On the Challenge of Defining Normal Precipitation with Medians

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1. Introduction

The Climate Prediction Center (CPC) produces probabilistic above or below normal precipitation outlooks on a variety of timescales and forecast leads. The first step in producing such an outlook is to find an appropriate threshold to define "normal" precipitation. A robust normal provides the proper context to end users of CPC's outlooks. Further, it is needed to make meaningful verifications. However, defining a normal from a climatological distribution of precipitation is not a trivial exercise because precipitation is non-continuous, positively skewed, and often characterized by alternating periods of rainy and dry conditions that can either be attributed to noise or physical drivers. A standard practice at CPC is to estimate the median climatology for precipitation as opposed to the mean, which can be sensitive to outliers. The median describes the "middle value" of an ordered set of values. For non-Gaussian variables, it does not describe the average value, nor can the variance about a median be easily described. As such, whether the median is estimated from an model's ensemble dataset or from observations offers unique challenges. Another complicating factor is that the distribution of precipitation can vary by region, time of year, and timescale of interest.

Here, we will discuss some of the challenges that arise when calculating precipitation climatologies in both observations and models, while proposing some potential methods that can be employed to overcome them. Our principal focus will be precipitation accumulations during 14-day periods, which is most relevant to CPC's Week 3-4 precipitation outlook. We would like to emphasize that our discussion is neither meant to be representative of the practices currently being employed at CPC nor conclusive. We wish simply to bring awareness to the challenges we have encountered while calculating precipitation medians in the hope of sparking dialogue and debate about the best practices to generate robust Week 3-4 precipitation climatologies in both observations and models.

2. Data

Observed climatologies of precipitation derive from CPC's Global Unified Gauge-Based Analysis of Daily Precipitation (Chen *et al.* 2008). Model climatologies for the 1999-2015 period are derived from reforecasts of the ECMWF (Vitart *et al.* 2017) and the models participating in the Subseasonal Experiment protocol (SubX; Pegion *et al.* 2019), including the ECCC GEM, EMC GEFS, ESRL FIM, NASA GMAO GEOS, NCEP CFS, NRL NESM, and RSMAS CCSM4.

3. Discussion

In the following, we will list several challenges that the calculation of precipitation climatologies poses and make a few brief discussion points on each.

a. Precipitation is inherently noisy.

Figure 1a depicts daily precipitation over the 2010-2015 period for a grid point near San Francisco. It is clear that San Francisco has dry summers and wet winters. However, there is a great deal of noise on daily, subseasonal, and interannual timescales for this location as well. It is possible to smooth some of the noise by summing over consecutive and overlapping 14-day windows, yet the subseasonal and interannual variability remain (Fig. 1b). This introduces another challenge in calculating a robust climatology in datasets with limited samples, such as the reforecasts analyzed here (1999-2015). For example, climate signals that drive interannual

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and subseasonal precipitation variability, such as ENSO and the MJO, may be dominant in one phase or another during shorter climate periods. One can envision a particular phase of the MJO occurring, by chance, more or less frequently for a given calendar day in a shorter climate period than it would in a longer climate period.

b. Precipitation has non-Gaussian distributions, with medians less than the means.

Figure 2 presents the mean and median climatologies along with their differences for accumulated precipitation across CONUS/AK for the 14-day windows beginning January 16th and July 16th during the 1999-2015 period. To enhance the sample size of the distribution beyond 17 values, all consecutive, overlapping 14-day periods that begin within +/- 9 days of January 16th and July 16th are included in their respective distributions. While +/- 9 days is arbitrary, it is arguably long enough to substantially boost the sample size of the distributions, despite possible serial correlations. Furthermore, it is short enough that seasonality does not have a significant impact. The non-Gaussian nature of precipitation distributions is clearly on display with nearly all grid points having means greater than their

Fig. 1 Observed (**a**) daily and (**b**) 14-day accumulated precipitation from January 1, 2010 to December 31, 2015 for a grid point near San Francisco, CA (38°N, 238°E) are shown, as derived from CPC's Global Unified Gauge-Based Analysis of Daily Precipitation.

