{ min}, 1 \text{ h})$ of 2.4 for Italy and a value of 1.7 for the United Kingdom. Mandeep and Hassan (2008) reported $C_{0.01\%}(1 \text{ min}, 1 \text{ h})$ ranging from $\sim 1.6$ to 1.9 for

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**Fig. 8.** Example hourly CMORPH CDFs for each season for the SC grid point marked by a red X in Fig. 1.

**Fig. 9.** CMORPH and ASOS precipitation rates for different probability of exceedance levels and effective resolutions (ASOS = 0 km; CMORPH = 8, 24, 40, 56, and 72 km) for JJA for the SC grid point marked by a red X in Fig. 1.
seven stations in tropical Southeast Asia. Karasawa and Matsudo (1991) reported lower $C_{0.01\%}(1 \text{ min}, 1 \text{ h})$ values from 1.3 to 1.9 for seven stations in Japan. The $C_{0.01\%}(1 \text{ min}, 1 \text{ h})$ values calculated in this study were found to vary by ±20% between seasons for each location. In general, it was found that $C_i(1 \text{ min}, 1 \text{ h})$ decreases from ~2 to 0.5 with increasing $P_e$ (Fig. 7), indicating that the most-extreme 1-min rates are farther from their corresponding hourly rates than are the less-extreme 1-min rates. This implies that the most-extreme 1-min rates are generally shorter in duration than the more-common events.

Differences between the 1-min and 1-h precipitation rates at a given $P_e$ become more evident when spatial variations are evaluated. At the 0.01% $P_e$ level, the ratio between DJF 1-min and 1-h rates, $C_{0.01\%}(1 \text{ min}, 1 \text{ h})$, is highest along the coasts and lowest in the interior, with a minimum located in the upper Great Plains (Fig. 14). It is important to note here that there is uncertainty associated with 1-min ASOS rates precipitation rates during periods of frozen precipitation, which can sometimes stick to the sides of the gauge before melting or evaporate from the heated surface of the funnel, particularly during very light precipitation (Jones et al. 2004). Therefore, care must be taken in interpreting the results from more-northern locations during the cold season. The higher $C_{0.01\%}(1 \text{ min}, 1 \text{ h})$ along the coasts is likely related to the more temporally nonuniform (e.g., showery) precipitation associated with the most-extreme precipitation events during this season, whereas the lower ratios in the interior likely are related to the more temporally uniform (i.e., stratiform) precipitation patterns of the most-extreme precipitation. As one makes a transition through the MAM season into the JJA season, one sees that the higher ratios are primarily in the eastern three-quarters of the United States, because warm-season convection tends to dominate this time of year. Of interest is that the highest values during JJA (associated with shorter-duration events) occur in the
upper Midwest and New England where upper-level winds are generally strongest and result in faster-moving convective systems than occur in the southern United States.

At the 0.1% $P_e$ level, the values of $C_{0.1\%}(1 \text{ min}, 1 \text{ h})$ decrease nearly everywhere across the United States, as compared with those of $P_e = 0.01\%$. There is also a more-distinct southeast-to-northwest gradient in the ratio in all seasons. For the most-common precipitation events ($P_e = 1\%$), the ratio is less than 1 everywhere, indicating that the hourly rates occur with a higher frequency than the 1-min rates because of the longer collection period. There is a clear north–south gradient, with the smallest ratios being in the south where precipitation events tend to be shorter lived, particularly in summer.

b. ASOS–CMORPH spatial conversion factors

Differences between the CMORPH and ASOS hourly precipitation maps can be quantified by taking the ratio of the precipitation rates at each $P_e$ level. Because the collection periods are identical, differences in the rates at each level are related to differences in the representative scale of the measurements (localized vs 8 km) and to systematic biases in the measuring devices, particularly those from satellite retrievals. The resulting maps of spatial conversion factors are shown in Fig. 15. The 0.01% $P_e$ level is not shown because there was too much apparent random scatter in the values because of small sample sizes. Values for $P_e$ of 0.1% range from 0.25 in the interior (especially in JJA) to greater than 4.0 in the north and along the West Coast in winter. The spatial conversion factor, $C_i($gauge, 8 km), indicates that hourly precipitation rates derived from CMORPH have a severe negative bias throughout the northern United States and the West Coast. This finding is consistent with the negative bias seen in the DJF comparison of daily mean precipitation rates shown in Figs. 3 and 4. In addition, the noisy pattern in this ratio for DJF indicates that the CMORPH data (and perhaps to some extent

