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ORIGINAL PAPER

On observed aridity changes over the semiarid regions of India in a warming climate

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Abstract
In this study, a quantitative assessment of observed aridity variations over the semiarid regions of India is performed for the period 1951–2005 using a dimensionless ratio of annual precipitation (P) and potential evapotranspiration (PET), estimated from five different observed gridded precipitation data sets. The climatological values and changes of this aridity index are found to be sensitive to the choice of the precipitation observations. An assessment of P/PET estimated using the ensemble mean precipitation shows an increase in aridity over several semiarid regions of India, despite the sensitivity of P/PET variations across individual precipitation data sets. Our results indicate that precipitation variations over the semiarid regions of India are outpacing the changes in potential evapotranspiration and, thereby, influencing aridity changes in a significant manner. Our results further reveal a 10% expansion in the area of the semiarid regions during recent decades relative to previous decades, thus highlighting the need for better adaptation strategies and mitigation planning for the semiarid regions in India. The sensitivity of aridity index to multiple PET data sets can be an additional source of uncertainty and will be addressed in a future study.

1 Introduction

The ecosystems over the semiarid dry lands are highly dynamic, fragile and are sensitive to the human-induced changes in climate as well as land use transitions (Evans and Geerken 2004; Reynolds et al. 2007; Solomon et al. 2007; Rotenberg and Yakir 2010; Reed et al. 2012). Globally, the semiarid dry lands are characterised by low annual mean rainfall and strong seasonal and interannual variations (D'Odorico et al. 2013). Due to the limited availability of water resources, the population over these regions mostly rely on rain-fed agriculture (Schwinning et al. 2004). Thus, any slightest alterations in temperature and rainfall patterns can have adverse impacts on ecosystem services, including water yield over these regions, putting at risk the livelihoods of millions. Thus, understanding the climatic changes over the semiarid regions in the context of a warming world is vital for a better management and policy making which enables to adapt to climate change in a way that minimises vulnerability and promotes long-term resilience.

Terrestrial aridity is widely used to indicate the degree of dryness over a region. Terrestrial aridity is also a measure of water availability for plants or the soil water content over a region and, thus, considered to be a better climate indicator particularly over dry regions from an ecohydrological perspective. One of such aridity indices which is most widely used and recommended by the Food and Agriculture Organization (FAO) is defined as the ratio of annual precipitation (P) to annual potential evapotranspiration (PET) (Middleton and Thomas 1997) and is used in many studies (Feng and Fu 2013; Scheff and Frierson 2015; Lu et al. 2016; Huang et al. 2016). For dry regions, annual P is less than annual PET, and thus, the aridity index value is low, whereas for a wet region, the annual P is more than PET, and hence, the value of aridity index is high. Since the aridity measures the balance between water supply and atmospheric demand over a region, the knowledge of how the terrestrial aridity changes in a warming world is essential for water resource and land use managements, especially over the semiarid dry land regions.

Many previous studies using various proxies to aridity have indicated an increase in terrestrial aridity and dry areas

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at global and regional scales (Dai 2011; Sheffield et al. 2012; Liu et al. 2013; Cook et al. 2014; Sherwood and Fu 2014; Scheff and Frierson 2015 ; Moral et al. 2017), during past few decades associated with warming temperatures. Observational-based studies have also reported the increasing trends in the semiarid regions world-wide (Feng and Fu 2013; Fu and Feng 2014; Gao et al. 2015; Huang et al. 2016), with little attention to the Indian region. The aridity maps and analysis of changes in aridity for the Indian region are either based on a relatively shorter time period or prepared only for few sub-regions of India like the Indo Gangetic plains and use various climatic variables (Raju et al. 2013; Behera et al. 2016; Matin and Behera 2017). In this study, we focus on the regional changes in aridity over the entire semiarid region of India.

Since precipitation is one of the major climatic parameter in deciding the aridity over a region, the quality of precipitation data set plays an important role in terms of understanding the extant and scale of terrestrial aridity over the region. However, for instance, over Indian region, multiple gridded precipitation data sets are available which are constructed from varying data sources of different instruments, quality control methodologies and algorithms. The uncertainties among the multiple gridded observation precipitation data sets over the South Asian monsoon region are well-documented in literature (Collins et al. 2013; Prakash et al. 2014; Kim et al. 2015). This observational uncertainty among the precipitation data sets gets transferred to uncertainties in the aridity index and varies when computed using various rainfall data sets. Thus, it is very important to examine the uncertainty arising in deciding the aridity over a region with multiple precipitation data sets for a reliable assessment. This study examines the sensitivity of different gridded precipitation data sets to the identification of the semiarid regions over India and makes reliable assessment of the observed regional aridity changes, which is important for decision-makers as a signalling mechanism to think about adaptation planning over the semiarid regions of India. Previous studies have noted that globally, the increase in aridity is due to the fact that the rise in atmospheric demand over land has outpaced the precipitation changes (Berg et al. 2016 and the references therein). However, a reduction in potential evapotranspiration is noted using observations over India during the recent decades (Padmakumari et al. 2013). In line with this view, in addition to identifying the changes in aridity using observations, we also investigate the relative role of precipitation and potential evapotranspiration in the aridity changes over the semiarid region of India. This paper is organised as follows. Section 2 provides a description of the data sets and the methodologies used for this work. Results from the analysis of aridity changes are described in Section 3. Finally, the conclusions are summarised in Section 4.

