Evaluation of the Reanalysis Products for the Monsoon Season Droughts in India

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ABSTRACT

Drought monitoring in near–real time is essential for management of water resources, irrigation planning, and food security. However, lack of availability of quality real-time observations leads to slow decision making and relatively poor natural resources management, especially during and after severe and prolonged droughts. The global reanalysis products that are available in near–real time could be valuable for drought monitoring and assessment. Three high-resolution reanalysis products—the Modern-Era Retrospective Analysis for Research and Applications (MERRA), the Interim ECMWF Re-Analysis (ERA-Interim), and the NCEP Climate Forecast System Reanalysis (CFSR)—are examined for their effectiveness in reproducing retrospective droughts during the period 1980–2005. All the selected reanalysis products show biases in the monsoon season precipitation and temperature. MERRA, ERA-Interim, and CFSR showed median bias in the monsoon season precipitation (temperature) of 10% (−0.39°C), 34% (−0.21°C), and 11% (−0.44°C), respectively. The reanalysis products largely fail to reproduce the observed trends in the monsoon season precipitation and temperature over India. All-India median changes in the monsoon season precipitation (temperature) shown by the observations and by MERRA, ERA-Interim, and CFSR were −2% (0.13°C), 26% (−0.42°C), 7% (0.24°C), and −8% (0.54°C), respectively, during the period 1980–2005. Despite the differences in the observed areal extent and severity of drought from those obtained from the individual reanalysis products, ensemble mean drought indices of different reanalysis products showed better performance for drought assessment during the monsoon season in India.

1. Introduction

Drought is a natural phenomenon arising from below normal precipitation, received over an extended period, season, or years (Wilhite 2011; Boken 2005). For instance, in India, a year is considered a drought year if the departure of the monsoon season [June–September (JJAS)] precipitation is below 10% of its long-term mean (based on the glossary available on www.imd.gov.in). Droughts due to deficient precipitation are termed as meteorological droughts. However, agricultural droughts may occur because of high temperatures (heat waves), which in turn lead to depleted soil moisture content (Wilhite 2011). Under the projected climate, the frequency of precipitation extremes, floods (Hirabayashi et al. 2008), and droughts (Sheffield and Wood 2008) is projected to increase. Frequent precipitation deficits and high temperature may result in intensification of meteorological drought to frequent soil moisture stress and agricultural droughts.

While droughts may have profound implications on various socioeconomic aspects, they most commonly affect agricultural production by influencing water availability. For instance, frequent and persistent droughts may lead to overall reduction in crop yields. Crop yield reduction can risk food security and have many other environmental consequences. For example, below-normal rainfall in 1979 caused an overall reduction in food grains by 20% in India. Moreover, droughts can affect the Indian economy as agriculture accounts for about 20% of the gross domestic product (GDP). India suffered financial losses of USD 1 498 722 due to droughts during the period 1988–2009, and over 350 million people were affected (Singh et al. 2009, and references therein). Moreover, a failure of crop yields due to extreme drought conditions may even lead to famine. For instance, drought in 1984–85 in the Horn of Africa led to famine, which
killed 750,000 people (http://earthobservatory.nasa.gov/Features/DroughtFacts/).

Monitoring and assessment of drought conditions in near–real time is essential to management of water and food resources. Timely monitoring of droughts can be helpful in mitigating droughts in real time and could help in alleviating detrimental impacts. Real-time monitoring requires quality meteorological data available in near–real time. While quality meteorological observations based on station data are valuable for drought monitoring and assessment, these are mostly not available in near–real time. Moreover, their spatial and temporal coverage can be an additional limitation in drought monitoring. On the other hand, historical observations may lack consistency and therefore cannot be used directly before quality checks (Bosilovich et al. 2013).

Retrospective analysis (or reanalysis) products are one of the alternatives and have been used as surrogates of observations (Kalnay et al. 1996). Reanalysis products can provide data for various climate and hydrologic variables (e.g., precipitation, maximum and minimum temperatures, and soil moisture) for the retrospective period. These reanalysis products are generated by assimilating disparate observations and remotely sensed data and forecasting using climate and land surface models (Kalnay et al. 1996; Dee et al. 2011a; Bosilovich et al. 2013). Moreover, the reanalysis products have been used for the development of various long-term datasets and to study implications of climate variability (Stefanova et al. 2011; Misra et al. 2012). Sheffield et al. (2006) developed the 50-yr high-resolution global dataset of meteorological forcings for land surface modeling using NCEP–National Center for Atmospheric Research (NCAR) reanalysis and observational datasets.