![Fig. 11. ASOS 1-min precipitation rate CDF maps for each season and probability of exceedance level.](image-url)
the ASOS data) in these regions have a large amount of uncertainty associated with them in winter. In contrast, for seasons other than DJF, variability in the spatial conversion factor is relatively small, except along the coasts. During these seasons, much of the interior of the country has values that are significantly less than 1 at both levels of exceedance shown, indicating CMORPH hourly rates tend to be positively biased relative to the ASOS hourly rates.

The spatial conversion factor can be explored in more detail by plotting the ratio as a function of $P_e$ for each region (Fig. 10). Three general patterns are evident. The most evident and expected pattern occurs in the SC, SE, and NC regions, with a general decrease in the ratio with increasing $P_e$. This relationship might be expected of a region in which the highest precipitation rates are associated with smaller-scale storms. The spatial scale of these storms is not fully resolved by satellite data, and thus their associated precipitation rates are underestimated.

A second notable pattern is for the Northwest and NE, where the ratio generally increases with $P_e$ level for $P_e > 0.1\%$ during the nonsummer seasons. This indicates that CMORPH likely misses and/or underestimates the intensity of many of the more-common light precipitation events. The third pattern is found in the IW and Southwest (SW), where there is generally no readily apparent change in the spatial conversion factor with increasing $P_e$. This indicates that the 8-km CMORPH data are proportional to the data collected at the gauge scale in terms of frequency of occurrence and intensity.

7. Scaled CMORPH precipitation rates

The CMORPH hourly precipitation rate CDFs can be scaled to represent 1-min, localized precipitation rates using both temporal and spatial conversion factors. This may be expressed as...
CDF_{CMORPHscaled,j} = C_i(1 \text{ min}, 1 \text{ h}) \times C_j(\text{gauge, 8 km}) \times CDF_{CMORPH,j},

where CDF_{CMORPHscaled,j} is the cumulative distribution function for the CMORPH hourly precipitation and the temporal and spatial conversion factors being a function of region, season, and $P_e$, as discussed above. The resulting scaled CMORPH dataset provides an unprecedented depiction of instantaneous precipitation-rate maps for $P_e$ values starting at 0.1% (Fig. 16). Maps of the 0.01% $P_e$ level are not included since the required spatial conversion factors could not be calculated because of small sample sizes. Note that the CMORPH data could have been scaled using ASOS data of any collection period that is evenly divisible by the 1-min ASOS temporal resolution. These digital maps retain the high spatial resolution (40 km) and continuous coverage intrinsic of the satellite-based retrievals while at the same time having systematic biases largely removed. The scaling is not possible in some localized areas because of insufficient data, particularly in dry areas and/or seasons with a limited number of precipitation events.

Comparisons of Figs. 11 and 16 reveal that the magnitudes of the CMORPH data scaled to represent 1-min localized precipitation rates are nearly identical to the 1-min ASOS rates at $P_e$ of 0.1% and 1.0%. At the same time, important mesoscale variability available from the CMORPH data has been maintained, revealing variations in precipitation patterns that are associated with complex geography (e.g., mountains, lakes, and coastlines) and varying weather patterns across the country and adjacent coastal regions. For example, the west–east precipitation gradient evident over the central Great Plains is much better resolved in the scaled CMORPH data than in the ASOS data. It is also interesting to note the local minima in precipitation rates that are evident in the scaled CMORPH data extending from the southern Appalachians into northern Arkansas in JJA.
8. Conclusions

This study demonstrates a method of scaling CDFs of remotely sensed precipitation rates to correct for biases that may be caused by sampling and/or retrieval errors. This technique may also be used to transform CDFs of datasets from one time and space scale to another. It is particularly useful for scaling satellite-derived precipitation rates, since precipitation events often occur over time scales that are much shorter than the averaging period used in satellite retrievals. In this study, ASOS data were used to develop conversion factors to correct biases in the CMORPH satellite-derived precipitation CDFs as well as to scale them to be representative of a much-shorter sampling or collection period. The resulting high-resolution, bias-corrected, CONUS-scale CDFs combine the relative strengths of both precipitation datasets.