2 Data and methods

2.1 Precipitation data sets

Five different gridded precipitation data sets based on rain-gauge measurements (Table 1) have been used to examine the sensitivity of precipitation data sets for computing aridity over the Indian region. The references for the selected five data sets (APHRODITE, IMD, UDEL, GPCC and CRU) are tabulated in Table 1. The spatial resolution of these data sets range from 0.25° to 0.5°, and the temporal resolution is either daily or monthly. A common period of 55 years during 1951–2005 is selected for the analysis. All the data sets have been regridded onto a common 0.5×0.5 lat-lon grid for intercomparison (e.g. Kim et al. 2015). The analysis grid has been selected to coincide with that of IMD land grid points over India.

2.2 Potential evapotranspiration and 2-m air temperature data

Monthly PET over land at $0.5° \times 0.5°$ resolution available from the Climatic Research Unit (CRU TS3.10; Harris et al. 2014) for the period 1951–2005 is used. Potential evapotranspiration is calculated from a variant of the Penman-Monteith (PM) formula as recommended by FAO (http://www.fao.org/docrep/x0490e/x0490e06.htm). The Penman-Monteith algorithm is based on physical principles of energy balance over a wet surface, and it is considered to be superior to empirically based formulations, which usually consider the effects of temperature and/or radiation only (Scheff and Frierson 2014; Huang et al. 2016). Monthly surface air temperature (T2M) data at $0.5° \times 0.5°$ resolution from CRU is also used in this study.

2.3 Aridity index and analysis methods

The terrestrial aridity of a region as represented by aridity index (AI) indicates the degree of climatic dryness and is defined in the literature as the ratio of annual mean P to the annual mean PET (e.g. Holdridge 1967; Middleton and Thomas 1997; Feng and Fu 2013; Scheff and Frierson 2015). This definition has been widely used and is most recommended, particularly by the Food and Agriculture Organization (FAO) (Fu and Feng 2014).

$$AI = P/PET \tag{1}$$

The regions with different AI values are classified as hyper-arid (AI < 0.05); arid ($0.05 \leq$ AI < 0.2); semiarid ($0.2 \leq$ AI < 0.5); dry sub-humid ($0.5 \leq$ AI < 0.65) and humid (AI ≥ 0.65).

Table 1 The details of the precipitation data sets used in this study

Data set	Resolution	Reference
APHRODITE (Asian Precipitation – Highly-Resolved Observational Data Integration Towards Evaluation of water resources)	Daily, 0.5° × 0.5°	Yatagai et al. 2012
IMD (India Meteorological Department)	Daily, 0.25° × 0.25°	Pai et al. 2014
UDEL (University of Delaware)	Monthly, 0.5° × 0.5°	Legates and Willmott 1990
GPCC (Global Precipitation Climatology Centre)	Monthly, 0.5° × 0.5°	Schneider et al. 2014
CRU (Climatic Research Unit)	Monthly, 0.5° × 0.5°	Harris et al. 2014

The sensitivity of AI to different precipitation data sets or the uncertainty in determining the aridity of a region due to the differences in observed precipitation data sets is estimated using the signal-to-noise ratio (SNR) defined as

$$\mathrm{SNR} = \mathrm{M}/\sigma \quad (2)$$

where M is the ensemble mean AI from multiple data sets, and σ is the standard deviation calculated over all the data sets included in the ensemble mean, i.e. σ is selected to represent the inter-dataset spread. Whilst SNR is a relative measure of the interdata spread, larger values of SNR indicate more consistency among the data sets. There is no threshold SNR value to define 'good' or 'poor' agreements between multiple data sets (Kim et al. 2015).

The long-term changes are analysed by computing linear trends, and the significance of the trends at 95% confidence level are tested using two-tailed Student's t test (see Balling et al. 1998). The relative roles of P and PET in the P/PET changes between two time periods are estimated following the methodology given by Feng and Fu (2013), using

$$\Delta\left(\frac{P}{PET}\right) = \frac{1}{PET}\,\Delta P - \frac{P}{PET^2}\,\Delta\,PET + \frac{P}{PET^3}\,(\Delta PET)^2 \quad (3)$$

where the left-hand side of the equation denotes the changes in aridity index, and the first term on the right-hand side indicates the changes in AI caused due to the changes in P (ΔP) whilst the second and the third terms on the right-hand side are the contribution of PET changes to AI changes. The changes in AI are computed for the time period 1986–2005 relative to 1951–1970.

3 Results and discussion

3.1 Annual climatology of precipitation and uncertainty among different data sets

Figure 1 shows the spatial distribution of the annual climatology of precipitation, the coefficient of variation (CV) based on the ensemble mean (ENS) of different data sets tabulated in Table 1 along with the SNR during the period 1951–2005. The large-scale pattern of climatological annual mean precipitation from ENS (Fig. 1a) displays rainfall maxima along the west coast, foot hills of Himalayas, Northeast India and lower rainfall over dry north-western parts of India and rain-shadow regions of South peninsula. These spatial features largely resemble the spatial distribution of summer monsoon seasonal precipitation, being the major contributor to the annual precipitation. It can also be noted from the spatial map of the CV of observed ensemble annual mean precipitation (Fig. 1b) that the regions with the strongest interannual variability coincide with either the lower rainfall regions or the driest desert regions. This relation is clearly evident over the rainfall gradient region (72.0–82.0 E; 27.0–29.0 N; box shown in Fig. 1a) that the rainfall variability increases as mean annual precipitation decreases (Fig. 1d). It indicates that the regions with lower rainfall and larger interannual variability are more vulnerable to climate change and need better water management plans for agricultural and other human practices.

