22. Emsley, P. and Cowtan, K., COOT: model-building tools for molecular graphics. *Acta Crystallogr.*, *Sect. D*, 2004, **60**, 2126–2132.
23. Murshudov, G. N., Vagin, A. A. and Dodson, E. J., Refinement of macromolecular structures by the maximum-likelihood method. *Acta. Crystallogr.*, *Sect. D*, 1997, **53**, 240–255.
24. Laskowski, R. A., MacArthur, M. W., Moss, D. S. and Thornton, J. M., PROCHECK: a program to check the stereochemical quality of protein structures. *J. Appl. Crystallogr.*, 1993, **26**, 283–291.
25. Choudhury, D., Roy, S., Chakrabarti, C., Biswas, S. and Dattagupta, J. K., Production and recovery of recombinant propapain with high yield. *Phytochemistry*, 2009, **70**, 465–472.
26. Whitmore, L. and Wallace, B. A., DICHROWEB, an online server for protein secondary structure analyses from circular dichroism spectroscopic data. *Nucl. Acids Res*., 2004, **32**, 668–673.
27. McGrath, M. E., The lysosomal cysteine proteases. *Annu. Rev. Biophys. Biomol. Struct.*, 1999, **28**, 181–204.
28. Vernet, T. *et al.*, Processing of the papain precursor. The ionization state of a conserved amino acid motif within the Pro region participates in the regulation of intramolecular processing. *J. Biol. Chem.*, 1995, **270**, 10838–10846.

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Capabilities of satellite-derived datasets to detect consecutive Indian monsoon droughts of 2014 and 2015

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India received anomalously deficit southwest monsoon rainfall during 2014 and 2015, which resulted in consecutive droughts across the country. Reliable detection and monitoring of droughts are crucial for the reduction in drought vulnerability and associated socio-economic impacts. In this study, the potential of multiple high-resolution satellite datasets is examined using distinct drought indices over India for these two successive monsoon seasons. The satellite-derived precipitation, soil moisture and land surface temperature estimates are capable of depicting the anomalous drought conditions with some exceptions. A non-parametric multivariate standardized drought index, based on precipitation and soil moisture estimates is proven to be better in the detection of droughts when compared to conventional standardized drought indices. Overall, remote sensing satellite datasets provide immense opportunity to detect and monitor different kinds of droughts using a composite of indices. However, limited temporal records of these high-resolution satellite datasets restrain their applicability from the climatological perspective.

Keywords: Drought, multi-satellite product, non-parametric multivariate drought index, Southwest monsoon.

DROUGHT is one of the inevitable and recurring natural hazards, having paramount socio-economic impacts. The regional variability of global hydrological cycle often leads to this devastating phenomenon. Historical observations and model simulations suggested a high risk of global drought and its patterns in the twenty-first century[1–6]. Droughts are generally classified into four categories – (a) meteorological, (b) agricultural, (c) hydrological and (d) socio-economic droughts. Among these, meteorological and agricultural droughts due to deficit in precipitation and soil moisture respectively, are crucial in the Indian perspective. Indian economy is largely dependent on the agriculture sector, and the southwest monsoon rainfall spanning from June to September (JJAS) plays a vital role in agricultural production. Hence, droughts associated with the interannual variations of southwest monsoon rainfall across India have crucial impacts[7–9].

The India Meteorological Department (IMD) using gauge observations, provides weekly, monthly, and seasonal rainfall and their departures from respective climatological normal at meteorological sub-divisions and district levels over India for the southwest monsoon season. In addition, IMD uses standardized precipitation index (SPI) method at monthly gauge-based rainfall data for meteorological drought monitoring and also uses an aridity index based on a climatic water balance technique to monitor drought severity[9,10]. Although rainfall is a crucial variable responsible for drought occurrence, other variables such as soil moisture, temperature, evaporation, terrestrial water storage, etc. should also be considered along with rainfall to effectively characterize the different aspects of drought and its associated impacts. Ground-based observations of these variables are not homogenous across the country and consequently they are not sufficient enough to monitor various aspects of drought. A constellation of the Earth-observation satellites provides reasonable precipitation, soil moisture, temperature, and vegetation estimates at regular spatio-temporal intervals[11,12]. However,