The monsoon season (JJAS) precipitation is critical for agriculture and water resources in India, as about 80% of the total annual rainfall occurs during this period. Monitoring and assessment of droughts during the monsoon season is underscored to manage natural resources and may have high importance for policy makers. The reanalysis products can provide valuable information at reasonable spatial and temporal resolutions for assessment of the retrospective and current droughts and their impacts (Karnauskas et al. 2008; Sheffield et al. 2012; Mo et al. 2011). However, the reanalysis products warrant careful scrutiny (Bosilovich et al. 2009; Kalnay et al. 1996) before they can be used for the assessments of the monsoon season droughts in India. Here we evaluate three high-resolution reanalysis products for the assessment of the monsoon season droughts in India. We use the National Aeronautics and Space Administration’s (NASA) Modern-Era Retrospective Analysis for Research and Applications (MERRA; Rienecker et al. 2011; Bosilovich 2014), the Interim European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-Interim; Dee et al. 2011a), and the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR; Saha et al. 2010) for the assessment of monsoon season retrospective droughts in India during the period 1980–2005. The overarching science question that we intend to address here is, to what extent do the reanalysis products provide skills for drought monitoring and assessment in India during the monsoon season?

2. Data and methods
   a. Observed and reanalysis datasets

Precipitation and temperature are among the most desirable climate variables for drought monitoring and assessment. For evaluating the reanalysis products, observed (OBS hereinafter) precipitation and temperature for the retrospective period (1980–2005) were obtained from the India Meteorological Department (IMD). Rajeevan et al. (2006, 2008) developed a 0.5° gridded precipitation dataset for the period 1971–2005 using observations from 6000 stations across India. The dataset was gridded using the method of Shepard (1968). Rajeevan et al. (2008) evaluated the gridded precipitation data against Asian Precipitation–Highly-Resolved Observational Data Integration Toward Evaluation of Water Resources (APHRODITE; Yatagai et al. 2012) and found underestimations in the APHRODITE precipitation. For the drought analysis in 2012, we used the 0.5° monthly precipitation dataset from the Tropical Rainfall Measurement Mission (TRMM, 3B42 v7; Huffman et al. 2007).

For temperature, we obtained from IMD a daily gridded dataset at 1° spatial resolution developed by Srivastava et al. (2009). The gridded temperature dataset was developed with the methodology described in Shepard (1968) using about 395 stations across India. The 1° temperature was further regridded at 0.5° spatial resolution to make it consistent with the precipitation and other reanalysis datasets. Regridding was performed using a 0.5° digital elevation model (DEM) and the methodology described in Maurer et al. (2002).

In this study, we evaluate the three high-spatial-resolution and latest-generation reanalysis products: MERRA (Rienecker et al. 2011), ERA-Interim (Dee et al. 2011a), and CFSR (Saha et al. 2010). The aim of the MERRA project was to use satellite-based observations for climate study (Rienecker et al. 2011). The MERRA, ERA-Interim, and CFSR data are available from 1979 onward and provide many variables associated with the...
hydrologic cycle. The MERRA (Ferguson et al. 2012; Koster and Mahanama 2012; Roundy et al. 2013; Lorenz and Kunstmann 2012), ERA-Interim (Seibert and Apel 2012; Mueller and Seneviratne 2012; Dutra et al. 2013), and CFSR (Misra et al. 2012; Mo et al. 2011) data have been widely used to assess the impacts of climate variability and regional and global hydrologic assessments. Further descriptions and characteristics of these reanalysis products are presented in Table 1.

For the evaluation of the reanalysis products, total monthly precipitation (millimeters) and mean monthly air temperature (at 2 m above surface; degrees Celsius) were extracted from each of the reanalysis products for the overlapping period 1980–2005 with the spatial resolutions shown in Table 1. The global-scale comparisons of the reanalysis products for precipitation and temperature can be found in Bosilovich et al. (2008) and Pitman and Perkins (2009). For the assessment of the drought during the year 2012, monthly precipitation and temperature were obtained from the real-time reanalysis extension of CFSR developed by the NCEP Climate Forecast System, version 2 (CFSv2; Saha et al. 2013). However, the reanalysis products were regridded against observations for the common period 1980–2005.