Many previous studies have shown that there is a considerable spread among the different observed precipitation data sets over India (Collins et al. 2013; Prakash et al. 2014; Kim et al. 2015). Since rainfall plays an important role in deciding the terrestrial aridity of a region (see Section 2.3 for the definition of aridity index), it is important to consider this uncertainty in the data sets whilst deciding the aridity of a region. The spread in the annual mean precipitation climatology over India, as measured by SNR, is shown in Fig. 1c. It indicates a good agreement (high SNR values) among the data sets over northern and central India regions whilst the spread is high (low SNR values) over South peninsula. Fig. S1 further shows the spatial distribution of the differences in the annual climatology of precipitation of different data sets (Table 1) with the ensemble mean (ENS) during the period 1951–2005. The large-scale features of annual precipitation as discussed above are qualitatively captured by all the data sets (figure not shown) whilst quantitative differences in the climatological annual precipitation between individual data sets (Fig. S1a-e), and ENS show large variations. The

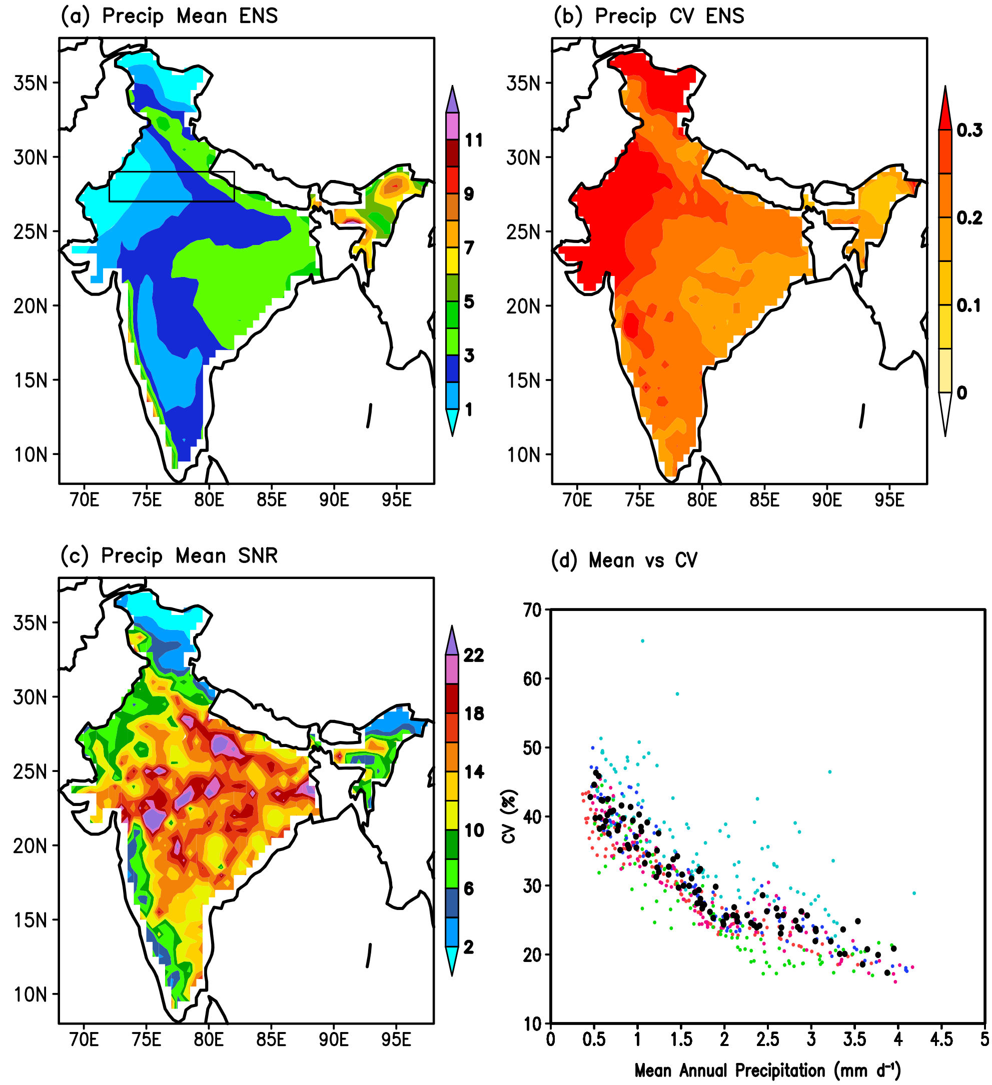

Fig. 1 Spatial maps of **a** annual mean precipitation, **b** coefficient of variation (CV) based on the ensemble mean and **c** signal-to-noise ratio of annual mean precipitation using data sets mentioned in Table. 1 for the period 1951–2005. **d** The relation between CV and mean annual precipitation over the box region shown in **a** for ensemble mean (black dots) and multiple data sets (various coloured dots)

geographical distribution of the bias in the annual mean climatology with ENS for GPCC (Fig. S1b) and APHRO (Fig. S1a) shows widespread positive and negative anomalies respectively whilst other data sets display regional heterogeneities with both positive and negative anomalies (Fig. S1c-e). The area averaged anomalies over the Indian region with respect to ENS for the data sets APHRO, GPCC, IMD, CRU and UDEL are −0.32, 0.19, 0.08, −0.08 and 0.14, respectively. The spread in the relation between annual mean precipitation and CV can also be seen from Fig. 1d. Thus, from the above analysis, it is clear that there exists considerable regional differences in the annual mean precipitation climatology among different data sets over the Indian region, and it can be expected that the spread in these data sets can lead to uncertainty in deciding the aridity of a region. Decision pertaining to aridity is important because it provides a scientific basis for regional and national governments to allocate scarce resources towards managing the development of these regions, and therefore, certainty pertaining to aridity measure is a critical input to the programmatic framework of the incumbent government.