medians. Indeed, over large swaths of the country, the mean exceeds the median by over 10 mm, which has important consequences for verifications of precipitation. For example, if the mean as opposed to the median were used as the threshold to define normal precipitation in a two category system, then most 14-day windows would be classified as below normal. Thus, one could opine that it would behoove the forecaster to forecast below normal more often than above if the reference forecast of choice was a climatology split evenly between above and below normal. However, using the median as a threshold has implications as well. Dry areas such as California during July have medians of 0 mm, which completely precludes the possibility of issuing a below normal forecast.

c. Raw annual cycles of precipitation climatologies may be non-physical.

Figure 3 shows the climatological annual cycles of medians for accumulated, 14-day precipitation for a grid point near San Francisco. The thick black line in Fig. 3a represents the raw annual cycle for the 1999-2015 period. It is characterized by medians of 0 mm during summer and non-zero medians during winter and the shoulder seasons. Interestingly, there are two large peaks occurring during December and February, surrounding a relatively dry spell during mid-winter. Also, there are two additional but smaller peaks during the fall and spring. Upon examination of this cycle, one may ask whether it has physical meaning. In a raw annual cycle that has been averaged over many years, one would expect seasonality to be dominated by the annual revolution
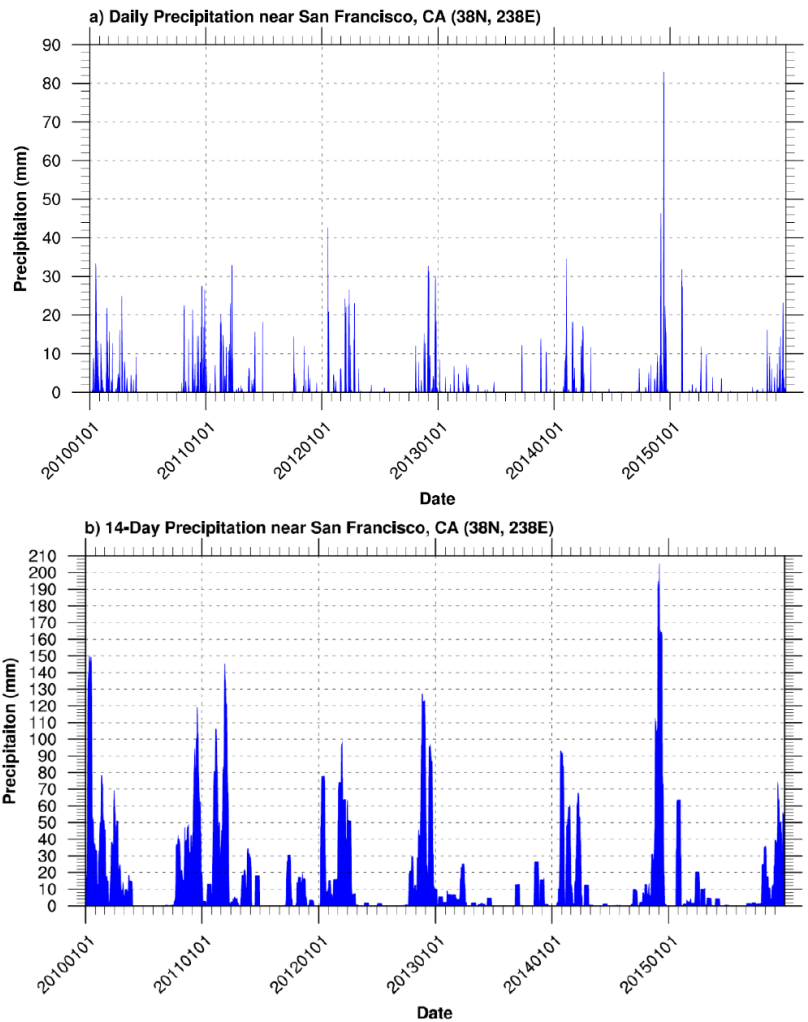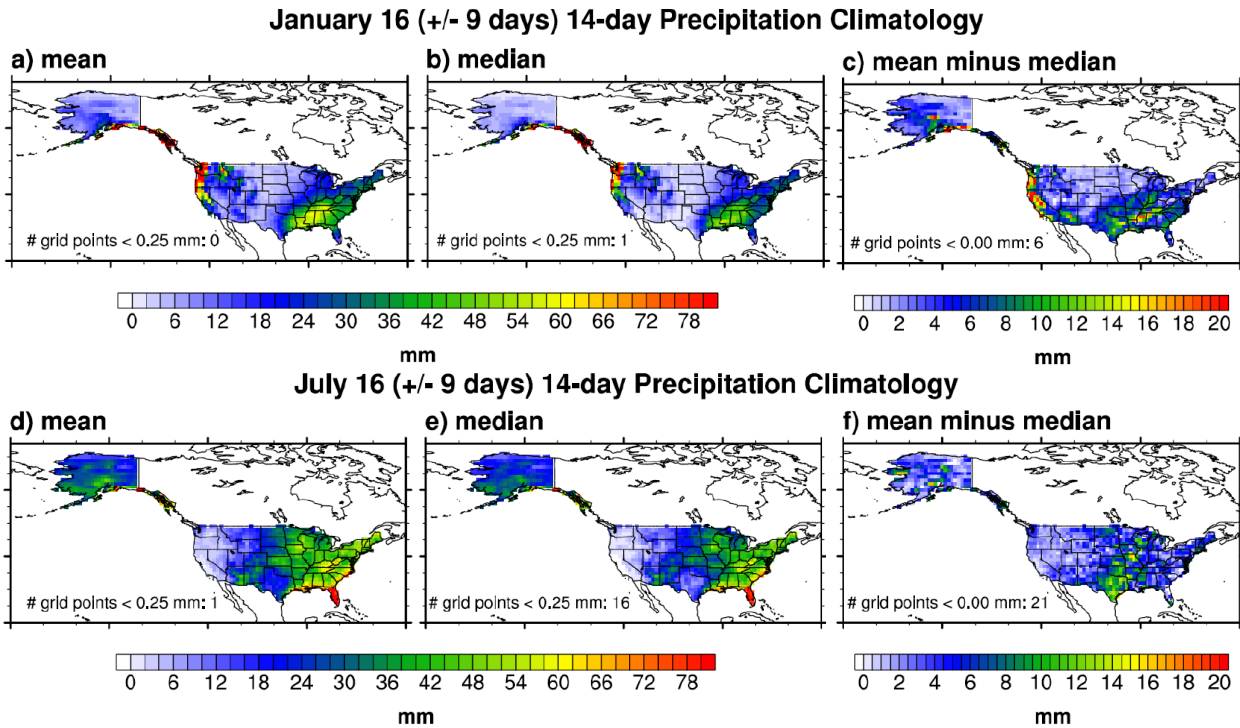
January 16 (+/- 9 days) 14-day Precipitation Climatology