b. Evaluation approach

To evaluate the reanalysis products for the monsoon season drought, precipitation and temperature from the reanalysis products were evaluated against OBS. OBS and all three reanalysis products have different spatial resolutions (Table 1); therefore, the reanalysis products were regridded to a common grid mesh of 0.5° across India. Precipitation was regridded using bilinear interpolation. Bilinear interpolation considers a 2 × 2 grid and interpolates values at required locations by taking the weighted average, which can be slightly biased for nonuniform grid cells. Temperature was regridded using a DEM to consider the lapse rate as described in Maurer et al. (2002). We estimated bias, correlation, and trends in precipitation and temperature from the reanalysis products that were evaluated against the OBS.

1) BIAS, CORRELATION, AND TREND ANALYSIS

We estimated bias (reanalysis − observed) and percentage bias [(reanalysis − observed) × (100/observed)] in mean monthly/seasonal temperature and precipitation. The Spearman rank correlation method was used to assess temporal correlation between the observed and reanalysis products. We used Spearman rank correlation as it is a nonparametric method and is less biased toward outliers.

The nonparametric Mann–Kendall trend (Mann 1945) and Sen’s slope (Sen 1968) methods were used to estimate trend in the monsoon season precipitation and temperature for the period 1980–2005. The Mann–Kendall trend test was also used to estimate changes in all-India-averaged monsoon season precipitation and temperature anomalies in the OBS as well as reanalysis datasets. Anomalies in the monsoon season precipitation (Ap) and temperature (At) for each grid cell for each dataset were estimated by using Eqs. (1) and (2),
respectively, where \( x \) is monsoon season precipitation or temperature from 1980 through 2005:

\[
Ap = \left( \frac{x}{\bar{x}} \times 100 \right) - 100 \quad \text{and} \quad (1)
\]

\[
At = x - \bar{x}. \quad (2)
\]

The trend was estimated at 5% significance level, and grid cells with significant positive/negative trends were identified and shown using stippling. The Mann–Kendall test has been widely used to estimate trends in hydrology, water resources, and climate (Mishra et al. 2010; Mishra and Lettenmaier 2011; Lins and Slack 1999; Westmacott and Burn 1997). Hydrologic and climate variables often show persistence; therefore, the effect of spatial and temporal correlations in the trend analysis was addressed using the method described in Yue and Wang (2002).

2) Drought Indices

We used the Standardized Precipitation Index (SPI; McKee et al. 1993) to estimate meteorological droughts during the monsoon season. SPI is a dimensionless index based on the probability distribution of precipitation, which can be generated for different time scales based on the requirement of monthly, seasonal, or long-term drought assessment. For estimating SPI, climatological precipitation data in each grid cell were fitted to the gamma distribution to represent precipitation in the form of a cumulative probability distribution. Drought intensity was identified using SPI ranges described in Svbodova et al. (2002). For instance, drought was categorized as an exceptional drought if the SPI was less than \(-2.0\), an extreme drought if the SPI was between \(-1.6\) and \(-1.9\), a severe drought if the SPI was between \(-1.3\) and \(-1.5\), and a moderate drought if the SPI was between \(-0.8\) and \(-1.2\). SPI is easy to estimate and simple to understand; therefore, it has been widely used for regional and global drought assessments (e.g., Mo 2008; Mishra et al. 2010; Mishra and Cherkauer 2010; Svbodova et al. 2008; Sohn et al. 2012; Khan et al. 2008).

One of the major limitations of the SPI is that it is based on precipitation and does not account for influence of temperature on drought occurrence.

The Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al. 2010) considers precipitation and potential evapotranspiration (PET) and combines them with the simplicity of the multitemporal nature of the SPI. SPEI is determined by fitting the current difference of precipitation and PET (P minus PET) to the gamma distribution of climatological P minus PET. In SPEI, PET is estimated using the empirical method Thornthwaite (1948) based on monthly temperature. The detailed description of SPEI can be found in Vicente-Serrano et al. (2010). They evaluated the performances of the Palmer drought severity index (PDSI), SPI, and SPEI for ecological, agricultural, and hydrological applications and found that SPEI outperforms PDSI and SPI.