3.2 Annual climatology of temperature and PET

The spatial distribution of annual mean T2M and PET climatology from CRU during 1951–2005 is shown in Fig. 2. The long-term annual mean climatology of 2-m air temperature shows lower temperature over northern and north-eastern parts of India and higher magnitude over South peninsula and north-western regions (Fig. 2a). The annual climatology of PET (Fig. 2b) depicts a kind of west to east gradient with higher values of above 5 mm d^{-1}over the western parts of India and rain-shadow regions of South peninsula along with a gradual decrease in the PET when moving towards the north and north-eastern parts of India. From the Figs. 1 and 2, it can be noted that the regions with lower rainfall roughly coincide

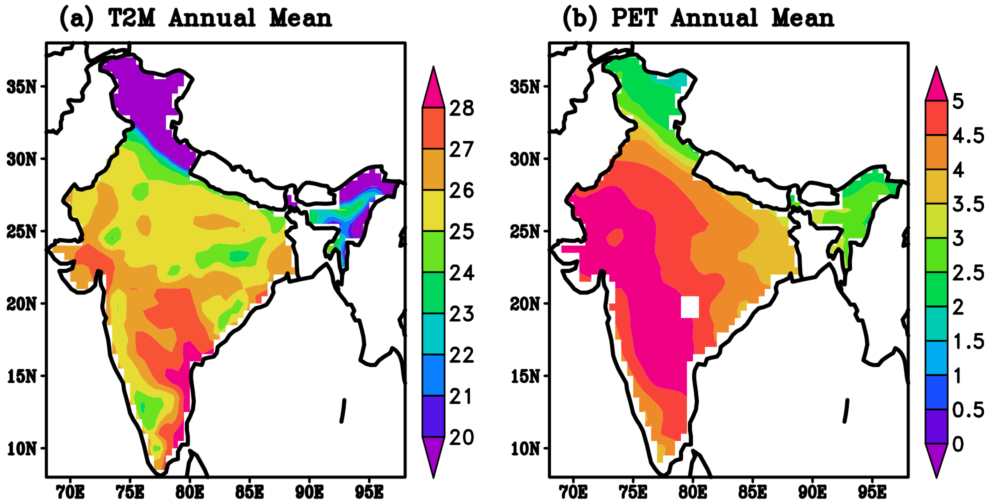

Fig. 2 Spatial distribution of annual climatology of **a** 2-m air temperature (T2M; °C) and **b** potential evapotranspiration (PET; mm d^{-1}) during the 55-year period 1951–2005 based on CRU data set

with the regions with relatively higher atmospheric demand (i.e. PET).

3.3 Sensitivity of aridity to precipitation data sets

Figure 3 shows the spatial distribution of climatological terrestrial aridity for the period 1951–2005 as measured by P/PET derived from the ensemble mean (ENS) of various precipitation data sets given in Table 1, along with the SNR. The derived spatial distribution of AI from ENS (Fig. 3a) indicates arid region (with $0.05 \leq \text{AI} < 0.2$) over north-western desert regions surrounded by the semiarid region ($0.2 \leq \text{AI} < 0.5$) in the north-south orientation from northern India to South peninsula. The semiarid regions are margined by dry sub-humid regions ($0.5 \leq \text{AI} < 0.65$) on the eastern side. The spatial distribution also shows wet humid regions ($\text{AI} \geq 0.65$) along narrow Western Ghats, sub-regions of Indo Gangetic plains, central India and north-eastern parts of the country. The qualitative distribution of different sub-categories of dry and wet regions over India found in this study is similar to that obtained in the previous studies (Feng and Fu 2013; Huang et al. 2016). The areal extent of dry land sub-types of arid, semiarid and dry sub-humid regions account for about 7, 34, and 14%, respectively, whilst the humid regions cover about 45% of the Indian land region. It can be noticed that the dominant dry land sub-type over India is semiarid region, with a significant portion of the population living in these regions and relying on rain-fed agriculture. The AI derived with individual precipitation data sets also show similar large-scale spatial patterns with variations in the areal extent of various sub-types of dry regions among the data sets (Fig. S2). The noticeable difference among the data sets is the areal extent of the semiarid and dry sub-humid regions in South peninsula and central India, with the area of the semiarid region ranging from 30 to 39% among the data sets. The same is expressed as signal-to-noise ratio among the data sets in deciding the semiarid regions over India for the period 1951–2005 in Fig. 3b. The SNR values are shown only for the semiarid region, which is decided based on the ENS mean AI values in Fig. 3a. It shows that the SNR is relatively high