July 16 (+/- 9 days) 14-day Precipitation Climatology

Fig. 2. 14-day precipitation climatologies, in terms of their means, medians, and differences, are shown as derived from the distribution of data gathered from the 14-day periods beginning +/- 9 days from (**a-c**) January 16th and (**d-e**) July 16th over the 1999-2015 period.

of the Earth around the Sun along with other plausible physical drivers such as the monsoon and the migration of the jet. With a short enough climate period, random variability associated with synoptic-scale cyclones, the MJO, convection, *etc.*, could happen to align on a given calendar day, producing the erratic peaks on display in Fig. 3a. In fact, when deriving the annual cycle over a longer 1979-2019 climate period, the smaller peaks during fall and spring completely disappear and the mid-winter dry spell is no longer as dry, resulting in a much smoother raw annual cycle which is likely more representative of the "true" climatology than that derived from the shorter 1999-2015 period. However, reforecasts datasets often have small sample sizes which obviates a smoothing of their raw annual cycle through the inclusion of more years. Thus, one must employ mathematical techniques to smooth, and they present their own set of challenges.

d. Smoothing the raw annual cycles of precipitation risks being arbitrary.

A common technique to smooth raw annual cycles and find the "true" climatology is to subject them to a Fourier analysis and then retain the mean and a specified number of n harmonics. This technique is a standard practice at CPC for deriving a smoothed climatology, but there is some debate concerning the optimal number of harmonics to retain. The colored lines in Figure 3 represent smoothed annual cycles with n = 1 to 14 harmonics retained. For small n, the multiple peaks during winter completely disappear, while for larger n, the raw cycle is nearly exactly reproduced by the smoothed cycle. Naturally, one may ask if there is an ideal number of harmonics that should be retained. We would argue that the number of cycles retained should be a reflection of the physical drivers that have a strong footprint on the raw annual cycle regardless of the length of the climate period in question. As discussed earlier, the secondary peaks in the raw annual cycle disappear using a longer 1979-2019 climate period, suggesting they might be non-physical and should not be considered normal for those calendar days. Alternatively, they could in fact be artifacts of low frequency events that should not be smoothed away. For example, the mid-winter dry spell, while less pronounced, is still evident and could be a reflection of the mid-winter suppression of the Pacific Jet. Therefore, perhaps an n should be chosen to reproduce the primary peaks, but perhaps not an n large enough to exactly reproduce them and the secondary

peaks out of fear of overfitting. After all, it is possible that using even a longer climate period than 1979-2019 may produce an even smoother raw annual cycle.

There are a few additional issues to note when smoothing. First, in the example provided with Fig. 3, the smoothed cycles represented by n < 4 are qualitatively similar for both climate periods. Thus, one could argue that using a small n not only alleviates the risk of overfitting, but it also works across different climate periods. However, for grid points like those near San Francisco, other physical processes may be at play that necessitate a higher number of harmonics and therefore the optimal n may vary from grid point to grid point. Second, a potential flaw with harmonic smoothing arises during completely dry periods with medians of 0 mm, as the summation of the harmonics will produce a smoothed cycle with artificial, non-zero values during those periods. A simple solution is to attempt to objectively set those values to zero when the raw annual cycle indicates they should be.

e. The calculation of precipitation medians from reforecasts is not a trivial task.

To calculate the precipitation medians from the reforecasts, we follow a method that is similar in concept to that described by Pegion *et al.* (2019). Essentially, to create a distribution from which to extract the median for a given

Fig. 3 Climatological 14-day precipitation medians are shown for a grid point near San Francisco, CA (38°N, 238°E) for (**a**) the 1999-2015 period and (**b**) the 1979-2019 period. The thick black line represents the raw annual cycle without smoothing while the thin colored lines represent smoothed cycles with the mean and 1 through 14 harmonics retained. Values during summer when the smoothed cycles are non-zero have been set to zero before plotting.

model, all ensemble members that have initialization dates within +/- 9 days of a particular calendar day are collected across all reforecast years. For example, NCEP CFSv2, which has reforecasts from 1999-2015 with four daily ensemble members, would have a distribution with 1292 values (17 years x 19 calendar days per year x 4 members per calendar day). Unlike, NCEP CFSv2, most models do not have reforecasts that are initialized daily. Thus, the +/- 9 calendar day window allows a distribution to be created for a given calendar day even if the model does not have any initializations that fall on that day. Because these distributions are both grid point and lead time specific, one can imagine that the computational expense of calculating the medians is relatively high.