Drought indices estimated using different reanalyses can show disparities, which can be associated with differences in precipitation and temperature. Therefore, we evaluated the ensemble mean of drought indices from different reanalysis products. To estimate ensemble mean, we first estimated drought indices from the individual reanalysis products, and then the mean was taken. In particular, this was done considering the large bias in the monsoon season precipitation and temperature in the reanalysis datasets; therefore, drought indices based on ensemble mean precipitation and temperature can be biased toward the reanalysis dataset that has higher mean. Moreover, ensemble mean of the reanalysis products may provide better estimates, as shown in Bosilovich et al. (2009) and John et al. (2009).

3. Results and discussion

a. Bias in precipitation and temperature

Figure 1 shows all-India-averaged monthly mean bias in precipitation (millimeters) and air temperature (2 m above surface; degrees Celsius) for the period 1980–2005. During the period 1980–2005, all-India-averaged OBS mean monsoon season (JJAS) precipitation was 857 mm. MERRA, ERA-Interim, and CFSR underestimated all-India-averaged monsoon season precipitation by 7, 292, and 105 mm, respectively. During the monsoon season, ERA-Interim and CFSR showed overestimation in precipitation (Figs. 1e,g), while MERRA showed slight underestimation, especially in the early monsoon season (Fig. 1c). Reanalysis datasets (ERA-Interim and CFSR) showed highest monthly bias in September during the monsoon season. Between 1980 and 2005, the all-India-averaged monsoon season mean monthly OBS temperature was 27.6 °C. MERRA, ERA-Interim, and CFSR underestimated the all-India-averaged mean monsoon season temperature by 1.39°, 1.62°, and 1.72°C, respectively. All the reanalysis products showed underestimation in all-India monthly mean air temperature during the period 1980–2005 (Figs. 1d,f,h).

Spatial biases in precipitation and temperature during the monsoon season are shown in Fig. 2. Observed precipitation varied between 107 and 4384 mm, with high precipitation in the Western Ghats, the Gangetic Plain, and southeastern and eastern regions and low
precipitation in the semiarid regions of Gujarat and Rajasthan (Fig. 2a). MERRA overestimated the mean monsoon season precipitation in semiarid regions of Rajasthan and the Deccan plateau and underestimated it in the Gangetic Plain, the foothills of Himalayas, and in the northern and northeastern regions (Fig. 2b). Underestimation of precipitation in MERRA in the Western Ghats and the foothills of the Himalayas can be attributed to the difference between the Global Precipitation Climatology Project (GPCP) and IMD precipitation datasets. Precipitation in MERRA is corrected through the coarse-resolution GPCP precipitation (Reichle et al. 2011), which might have a negative bias in the regions with high season-mean precipitation during the monsoon season (e.g., Western Ghats, foothills of the Himalayas, and northern India). ERA-Interim overestimated the mean monsoon season precipitation in the north, northeast, and eastern regions and underestimated precipitation in Gujarat and the Eastern Ghats (Fig. 2c). Positive bias associated with the monsoon season precipitation is consistent with the findings of Bosilovich et al. (2008), which could be associated with overestimation in moisture content, and hence precipitable water, by the observation system. Large overestimation in precipitation in ERA-Interim data could be related to representation of aerosols in the Gangetic Plain region. The presence of aerosols suppresses the monsoon season precipitation (Chung and Ramanathan 2006; Bollasina et al. 2011). Variational bias corrections were used to adjust for the effect of aerosols, which results in injection of a large quantity of moisture in the tropical atmosphere to adjust the humidity field (Dee and Uppala 2009). However, Zhang et al. (2013) reported that ERA-Interim [and the 40-yr ECMWF Re-Analysis (ERA-40)] adjusted with variational bias correction was not able to improve precipitation over South Africa. CFSR showed overestimation in precipitation in the regions located in northeastern, eastern, and southern India and underestimation in parts of the northern and northwestern regions (Fig. 2d). MERRA, ERA-Interim, and CFSR showed positive median biases of 10%, 33%, and 11% in the monsoon season precipitation, respectively.