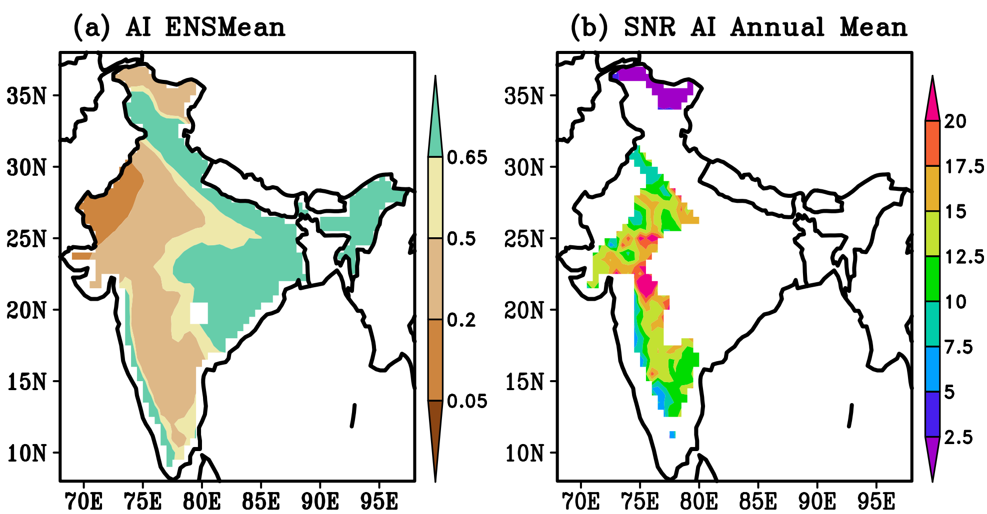

Fig. 3 Spatial maps of **a** ensemble mean annual aridity index (AI) and **b** signal-to-noise ratio (SNR) over the semiarid regions during 1951–2005

over the semiarid region over North India, whilst the SNR is relatively low over South peninsular India. This indicates that there is a good agreement (high SNR) among different data sets in deciding the semiarid regions over northern regions whilst there is considerable spread (low SNR) among the data sets over South peninsular regions. For further analysis, we considered the ENS mean AI in this study.

3.4 Long-term changes in precipitation, temperature, PET and terrestrial aridity over the semiarid regions of India

The geographical distribution of the long-term trends in annual mean precipitation, T2M, PET and aridity for the semiarid regions over India using ENS mean of various observed data sets during the period 1951–2005 is shown in Fig.4. A significant drying in annual rainfall over large portion of the semiarid regions of India is noted in ENS (Fig. 4a) whilst wetting trend is observed over the semiarid regions of south-east India and over extreme northern regions. Several recent studies have reported similar significant negative trends in the observed seasonal monsoon precipitation, which is a major contributor to the annual precipitation, at regional and sub-regional scales over South Asia since the 1950s (e.g. Guhathakurta and Rajeevan 2006; Chung and Ramanathan 2006; Bollasina et al. 2011; Krishnan et al. 2013, 2015; Ramarao et al. 2015; and the references therein). The consensus in the decreasing trends in rainfall among the data sets is shown in Fig. S3. Striping indicates where at least four rainfall data sets concur on an increase (vertical) or decrease (horizontal) in linear trend. The spatial pattern of long-term trend in observed T2M (Fig. 4b) shows significant warming over the semiarid regions of India, except a small region during 1951–2005. Similar increasing trends were previously reported by many studies over India (Kothawale et al. 2010; Jain and Kumar 2012; and the references therein). The spatial

