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Key Points:
- This commentary highlights and contextualizes Lin and Huybers (2018) findings and discusses broader implications for climate research
- Spatial and temporal features of the weather station network used in gridded data sets result in biases in climate trends
- Uncertainty quantification, better data sets, and an accurate understanding of recent climate change requires access to raw station data

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Implications of a Varying Observational Network for Accurately Estimating Recent Climate Trends

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Abstract Gridded data sets that are widely used to characterize recent historical trends in regional and global climate are derived from a temporally varying and spatially inhomogeneous observational network. Lin and Huybers (2018, https://doi.org/10.1029/2018GL079709) demonstrate that such network variations underlying two widely used precipitation data sets have biased trends in mean and extreme rainfall over India. I highlight similar concerns raised by studies over other regions and discuss the implications for climate change research. Evaluating uncertainties arising from such nonclimatic factors requires access to underlying station data that is currently unavailable for several vulnerable regions but is critical for accurately characterizing recent climate change and evaluating climate models.

Plain Language Summary Gridded climate data sets derived from weather stations provide spatially complete estimates of weather conditions and are often used to analyze climate trends. The density of weather stations, which provide point-based measurements, varies across the globe. In addition, the network of weather stations has undergone various changes over the years. Could trends in climate variables based on gridded data sets that utilize this changing network be subject to biases resulting from these changes? A recent article by Lin and Huybers (2018) proposes a method to quantify these biases using spatially uniform satellite measurements and information about the underlying station network. They apply their method to highlight potentially substantial biases in reported trends of mean and extreme precipitation during the Indian summer monsoon season, an area of intensive research. Their work, along with other studies of global and regional data sets that address similar issues, underscores the importance of carefully examining the artificial trends and uncertainties induced by such network inhomogeneity issues in commonly used data sets and continuing efforts to improve these data sets to better quantify recent climate change. However, these efforts are limited by the unavailability of raw station data from several institutions in critical regions of the world.

1. Observed Climate Data Sets

A reliable observational record is central to quantifying historical climatic changes, evaluating our climate models, and identifying the influence of historical climate forcings. The main sources of observations for the fundamental climate indicators of the recent historical period—surface temperature and precipitation—are weather station-based instrumental records and satellite-based measurements. Satellite instruments provide the advantage of spatially complete measurements for these climate indicators, and several satellites have global coverage. However, satellite data is available starting in the late-1970s, and estimates of climate variables derived from them have several known biases. In contrast, station-based records are irreplaceable, as they provide more reliable direct measurements of weather conditions and are essential for calibrating and validating space-based and other proxy measurements (e.g., Krishnamurti et al., 2009). Station records in several regions also extend further back, facilitating a better understanding of the long-term evolution of climate.

One of the main limitations of the station-based records is that, unlike satellites, they do not have global coverage and have considerable spatial differences in station density. The surface observational network has expanded and changed over time. For surface temperature, the number of stations with a consistent, monthly record grew from ~1,500 at the beginning of the 20th century to ~6,000 in the 1970s (Lawrimore et al., 2011). Similarly, the spatial coverage of the station-based network of rain gauges has varied dramatically over the last century (Vose et al., 2016). The number of stations in the Global Precipitation Climatology Center database, the largest for station-based precipitation records, increased fourfold from the early 20th century till 1986/1987 when there were 47,000 reporting stations (Schneider et al., 2014). Several nonclimatic factors contribute to inhomogeneities in these long-term station-based records, which could artificially influence the estimation of historical trends (Alexander, 2016). Some of these well-known factors include changes in the instrumentation, in situ conditions (such as land use changes), the location of stations, and the time of data collection (Lawrimore et al., 2011; Trewin, 2010). In particular, the effects of land use change associated with urbanization and irrigation on long-term temperature trends, while not significant for global-average temperatures, can be substantial for regional-average temperatures in rapidly developing areas when derived from unadjusted raw station measurements (Hartmann et al., 2013). Recent work also suggests the potential for additional factors such as civil conflict and political instability (Schultz & Mankin, 2019) and extreme weather events (Lin & Huybers, 2018) to influence regional weather records by affecting reporting stations.