Observed mean monsoon season air temperature varied between 10\degree and 33\degree C. The regions showing higher mean monsoon season temperature were located in north-central and western India (Fig. 2e). MERRA, ERA-Interim, and CFSR showed negative median biases of 0.39\degree, 0.21\degree, and 0.44\degree C in mean monsoon season temperature, respectively (Figs. 2f–h). Cold bias in temperature in northern and western India, which is consistent in all the reanalysis products, could be related to the quality of observations as well as bias in the monsoon season precipitation. For instance, as
gridded observed temperature is based on only 395 stations across India, the lower station density in the northern and western regions could cause errors and uncertainty in observed temperature. The precipitation bias (in western India) in MERRA and CFSR could lead to a bias in temperature as precipitation and temperature are tightly coupled during the monsoon season. The other reason for spatial variability in biases could be associated with the coarser resolution of the reanalysis products, which fail to resolve topography and spatial heterogeneity (Soares et al. 2012). Moreover, for temperature bias, somewhat similar patterns (for 1979–2001) were obtained for MERRA and ERA-Interim products by Wang and Zeng (2013) in a global analysis. They reported that reanalysis temperature is strongly affected by the land surface scheme adopted by reanalysis and atmospheric boundary layer turbulence.

Figure 3 shows the standard deviation in the monsoon season precipitation and air temperature for the period 1980–2005. Observed precipitation showed higher variability in the southern peninsula and eastern India during the monsoon season (Fig. 3a). All of the reanalysis datasets underestimated variability in the southern peninsula (Figs. 3b–d). However, ERA-Interim and CFSR overestimated variability in eastern regions. All-India-averaged standard deviations of mean monsoon season precipitation shown by OBS, MERRA, ERA-Interim, and CFSR were 259, 174, 255, and 310 mm, respectively. Among the reanalysis products, ERA-Interim successfully reproduced observed variability in temperature during the monsoon season. Disparities in variability (spatial and temporal) can be attributed to the differences in land surface schemes and land–atmosphere interactions (Misra et al. 2012) and are partially due to bias and trends present in different datasets. Spatial and temporal variability in precipitation and temperature during the monsoon season is associated with large-scale atmospheric and oceanic phenomena (Mishra et al. 2012); therefore,
some of the difference can be attributed to the different SST datasets used in the reanalysis products, as shown in Kumar et al. (2013).

b. Correlations and trend analysis

Figure 4 shows the spatial variation of temporal correlation between the reanalysis products and OBS for mean monsoon season precipitation and air temperature during the period 1980–2005. The reanalysis products showed high correlations with the OBS precipitation in western India and weaker correlations in north-central and northern India (Figs. 4a–c). All-India median correlations shown by precipitation in MERRA, ERA-Interim, and CFSR with OBS precipitation were 0.40, 0.42, and 0.38, respectively.

The reanalysis products captured temporal variability in the mean monsoon season temperature reasonably well, except in a few regions and especially in the foothills of the Himalayas (Figs. 4d–f), which could be attributed to a bias in temperature and the quality of observed data as well as complex topography in these regions. All-India-averaged correlations between MERRA, ERA-Interim, and CFSR with the OBS were 0.65, 0.82, and 0.66, respectively. Among the reanalysis products, ERA-Interim showed the best performance in reproducing the OBS temporal variability in mean monsoon season temperature.

We evaluated changes using the nonparametric Mann–Kendall test in the monsoon season precipitation and air temperature from the reanalysis products against the OBS between 1980 and 2005 (Fig. 5). The OBS showed overall changes in precipitation between 2120% and 87%, with a mix of significant (shown by stippling) positive and negative trends in the western region, the Gangetic Plain, and the Western and Eastern Ghats (Fig. 5a). Spatial patterns of the OBS changes in the monsoon season precipitation were not successfully captured in precipitation from the reanalysis products (Figs. 5b–d). For instance, MERRA and ERA-Interim overestimated the area with positive trends in precipitation (Figs. 5b,c) while CFSR overestimated the area with negative trends (Fig. 5d). All-India median trends shown by OBS, MERRA, ERA-Interim, and CFSR were −0.2%, 26%, 7%, and −8%, respectively. Some of
the spurious trends in MERRA could be attributed to the introduction of the Advanced Microwave Sounding Unit-A (AMSU-A) in 1998, which might have affected the quality of observations in the tropics (NCAR 2014; Robertson et al. 2011).

Changes in the monsoon season temperature in the OBS and reanalysis products were estimated for the period 1980–2005 (Figs. 5e–h). The OBS showed changes in the monsoon season temperature anomaly between 2.0° and 2.5°C during the period 1980–2005, with significant warming in the regions located in the north-central regions, especially in the upper Gangetic Plain and northeastern and southern India (Fig. 5e). All of the reanalysis products failed to reproduce OBS trends in the monsoon season temperature (Figs. 5f–h). For instance, MERRA showed significant cooling in most of central India (Fig. 5f), while ERA-Interim underestimated warming in regions located in northern and north-central India (Fig. 5g). On the other hand, the CFSR overestimated changes in the monsoon season temperature in the southern peninsula (Fig. 5h). OBS, MERRA, ERA-Interim, and CFSR showed all-India median trends of 0.13°, 0.42°, 0.24°, and 0.54°C, respectively. ERA-Interim captured the trend and its spatial extent best among all of the reanalysis products. The large negative (positive) bias associated with the monsoon temperature in MERRA (CFSR) could be associated with the high positive (negative) bias in the monsoon season precipitation.