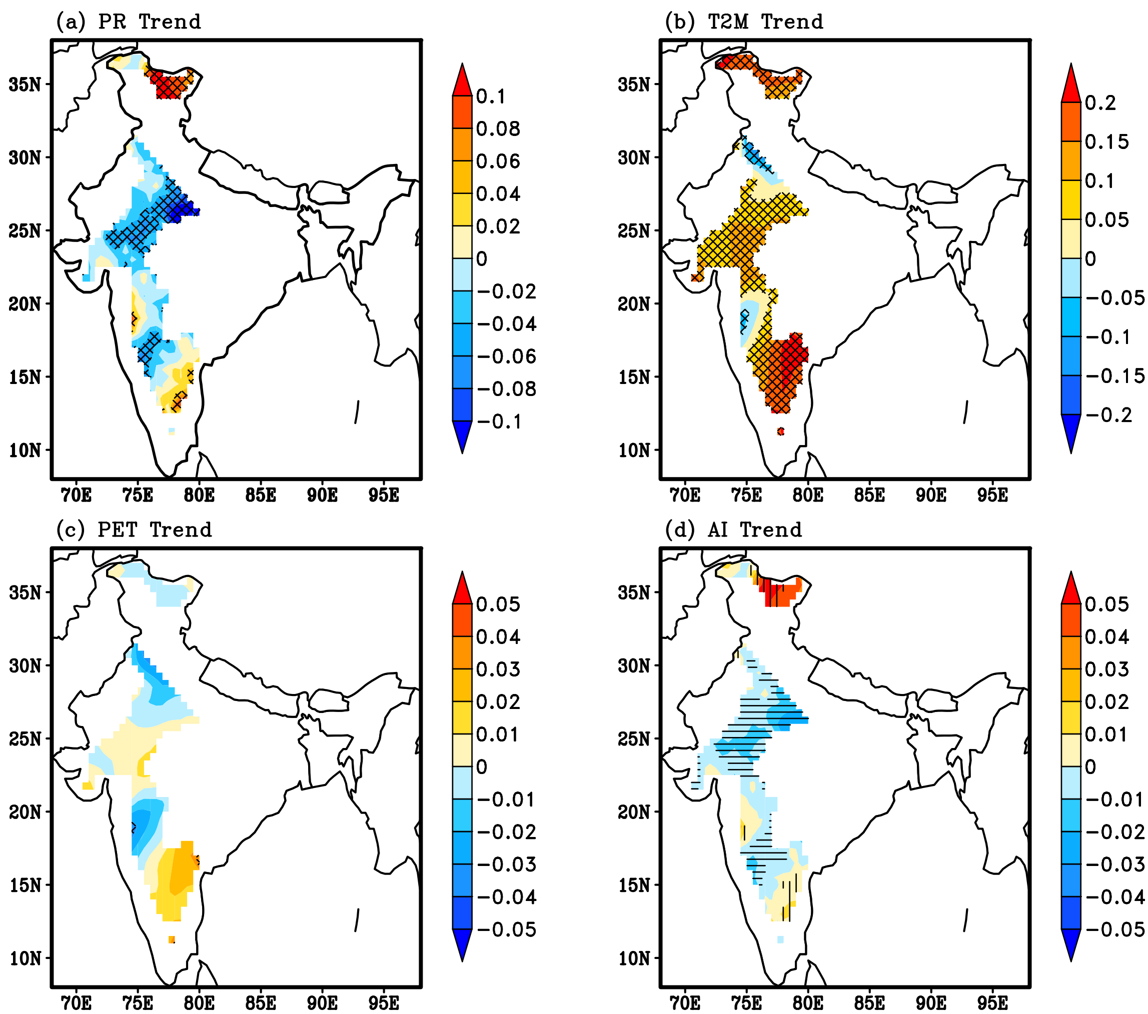

Fig. 4 Spatial distribution of linear trends in annual mean **a** ENS precipitation (P; mm/d/decade), **b** 2-m air temperature (T2M; °C/decade), **c** PET (mm/d/decade) and **d** ensemble mean AI (/decade) for the semiarid regions during the 55-year period 1951–2005. Hatching indicates that the trends at those grid points are significant at 95% confidence level according to a two-tailed Student's *t* test. Striping in **d** indicates that at least four AI estimates concur on an increase (vertical) or decrease (horizontal) in linear trend

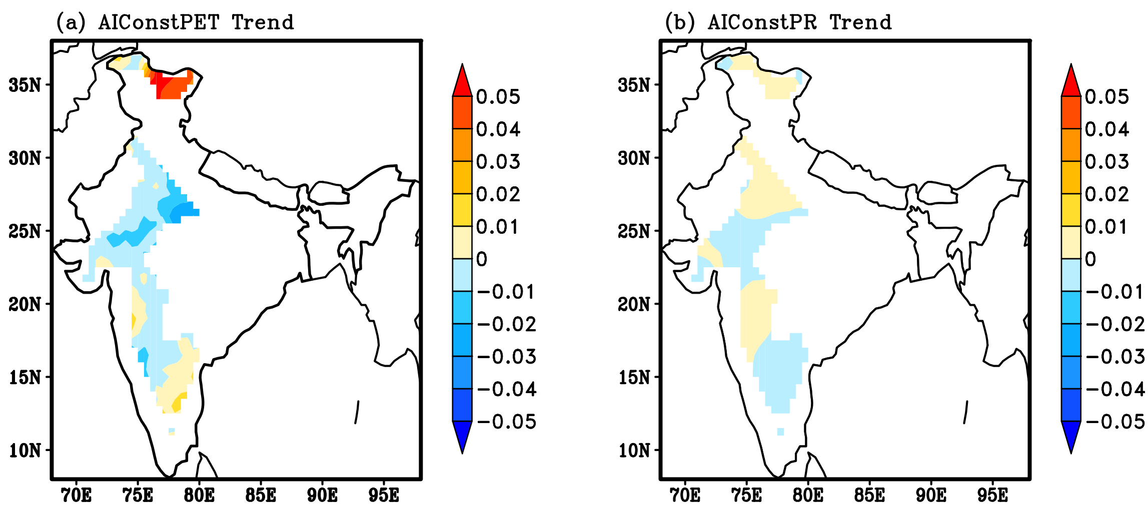

Fig. 5 Spatial distribution of linear trends in annual mean aridity index computed by using **a** climatological PET (AI-ClimPET) and **b** climatological ENS precipitation (AI-ClimP) for the semiarid regions over India during 1951–2005. Linear trends are expressed as change over a decade (/decade)

pattern of long-term trend in PET (Fig. 4c) shows an increase over the semiarid regions of central and South peninsular India whilst it decreases over other parts of the semiarid regions of India. However, the linear trends in PET are not significant at 5% level. The observed decreasing trend in atmospheric moisture demand over India has previously been reported by Padmakumari et al. 2013. It is important to note here that despite significant warming over the semiarid regions, PET which indicates the atmospheric demand of water vapour does not show significant trends. This is because the PET over a region not only depends on temperature but also on other factors such as net radiation, relative humidity and wind speed. These long-term regional changes in precipitation and PET associated with warming temperatures (Fig. 4a, c) can lead to changes in AI over time and can also lead to alterations in the areal extent of the semiarid regions. The linear trends in AI from ENS in the semiarid regions (derived from ENS mean AI) for the period 1951–2005 are shown along with the consensus in the sign of trend among the data sets in Fig. 4d. The trends in AI from individual data sets are shown in Fig. S4. The ensemble mean AI indicates an increasing trend in aridity (decrease in AI) over most of the SARs ($0.2 \leq AI < 0.5$) except in Jammu and Kashmir, a small portion of Maharashtra and south-eastern region of the peninsular India during 1951–2005. Striping indicates where at least four AI estimates concur on an increase (vertical) or decrease (horizontal) in linear trend. Thus, from Fig. 4, it is clear that the increasing aridity over the semiarid regions is certain among the data sets during this analysis period. It is also noticed that the patterns of trend in precipitation are consistent with those of AI, indicating the dominant role of precipitation.