Gridded climate data sets often used for analyses of spatial and temporal climate variability, modeling of other Earth system elements, and decision making are derived from these individual station measurements to provide more spatially complete information. Algorithms used to interpolate station-based point measurements onto a uniform grid aim to account for several nonclimatic inhomogeneities while still maximizing the number of stations used. Although homogeneity adjustments are applied, there are still uncertainties associated with these methods and factors (Hartmann et al., 2013). Limiting stations to only those with a consistent, long-term record would dramatically reduce the number of available stations, affecting the spatial coverage or the temporal extent of these data sets (Alexander, 2016), particularly in large parts of Africa, South America, and Central and Southeast Asia, where reliable weather station records extend back less than 50 years (Lawrimore et al., 2011; Rennie et al., 2014). Global average temperature trends have limited sensitivity to these nonclimate inhomogeneities in the underlying data (Easterling & Peterson, 2000). However, these inhomogeneities are amplified at regional to subregional scales, and at daily to subdaily scales (Alexander, 2016), which contribute to uncertainties in the representation of daily extremes and their trends (e.g., Alexander, 2016; Donat et al., 2014; Hofstra et al., 2010). In addition, these uncertainties are identified as a greater concern for precipitation extremes than for temperature extremes (Donat et al., 2014).

2. Lin and Huybers (2018) findings on Indian Rainfall Trends

In a recent article, Lin and Huybers (2018) explore the implications of gridded products and the underlying network inhomogeneity issues for studying mean and extreme rainfall patterns, using the case of the Indian summer monsoon. A number of studies have identified a long-term decline in mean precipitation over the core Indian monsoon region (Turner & Annamalai, 2012) and significant long-term trends in various metrics of extreme precipitation, as summarized in Singh et al. (2019). A majority of the studies on extreme precipitation rely on the widely used daily, gridded precipitation data sets provided by the Indian Meteorological Department (IMD) at $1° \times 1°$ (Rajeevan et al., 2010) and $0.25° \times 0.25°$ (Pai et al., 2015) resolutions, which are derived from rain gauge station records. India's extensive rain gauge network was established during the British colonial era in the 1870s to aid in monitoring and predicting the monsoons that are vital for the country's agriculture, water resources, and economy. This network has varied considerably over the instrumental record with a near tripling in the number of stations over the 20th century (Figure 1). It also has considerable spatial variations with the highest density of stations in peninsular India and the lowest density in the northern mountainous areas and eastern-central India.

The IMD $1° \times 1°$ data set uses nearly 1,803 stations that have at least 90% data availability between 1951 and 2003 (Rajeevan et al., 2006). Although it is based on a fixed number of stations, temporal variations can result from variations in the number of stations reporting data on a given day (Figure 1). The $0.25° \times 0.25°$ data set incorporates a much larger network of 6,955 stations that have considerable temporal variations in data availability between 1901 and 2010 (Pai et al., 2015; Figure 1). Both data sets have a large decline in the number of reporting stations since the early 2000s due to delays in archiving data (Figure 1). Lin and Huybers (2018) propose a novel method to demonstrate that the networks spatial distribution does not adequately capture the spatial complexity of rainfall and its temporal features have created substantial biases in trends derived from these data sets, with contrasting effects on seasonal mean precipitation and the frequency of extreme events (defined as the number of grid boxes exceeding an extreme precipitation threshold of 100 mm/day).

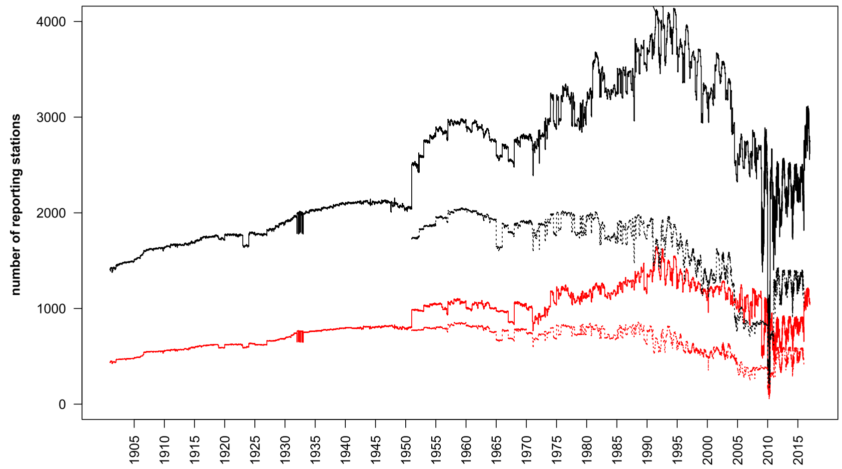

Figure 1. Daily variations in the number of reporting weather stations used in the Indian Meteorological Department 0.25° × 0.25° (solid line) and 1° × 1° (dashed lines) gridded rainfall products across All India (black) and Central India (red) domains. The Central India domain encloses the region (16.5-26.5°N and 74.5-86.6°E) used in Lin and Huybers (2018).