The scaling and bias correction are done by matching the collection period in the “truth” dataset (e.g., ASOS) with that of the satellite-retrieved dataset (e.g., CMORPH). The scaling and bias correction were accomplished using both the temporal and spatial conversion factors, which were found to vary by region and time of year. With two notable exceptions, the spatial conversion factor was found to be less than 1 over most of the CONUS for all seasons, indicating that CMORPH retrievals have a positive bias relative to the ASOS data over land. Two exceptions to this rule occurred across the northern United States and West Coast in winter and over the southeastern United States in summer where the spatial conversion factors were greater than 1. The large spatial conversion factors found in winter may be due to contamination of the CMORPH retrievals by snow and/or snow cover and by the uncertainties associated with measuring the liquid water equivalent of snow with the
ASOS gauges. In the summer over the SE, the high conversion factor may indicate a negative bias in CMORPH that likely is related to the undersampling of short-lived convective events.

Temporal conversion factors were developed to relate CDFs of 1-min precipitation rates to those observed over a 1-h period using ASOS data from across the contiguous 48 United States. The values of the 1-min-to-1-h temporal conversion factor at $P_e = 0.01\%$ ranged from 1.5 to 3.0 across the United States. These values are similar to those reported in previous studies and satellite retrievals for the most-extreme events (e.g., Watson et al. 1981; Mandep and Hassan 2008). This study extends their work by applying the temporal-scaling concept to the entire CDF rather than to individual $P_e$ levels and by creating CONUS-scale maps of the conversion factors. Two issues influence the temporal conversion factor: 1) the overall frequency of occurrence of precipitation events and 2) the duration of the precipitation events. For most of the country, the event duration dominates the temporal conversion factor as indicated by values that are greater than 1. In areas where the
conversion factor is less than 1, precipitation events are much less frequent (e.g., the SW in JJA).

The CONUS-scale spatial conversion factors described above provide a depiction of the regional and seasonal variability in the accuracy of satellite-based precipitation datasets. This can be used to more confidently assess the precipitation analyses available from the current suite of reanalyses with ever-increasing temporal resolution [e.g., hourly precipitation rates from the Defense Threat Reduction Agency–Climate Four-Dimensional Data Assimilation (DTRA–FDDA); Monaghan et al. 2010] and spatial resolution [e.g., 32-km resolution from the North American Regional Reanalysis; Mesinger et al. 2006]. The improved accuracy of the CDFs and the full CONUS coverage afforded by this technique could be of value for water resource planners and hydrometeorologists. This technique may prove to be valuable in mountainous regions where it can be used to develop calibrated CDFs that have much better coverage than operational rain gauge networks.

The technique described herein also allows for the estimation of precipitation rates for collection periods
of varying duration. A number of applications require information on the frequency of occurrence of near-instantaneous precipitation rates. For example, manufacturers of materials used to build high-speed airborne projectiles (e.g., rockets or space vehicles) can use the instantaneous precipitation rates of a given probability of occurrences to model the ablation of a substrate with a given velocity and attack angle (Murray 2005). This type of information can be used to determine the types of conditions that a projectile must be engineered to withstand. Also, with the proliferation of wireless technologies, from cellular telephones to satellite communications, knowledge of the frequency and variability of intense, short-duration precipitation events is needed to assess the power and arrangement requirements for communications transmissions.

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REFERENCES


Sohn, B. J., H. Han, and E. Seo, 2010: Validation of satellite-based high-resolution rainfall products over the Korean Peninsula.