Further, we investigated this issue by computing the annual AI either by using a climatological PET (AI-ClimPET) or climatological P (AI-ClimP) for the period 1951–2005. Whilst keeping the climatological value of PET at each grid point, the computation of AI-ClimPET retains the variations of precipitation only. Similarly, AI-ClimP indicates the changes in AI due to the PET changes alone. The similarity in the spatial patterns of trends in AI-ClimPET (Fig. 5a) and AI (Fig. 4d) shows that the regions with increasing aridity are strongly dominated by the drying trends in rainfall over the semiarid regions of India. It can also be noticed that the increasing trend in

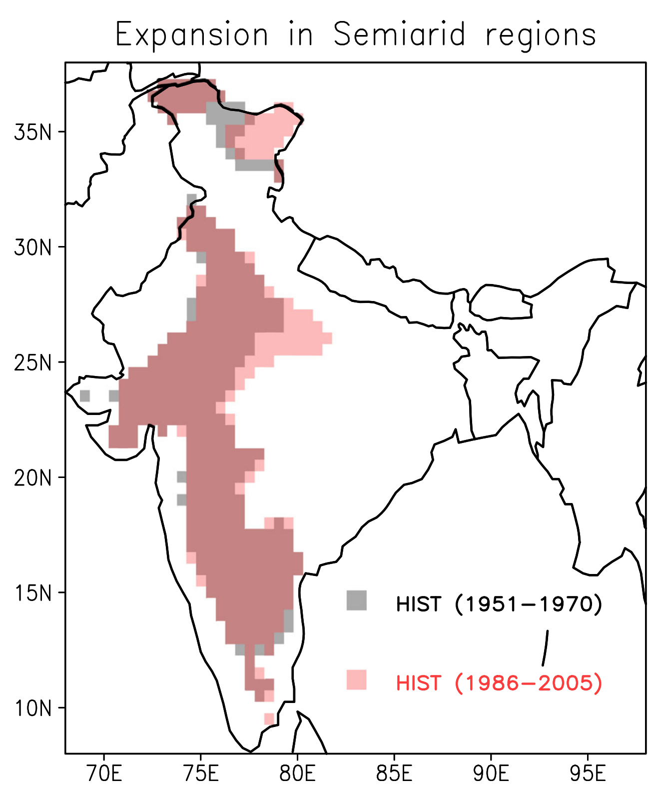

Fig. 6 Spatial distribution of the estimated semiarid regions over India between the periods 1951–1970 (grey) and 1986–2005 (red) shows an expansion of the semiarid regions towards central India during the recent period

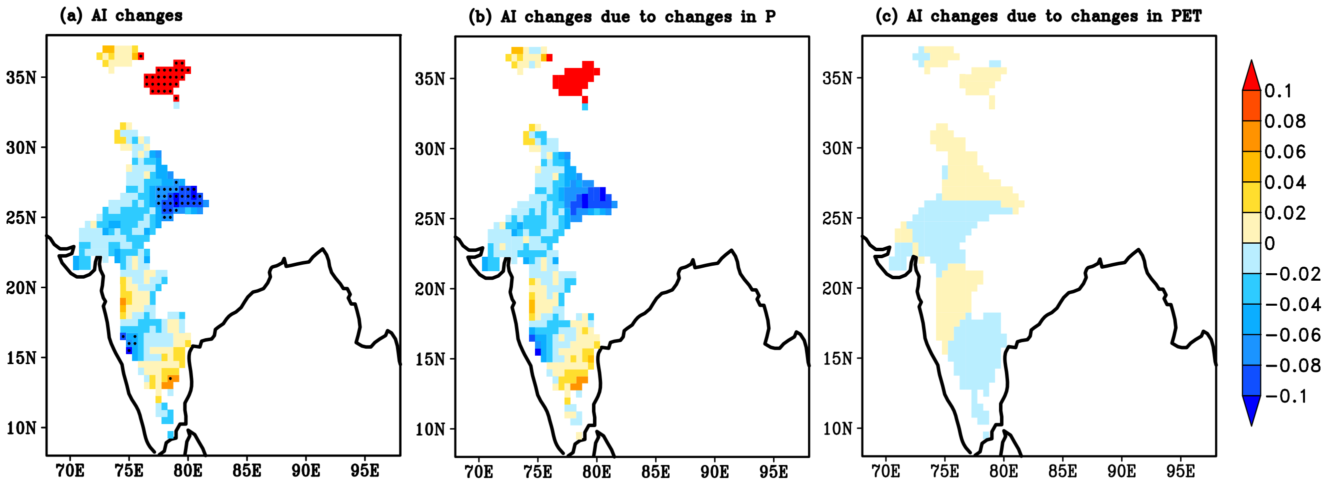

Fig. 7 **a** The changes in AI for 1986–2005 relative to 1951–1970 from ensemble mean of observations and contributions of **b** precipitation and **c** PET to changes in AI. Grid points are stippled where the differences in AI are significant at 95% confidence level using a two-tailed Student's *t* test. The regions shown are the semiarid regions identified for the period 1986–2005