Figure 4 displays the raw annual cycle of reforecast-derived medians (colored lines) juxtaposed against the observed raw annual cycle from the 1999-2015 (black lines) and 1979-2019 (gray lines) periods. The corresponding dashed black and gray lines represent the smoothed annual cycles using n = 3 harmonics. In Fig. 4a, the reforecast medians are calculated using the first 14 days of lead time (Week 1-2) while Fig. 4b uses the
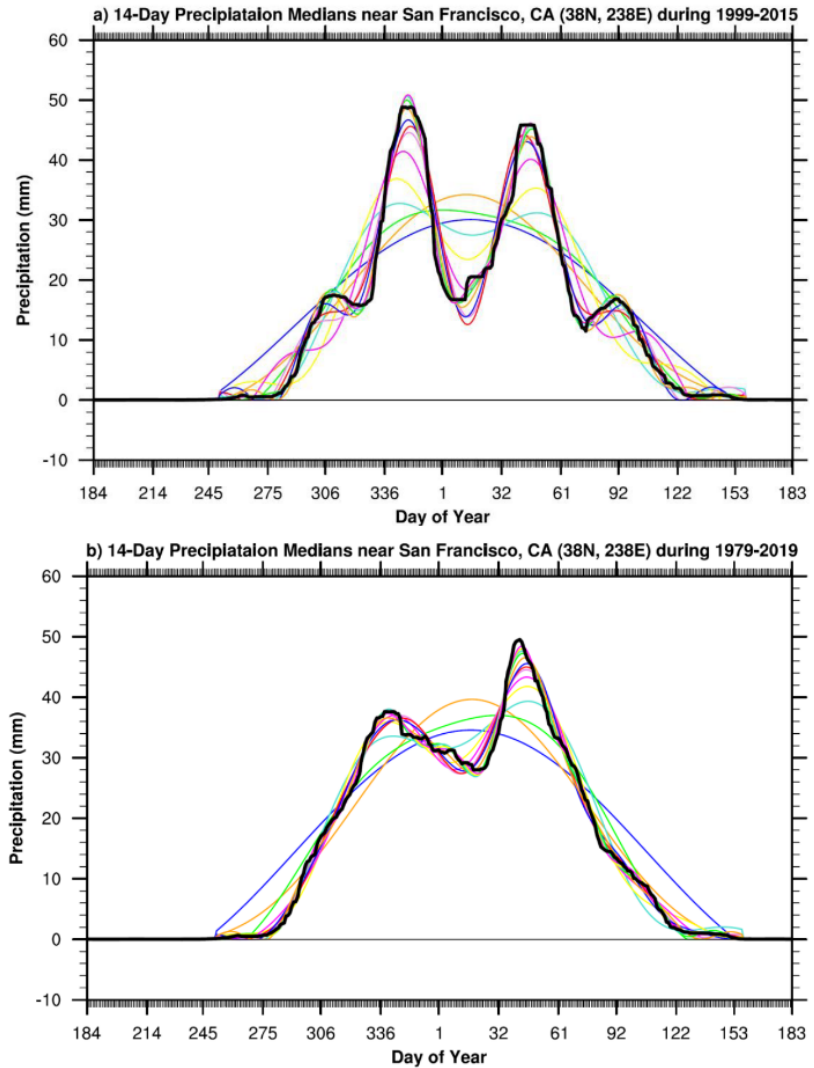
following 14 days of lead time (Week 3-4). There are several interesting features that can be discerned from this figure. The models clearly have biases – sometimes with medians greater than observations and sometimes less. These biases vary as a function of model, calendar day, lead time, and grid point. Interestingly, the models during their Week 1-2 reproduce the observed raw annual cycle for the 1999-2015 period. The four peaks and mid-winter dry spell are visible for nearly each model. Because the reforecasts are expected to reproduce the observed weather at Week 1-2 with some fidelity, one would expect their climatologies to more or less reproduce the observed climatology. However, these features largely disappear in the modeled climatologies derived from Week 3-4. At this lead, predictability that derives from the atmospheric initial conditions is lost to noise. Thus, one may ask which climatology is more representative of a "true" precipitation climatology – the observed or that modeled at Week 3-4. While, we do not have an answer to this question, Fig. 4b does show that the raw annual cycles derived from the models at Week 3-4 generally match the smoothed cycles derived from observations. Thus, there is likely important information that can be gleaned from both observations and model space if one wishes to determine the "true" precipitation climatology for a given location. We would also expect that bias correction and calibration techniques would help to align model data with the observed record.

Fig. 4 Climatological 14-day precipitation medians are shown for a grid point near San Francisco, CA (38°N, 238°E). In both (**a**) and (**b**), the solid black and gray lines represent the raw annual cycles for the 1999-2015 and 1979-2019 periods, respectively, while the dashed black and gray lines are the smoothed versions of these raw cycles using n = 3 harmonics. The colored lines are the raw cycles derived from the subseasonal models for their (**a**) Week 1-2 and (**b**) Week 3-4 lead times. Values during summer when the smoothed cycles are non-zero have been set to zero before plotting.