Combining available station information and microwave-sensed rainfall estimates from the Tropical Rainfall Measuring Mission (TRMM) Multi-Satellite Precipitation Analysis 3B42 v.7 data set (1998-2015), Lin and Huybers (2018) isolate the effect of temporal changes in the underlying rain gauge network on regional-average precipitation estimates over central India, commonly referred to as the core-monsoon region (Singh et al., 2014). They compare precipitation for the overlapping period of the TRMM and IMD data sets. In addition, they generate a series of "artificial" rainfall maps from the spatially complete TRMM data based on the daily station availability in the IMD by substituting rainfall in a grid box with no reporting stations on a given day with a value interpolated from neighboring grid boxes. These maps are subsequently used to calculate precipitation metrics. Temporal variations in the metrics of mean and extreme precipitation derived from this "artificial" data, therefore, only reflect spatial changes within the rain gauge network (Lin & Huybers, 2018).

To illustrate the extent of biases due to a sparse network using this artificial data, Lin and Huybers (2018) show that a day with 60 extreme events over central India estimated from TRMM has as few as 33 extreme events when estimated from an artificial map created by imposing the TRMM rainfall pattern on an IMD (0.25° × 0.25°) grid corresponding to a day with relatively few reporting stations. On average, such grid variations induce negative biases in the frequency of extreme events over Central India, which amount to approximately 18% relative to the original TRMM data (Lin & Huybers, 2018). The seasonal mean and frequency of extreme events calculated from this artificial rainfall data set exhibit positive trends, resulting from the increase in rain gauge density during 1975–2000. For seasonal mean precipitation over Central India, the average magnitude of this artificial trend is ~14% of the observed rainfall decline derived from the IMD 1° × 1° data set, suggesting an underestimation of the seasonal drying trend over the recent historical period (Lin & Huybers, 2018). Similarly, for extreme event frequency, the magnitude of this artificial positive trend can be as high as 25% of the observed increasing trend (e.g., Goswami et al., 2006; Roxy et al., 2017), suggesting an overestimation of historical changes (Lin & Huybers, 2018). Such biases, though weaker, are still substantial in the higher-resolution data set.

An implicit assumption in the Lin and Huybers (2018) method is that the TRMM satellite measurements are the true rainfall estimates. However, TRMM 3B42 v.7 has reported biases in daily rainfall across different parts of India, including overestimating daily mean precipitation and the frequency of and total precipitation contribution from extreme events over large areas of central and eastern India and underestimating precipitation over regions of topographic complexity (Prakash et al., 2015; Shah & Mishra, 2016). In addition, studies have shown that TRMM underestimates precipitation rates associated with extreme events associated with deep convective storms (Rasmussen et al., 2013) such as those that occur over the Indian subcontinent during the monsoon season. Therefore, while useful for demonstrating the presence of biases, TRMM might not be the best baseline for estimating their magnitudes. An accurate quantification of these biases and uncertainties induced in creating these gridded data sets requires the availability of raw precipitation data that include information about the location of stations and their reporting intervals. A fraction of the IMD stations are publicly available as part of the Global Historical Climate Network database (Vose et al., 2016) but the sparse spatial coverage of this subset limits their utility, particularly for studying extreme events.

3. The Indian Summer Monsoon Revival

Jin and Wang (2017) recently evaluated the long-term trends in the Indian summer monsoon rainfall with multiple independent data sets and found that the historical (1950-2000) declining trend (Bollasina et al., 2011) had reversed since 2002, indicating a monsoon "revival." Seasonal mean trends for the 1950-2002 period derived from the IMD 0.25° × 0.25° data set are the weakest among all data sets considered. Further, it is the only data set that does not show a revival post-2002 (Jin & Wang, 2017), which is also the period with a sharp decline in the number of included stations (Figure 1, solid lines). The other rain gauge-based data sets used in their analysis include Climate Research Unit TS v.4.00 (Harris et al., 2014), Global Precipitation Climatology Centre data v7 (Schneider et al., 2014), U.S. National Oceanic and Atmospheric Administration PREC/L data set (Chen et al., 2002), and Global Precipitation Climatology Project version 1.2 (Adler et al., 2003), which all agree with the post-2002 positive rainfall trends in TRMM.