precipitation is outpacing the increasing trend in PET and is leading to a decrease in aridity over eastern part of peninsular India. This result suggests that precipitation is a dominant factor that affects AI changes over the semiarid regions of India. The examination of the temporal variations in the percent area of SAR over India during the period 1951–2005 shows a long-term trend in addition to the year to year fluctuations (figure not shown). Thus, here, the changes in the semiarid regions (SARs) over India during 1986–2005 relative to 1951–1970 periods are analysed using the ensemble mean of the observed aridity index (AI) estimates. Observations show an expansion in the boundaries of the semiarid regions (Fig. 6) during the recent 1986–2005 period (35%) which is relatively 10% larger than that of the 1951–1970 period (31%). The increase in SAR area is equal to 4% of total Indian land area. From the figure, it can be noted that the eastern boundaries of the semiarid regions in North India have expanded converting the dry sub-humid regions into semiarid regions. The method explained in Section 2.3 (Eq. 3) is used to identify the relative contributions of P and PET in causing the expansion of the semiarid region during the recent period 1986–2005 relative to 1951–1970 and is shown with the changes in AI with significance in Fig. 7. The region shown in the figure corresponds to the semiarid region observed during 1986–2005 which also includes the newly expanded semiarid region. The decrease in AI (increase in aridity) during the recent period is clearly evident from the figure with significant changes over the parts of the newly formed semiarid regions (Fig. 7a). It is also clear that the contribution from a decrease (increase) in P (Fig. 7b) leads to an increase (decrease) in aridity (i.e. a decrease in AI) everywhere irrespective of the weaker contribution of PET to changes in AI (Fig. 7c). Thus, it is clear from the observations that the recent changes in aridity over Indian region are largely driven by the changing patterns of precipitation over India.

4 Conclusions

The effective wetness or dryness of climate over a land region is determined by the terrestrial aridity of that region, which is measured by the ratio of annual mean precipitation to the annual mean potential evapotranspiration. The changing regional precipitation patterns in association with rising temperatures due to global warming can cause changes in terrestrial aridity. Increases in aridity, along with extensive land use practices leading to sever land degradation, can amplify the near-surface climatic changes and lead to further desertification over longer periods (D'Odorico et al. 2013; Berg et al. 2016). Thus, quantification of changes in terrestrial aridity is essential for planning and development of adaptation strategies for the semiarid dry regions. In this study, we have identified the semiarid regions of India and assessed long-term trends in aridity during the period 1951–2005, by taking into consideration uncertainties in the available precipitation data sets. Given the inherent sensitivity of aridity index to precipitation, we estimated the signal-to-noise ratio (SNR) for quantifying uncertainty in aridity variations. The spread among the data sets in quantifying aridity (as indicated by low SNR values) is relatively high over South peninsula than in the northern regions of India. By considering the ensemble mean AI values, we identified that out of all subtypes of dry lands in India, the areal extent of the semiarid region is the largest, accounting for about 34% of total area during the period 1951–2005. Further analysis indicates a reduction in precipitation, and increase in PET over the semiarid regions has led to an increase in the aridity over most parts of the semiarid region of India with consensus among the data sets. The present analysis identifies an expansion in the semiarid area during recent decades with a relatively 10% larger area than the corresponding area during previous decades, and the newly formed semiarid region accounts to 4% of total Indian land area. This newly formed semiarid region in the Northern India is found to be transformed from the previously dry sub-humid and humid parts leading to a drier climate over the region. It is also found that the drying rainfall pattern has larger contribution to the increasing aridity and to the expansion of the semiarid region in India during the recent decades. Several recent studies have reported similar significant negative trends in the observed seasonal monsoon precipitation, which is a major contributor to the annual precipitation, at regional and sub-regional scales over South Asia since the 1950s (e.g. Guhathakurta and Rajeevan 2006; Chung and Ramanathan 2006; Bollasina et al. 2011; Krishnan et al. 2013, 2015; Ramarao et al. 2015; and the references therein), and there is a growing evidence to the role of increasing anthropogenic aerosol emissions in controlling the declining precipitation trends over India (e.g. Chung and Ramanathan 2006; Bollasina et al. 2011; Sanap et al. 2015; Krishnan et al. 2015). Even though, identifying the cause of precipitation reduction over India is not the focus of this study, it is important to know that the present-day aerosols tend to increase aridity in India by suppressing the precipitation (Lin et al. 2016).

It is to be noted that only one PET estimation available from CRU is considered for the computation of aridity index in the current study. However, in reality, the reliable PET estimation is subjected to the uncertainty on account of many existing formulae and different input data reliabilities (Kingston et al. 2009; Sheffield et al. 2012; Trenberth et al. 2014). Thus, one can expect that the uncertainty in PET estimations can be an additional source of ambiguity in the computation of aridity index. Various PET method intercomparison studies confirm that physically based Penman-Monteith (PM) method gives the most reliable estimation of PET in the regions where sufficient meteorological data is available (e.g.,Vörösmarty et al. 1998; Lu et al. 2005; Kingston et al. 2009). Hence, FAO recommended PM method as the single standard method for computing PET. Thus, we used PM method-based PET estimations available from CRU in this study. Identifying the sensitivity of aridity index to the uncertainty in PET estimation is not addressed here and will be taken up as a future study.

Since aridity changes are primary indicators of desertification from the climate perspective, any irreversible changes in aridity persisting for several decades along with the land degradation, loss of soil nutrients induced by human action can lead to desertification over the dry regions. A multi-disciplinary analysis approach is needed to better quantify the effects of vegetation changes, land degradation, soil erosion, shifts in ecosystems, desiccation of soils, etc. on desertification and is beyond the scope of the present study.

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Compliance with ethical standards

Disclaimer The views expressed in this work are those of the creators and do not necessarily represent those of DfID and IDRC or its Board of Governors.

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