However, any nuanced, non-Gaussian behavior that could be meaningful for individual grid points would be lost because calibration methods often treat all variables with the same correction technique, regardless of the underlying distribution for a given grid point.

4. Conclusion

Here, we have discussed various challenges we wrestle with at CPC when defining normal precipitation with medians for 14-day periods. In general, we appreciate that estimating climatologies is simply that – an estimate. However, in the arena of forecasting weather and climate, forecasting is in lock-step with verification. Understanding the skill of one's forecast will be inherently linked to understanding the climatological distribution for which the threshold is defined. The points we have raised are neither meant to be all-inclusive nor conclusive. Rather, we wish to raise awareness of some of the pitfalls that are present when working with
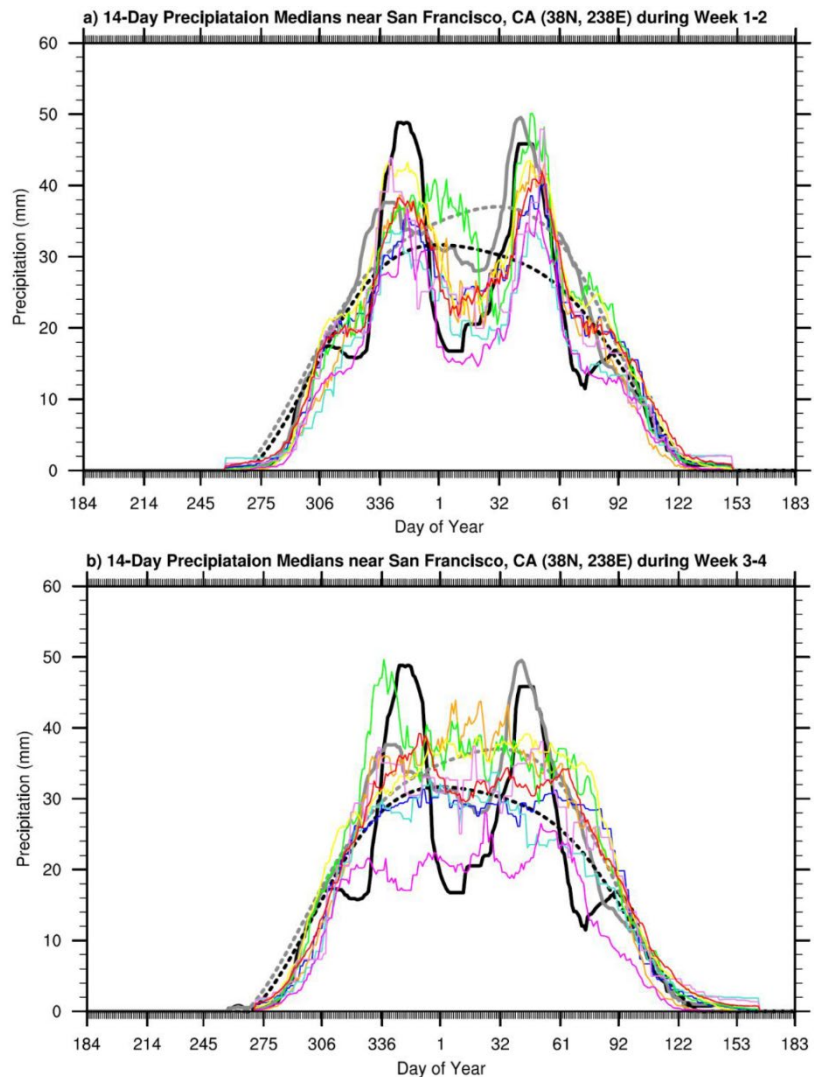
a non-Gaussian, noisy variable such as precipitation. The hope is that this heightened awareness will lead to the development of robust, meaningful climatologies that are useful to the research and forecasting community.

References

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