The bias in the monsoon season precipitation and temperature over India could be associated with their inability
to reproduce the observed trends. For instance, Bosilovich et al. (2008) found that reanalysis products have large undesirable and sometimes nonphysical biases that limit their ability to capture long-term trends. Disparities in the observed and reanalysis trends in the monsoon season precipitation and temperature could be associated with many factors, such as the availability of long-term observations and issues related to the quality of available datasets and with model parameterizations (see Thorne and Vose 2010 and Dee et al. 2011b for details). Robertson et al. (2011), Bosilovich et al. (2011), and Zhang et al. (2012) reported changes from negative to positive sign in water vapor, due to changes in observations after 1998. These changes may not only influence precipitation trends, but may also result in high/low temperature anomalies.

Year-to-year variability in all-India-averaged monsoon season precipitation and temperature anomalies is shown in Fig. 6. All the reanalysis products showed disparities in year-to-year variability; however, variability was somewhat better captured prior to 1998 (Figs. 6c,e,g). Between 1980 and 2005, all-India-averaged OBS monsoon season precipitation increased by 1% (p value > 0.05; Fig. 6a). Among the reanalysis products, ERA-Interim (Fig. 6e; 5.88%, p value > 0.05) and CFSR (Fig. 6g; −5.3%, p value > 0.05) reasonably reproduced the OBS all-India-averaged monsoon season precipitation; however, CFSR showed higher variability in dry and wet anomalies (Fig. 6g). MERRA showed a positive trend of 23% during the period 1980–2005 against the observed trend of 1% in the all-India-averaged monsoon season precipitation (Fig. 6c). In the observed data, mean monsoon season precipitation was below 10% of normal in 1982, 1986, 1987, and 2002 (marked as red lines). The monsoon season precipitation from MERRA did not capture the deficit in precipitation in the year 2002, which once again highlights changes in the observation system after 1998.

All-India-averaged monsoon season observed temperature anomalies showed a negative trend of 0.09°C (p value > 0.05) during the period 1980–2005 (Fig. 6b). Among the reanalysis products, ERA-Interim captured a trend in the OBS all-India-averaged monsoon season temperature (0.19°C, p value > 0.05; Fig. 6f). MERRA showed cooling of −0.38°C (p value > 0.05), while the CFSR exhibited warming of 0.64°C (p value > 0.05) during the period 1980–2005 (Figs. 6d,h). While MERRA showed spurious trends in precipitation and temperature,
trends in ERA-Interim agreed well with observed trends in precipitation and temperature.

c. Retrospective droughts in the observed and reanalysis datasets

Figure 7 shows drought in the years 1987 and 2002, estimated by using 4-month SPI and SPEI at the end of September (representing the entire monsoon season). Most of the reanalysis products and their ensemble mean (ENS) reproduced the severity and areal extent of the 1987 drought successfully across India, except in the parts of north-central India for both SPI as well as SPEI (Figs. 7a–l). The OBS, MERRA, ERA-Interim, CFSR, and ENS showed 30.75%, 55.50%, 53.70%, 48.80%, and 51.68% areal extent of severe, extreme, and exceptional drought estimated using SPI, respectively (Fig. 7f). On the other hand, using SPEI, for the 1987 drought, the OBS, MERRA, ERA-Interim, CFSR, and ENS showed 43.49%, 63.10%, 60.80%, 54.70%, and 58.40% areal extent, respectively (Fig. 7l). The difference in areal extent of droughts estimated using SPI and SPEI could be due to differences in temperature during the monsoon season of 1987 in the reanalysis datasets.