Although the observed rainfall reversal is corroborated by a reversal of tropospheric temperature trends over land that influences the strength of the monsoon (Jin & Wang, 2017), the discrepancies between these data sets warrants further investigation in light of Lin and Huybers (2018) findings. Is the large decline in input stations in the early 2000s primarily responsible for the weaker IMD trend relative to other data sets? If the biases in the IMD-derived rainfall trends follow the trend in number of stations as Lin and Huybers (2018) suggest, the answer to this question might be "yes." However, each of these data sets is susceptible to the variability and decline in the number of input stations from the late-20th to early-21st centuries (Chen et al., 2002; Harris et al., 2014; Schneider et al., 2014), and the IMD data set incorporates a substantially higher number of stations over India (Roxy, 2017). Different interpolation methodologies utilized in these data sets may potentially result in systematic biases, but these not apparent here. Instead, spatial and temporal variations in the stations are more likely the cause of such differences and can only be resolved with the underlying raw station data in each data set. Resolving these differences to more accurately quantify historical trends over India is critical for identifying the impact of several competing anthropogenic forcings over the region (Singh et al., 2019) and an important need for effectively planning for future changes in their natural resources.

4. Broader Implications and Future Directions

Although the IMD data sets are the focus of Lin and Huybers (2018) article, such network inhomogeneity issues exist in most gridded products, which often use the largest number of suitable reporting stations to better capture the spatial variability in climate (e.g., Harris et al., 2014; Schneider et al., 2014). For the Indian domain, substantial differences exist between various precipitation data sets, as demonstrated in Singh et al. (2019), for several reasons including their use of a fraction of the IMD rain gauge stations, incorporation of satellite data, different spatial resolutions, and different interpolation techniques. Similar issues and uncertainties associated with a changing observational network have been evaluated and reported for other regional (e.g., Hofstra et al., 2010, for Europe and King et al., 2013, for Australia) gridded products.

Although the gridded data sets are an invaluable resource for the community, the existence of such biases arising from network inhomogeneities underscores the need for future work to incorporate multiple data sets (e.g., Donat et al., 2014) and complement analyses of gridded data sets with station-based records. Future research efforts in the following areas could help address these issues. First, an in-depth evaluation of the effects of these inhomogeneities in gridded data sets on historical trends, particularly in extremes and in areas that have experienced substantial changes in their observing network, using similar approaches (e.g.,Donat et al., 2014; Hofstra et al., 2010; King et al., 2013; Lin & Huybers, 2018). Second, an investigation of the effects of network inhomogeneities on different climate indices at various spatial and temporal scales to identify trade-offs. For instance, while on a global-scale and at fine spatial scales in data rich areas, climate indices might not be sensitive to these issues, they could be a larger concern for intermediate spatial scales and in areas with a sparse network (e.g., King et al., 2013). Further, such inhomogeneities might be less of a concern at annual or monthly timescales but more problematic for daily-scale extremes (e.g., Hofstra et al., 2010). Third, improvements in interpolation techniques by accounting for factors such as topographic effects, as is done in the Parameter-elevation Regressions on Independent Slopes Model data set (Daly et al., 2001), and assessment of the uncertainties arising from using various interpolation techniques used in developing gridded data sets from the raw station data. For example, Chen et al. (2002) evaluated four interpolation schemes in creating the PREC/L data set and found that the differences between schemes are amplified at daily timescales relative to monthly timescales. Four, complementing analyses of climate variables with contributing thermodynamic and dynamic factors to provide a supporting physical mechanism for interpreting observed climatic changes such as for mean (Jin & Wang, 2017) and extreme precipitation (Singh et al., 2014) of the Indian Summer Monsoon.

The potentially large magnitude of biases associated with nonclimate inhomogeneities raise important questions about their influence on reported trends in numerous studies, particularly when using gridded data sets in data-sparse areas and areas that have experienced rapid changes in their observational network due to factors including political instabilities (Schultz & Mankin, 2019). Several areas where these inhomogeneities are prominent are also areas that are vulnerable to climate variability and change. Addressing these biases have important implications for accurately characterizing historical trends in several critical regions of the world and attributing them to natural or anthropogenic causes. These nonclimatic inhomogeneities in data sets also contribute to observational uncertainties that have implications for the evaluation of climate models (Collins et al., 2013). Examining such issues in observations will, therefore, also contribute toward model development through accurately characterizing their existing biases. Efforts to characterize and incorporate such biases and uncertainties in the instrumental record require monitoring organizations in several countries to make the raw station data available to the research community. Accurate quantification of the long-term climate trends and their uncertainties is critical for advancing our understanding of how the climate system has changed and how it will change in coming decades.

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