The areal extent and severity of drought in 2002 in the observed and the reanalysis products are presented in Figs. 7m–x. The OBS 2002 drought estimated using SPI showed that most of India experienced drought, except some regions in the northern, north-central, and northeastern regions (Fig. 7m). The 2002 drought estimated using SPEI underestimated the severity of the drought, as compared to that estimated using SPI in the western semiarid regions (Fig. 7s). All of the reanalysis products and their ENS underestimated the severity of the drought, as compared to that estimated using SPI in the western semiarid regions (Fig. 7s). All of the reanalysis products and their ENS underestimated the severity of drought in western India (Figs. 7m–q, s–w), which could be associated with changes in precipitation and temperature in the reanalysis products after 1998. The SPI-based drought in the OBS, MERRA, ERA-Interim, CFSR, and ENS showed areal extents of severe to exceptional droughts of 26.44%, 6.20%, 3.50%, 16.00%, and 3.96%, respectively (Fig. 7r), while in SPEI-based droughts, areal extents were 32.64%,
8.40%, 5.90%, 18.10%, and 4.82%, respectively (Fig. 7x). For the 1987 and 2002 droughts, CFSR performed better than other reanalysis products in capturing the areal extent of droughts. On the other hand, ENS showed better spatial correlation than the reanalysis products during 1987 and 2002 droughts.

We estimated frequency and areal extents associated with severe, extreme, and exceptional droughts over India during the period 1980–2005 (Fig. 8). The observed frequency of severe, extreme, and exceptional droughts (i.e., SPI/SPEI < −1.3) varied between 2 and 4, which was successfully reproduced by all of the reanalysis products and their ENS (Figs. 8a–j). Areal extents for observed severe, extreme, and exceptional droughts estimated using SPI and SPEI (<−1.5), respectively.

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Fig. 7. Intensity and areal extent of the monsoon season drought during 1987 and 2002 in the observed and reanalysis products obtained using SPI and SPEI. SPI and SPEI during 1987 are shown for (a), (g) OBS; (b), (h) MERRA; (c), (i) ERA-Interim; (d), (j) CFSR; and (e), (k) ENS, respectively. Similarly, SPI and SPEI during 2002 are shown for (m), (s) OBS; (n), (t) MERRA; (o), (u) ERA-Interim; (p), (v) CFSR; and (q), (w) ENS. Areal extents are shown for (f), (l) 1987 and (r), (x) 2002 for the extreme and exceptional droughts estimated using SPI and SPEI (<−1.5), respectively.

The OBS drought frequency estimated using SPEI varied between 1 and 5 droughts between 1980 and 2005.
The reanalysis products and their ENS successfully reproduced the drought frequency during the retrospective period (Figs. 8f–j). Observed areal extent of severe, extreme, and exceptional droughts estimated using SPEI varied between 1% and 50%, with the two most widespread droughts in 1987 and 2002 (Fig. 8l). The reanalysis products and their ENS successfully captured temporal variability in areal extent of droughts (Fig. 8l). Drought extent and frequency estimated by SPEI were generally higher than those estimated using SPI, which exhibited the importance of temperature in drought assessment during the monsoon season in India.

d. The drought of 2012

We estimated the areal extent and severity of the 2012 droughts using the reanalysis products and their ENS. Updated observations for the year 2012 were not yet available; therefore, precipitation data from TRMM were used to estimate SPI, which was compared with SPI from the reanalysis products. Moreover, our comparisons were solely based on SPI, as observed temperature data for 2012 were not available. The 2012 drought exhibited large temporal variability as most of the monsoon season rainfall occurred during the late monsoon season. To study the progressive nature of drought, we used 1-, 2-, 3-, and 4-month SPI to evaluate drought conditions at the end of June, July, August, and September.

Figures 9a–e show 1-month SPI at the end of June 2012, estimated using MERRA, ERA-Interim, CFSR, and ENS. The June 2012 drought was more severe in regions located in the northwestern, north-central, and western coast of peninsular India (Fig. 9a). The SPI-based drought estimated using precipitation from MERRA and ERA-Interim showed extreme and exceptional category
drought in the southern peninsula and the Gangetic Plain region, respectively (Figs. 9b,c). On the other hand, CFSR showed moderate category droughts mostly located in north-central India (Fig. 9d).

SPI based on TRMM showed severe to exceptional drought in the western region and the western portion of peninsular India based on 2-month SPI at the end of July (Fig. 9f). Most of the reanalysis products and their ensemble mean showed severe to exceptional drought in the majority of the western India, the southern peninsula, and the Gangetic Plain (Figs. 9g–j). MERRA showed higher severity of drought in the southern peninsula, ERA-Interim showed that drought was widespread in the upper half of country, and CFSR...
underestimated the extent of the drought (Figs. 9g–i). ENS was able to capture the areal extent of the drought shown by TRMM, but showed lower severity than that of TRMM (Fig. 9j).

TRMM showed that by August 2012, most of northern India was relieved from drought, while Gujarat and the southern peninsula experienced severe and extreme category drought based on 3-month SPI (Fig. 9k). MERRA showed lower areal extent of drought in India (Fig. 9l), while CFSR showed higher drought severity than TRMM in the southern peninsula (Fig. 9n).

Figures 9p–t shows 4-month SPI at the end of September 2012 to represent drought condition in the entire monsoon season (JJAS). SPI based on TRMM showed reduction in severity of drought in western regions (Fig. 9p). All the reanalysis and their ENS captured drought in the southern peninsula and the Ganges basin (Figs. 9q–t); however, CFSR overestimated the severity of the drought (Fig. 9s). Reanalysis products and ENS showed disparities in both areal extent and severity during the 2012 drought.

We find none of the reanalysis products consistently performs better than the others for all the drought events and associated matrices (e.g., areal extent, frequency, and severity). To evaluate the performance of the reanalysis products and their ensemble mean, we performed regression analysis between 4-month SPI/SPEI at the end of September from the reanalysis products and their ensemble mean against the observed SPI/SPEI for each grid cell for the period 1980–2005 (Fig. 10). Results based on regression analysis show a lower (less than 0.5) coefficient of determination $R^2$ in a majority of India, except for the western region. Moreover, median $R^2$ values indicate that ensemble mean SPI/SPEI of the reanalysis products perform better than that of individual reanalysis products, which could be attributed to disparities related to bias, trends, temporal and spatial variability in the monsoon season precipitation, and temperature from the re-analysis products.

4. Conclusions

We evaluated the three latest generation reanalysis products (MERRA, ERA-Interim, and CFSR) for monitoring and assessment of droughts during the monsoon season in India. The monsoon season precipitation and temperature from the reanalysis were evaluated using the mean seasonal bias, correlations, trends, and year-to-year variability. Moreover, the most recent drought in India (2012 drought) was analyzed using the precipitation from TRMM. On the basis of the results, the following conclusions can be made.

The reanalysis products exhibited a significant positive (cold) bias in the monsoon season precipitation.
(temperature) across India. MERRA, ERA-Interim, and CFSR showed median biases in the monsoon season precipitation (temperature) of 10% (0.39°C), 33% (0.21°C), and 11% (0.44°C), respectively. The majority of the reanalysis products showed a high warm bias in the monsoon season temperature in northwestern India and parts of the Gangetic Plain, while a high cold bias was located in the Kashmir and southern peninsula regions. Most of the reanalysis products showed higher year-to-year variability in the monsoon season temperature and precipitation than that observed during the period 1980–2005.

The Mann–Kendall trend analysis of the monsoon season precipitation and air temperature revealed large disparities between trends in observations and the reanalysis products. For instance, most of the reanalysis products fail to reproduce the observed magnitude and spatial patterns in trends associated with the monsoon season precipitation and air temperature. All-India median changes in the monsoon season precipitation shown by the OBS, MERRA, ERA-Interim, and CFSR were −0.2%, 26%, 7%, and −8%, respectively, during the period 1980–2005. On the other hand, the OBS, MERRA, ERA-Interim, and CFSR showed all-India median changes in the monsoon season air temperature of 0.13°C, −0.42°C, 0.24°C, and 0.54°C, respectively.

Reanalysis products showed disparities in bias, trends, and spatial and temporal variability in the monsoon season precipitation. None of the reanalysis showed better performance for both monsoon season precipitation as well as temperature. For instance, CFSR showed better performance for precipitation while ERA-Interim was better for air temperature. Because of these disparities, the ensemble mean SPI/SPEI showed better performance for drought assessment than that of any individual reanalysis product.

Near-real-time precipitation and temperature from the reanalysis products can be used along with other observational datasets (mostly satellite based) to improve monitoring and assessment of drought conditions in India. Additionally, our results may provide valuable information for the climate model community, who often use reanalysis products to provide initial conditions for downscaling and elevations corrections (Sheffield et al. 2006). While our results highlight the strengths and weaknesses of the reanalysis products over India, additional efforts will be needed to better quantify uncertainty associated with drought assessment using the reanalysis datasets.

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