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these datasets are available for a rather short period of time, e.g. for about two-three decades. These high-resolution multi-satellite datasets are proven to be promising for several hydro-meteorological applications. Several drought indices utilizing various satellite-based variables have been proposed to assess the severity and frequency of droughts[13–19]. Following the launch of Kalpana-1 satellite by the Indian Space Research Organisation (ISRO), an indigenous rainfall retrieval scheme – INSAT Multi-Spectral Rainfall Algorithm (IMSRA) was developed at the Space Applications Centre (SAC), ISRO[20]. The rainfall estimates from this operational algorithm were successfully utilized to monitor meteorological droughts over India at meteorological sub-divisional scale and the results were provided as space inputs to various government forums for drought assessment[8,21]. Hence, the use of remote sensing satellite data along with ground-based observations would provide better understanding of droughts at distinct spatial and temporal scales.

A high-resolution, bias-corrected, precipitation and temperature dataset was recently developed by a combination of observational datasets and numerical model outputs at the Indian Institute of Technology, Gandhinagar to monitor near real-time drought severity and extent over South Asia[22]. Furthermore, the National Agricultural Drought Assessment and Monitoring System (NADAMS) project utilizes satellite remote sensing along with ground-based observations for operational assessment of agricultural drought at state, district and sub-district levels in India[23,24]. The NADAMS project (http://www.ncfc.gov.in/nadams.html) was developed by the National Remote Sensing Centre (NRSC), ISRO and implemented by the Mahalanobis National Crop Forecast Centre (MNCFC), Ministry of Agriculture and Farmers Welfare. Various crop indices such as normalized difference vegetation index (NDVI), normalized difference water index (NDWI), shortwave angle slope index (SASI), and soil moisture index (SMI) are being used under this project to assess multi-scale agricultural drought and crop status across the country[23,24].

India witnessed two successive monsoon droughts in 2014 and 2015 (refs 25, 26). These consecutive droughts had substantial social and economic consequences. The present study aims at assessing the capabilities of high-resolution global multi-satellite precipitation and soil moisture estimates in the detection of meteorological and agricultural droughts over India for the southwest monsoon of 2014 and 2015. Three non-parametric drought indices and four condition-based drought indicators are used to assess the potential of satellite-based estimates in drought detection across the country.

In order to assess the rainfall anomaly during the monsoon seasons of 2014 and 2015, gauge-based gridded rainfall data over India from 1971 to 2015 were used. This daily rainfall dataset, developed by IMD using a good network of gauge stations across the country, is available at 0.25° latitude/longitude resolution[27]. This dataset was used as reference rainfall dataset for a wide range of applications. Moreover, multi-satellite precipitation and soil moisture estimates were used to assess the capabilities of satellite-based estimates in the detection of droughts over India. Multi-satellite datasets integrate the relative merits of various available satellite estimates. The Tropical Rainfall Measuring Mission (TRMM) Multi-satellite Precipitation Analysis (TMPA)[28] version 7, available from the NASA Goddard Earth Sciences Data and Information Services Centres, is one of the best TRMM-era multi-satellite precipitation estimates[29,30]. Although the Global Precipitation Measurement (GPM)-based multi-satellite precipitation estimates are available at finer spatio-temporal scales with improved accuracy as compared to the TMPA[31], TRMM-based TMPA dataset has been used in this study due to its longer temporal record. The combined active and passive microwave soil moisture estimates version 3.2 (ref. 32) developed by the European Space Agency (ESA) as part of its Climate Change Initiative (CCI) programme was also used. Both precipitation and soil moisture estimates are available at 0.25° spatial resolution. As ESA-CCI datasets are derived from available active and passive microwave measurements, the data void regions of India are filled using the corresponding Modern-Era Retrospective Analysis for Research and Applications (MERRA) – land reanalysis upper layer soil moisture product[33]. Additionally, the land surface temperature (LST)[34] and NDVI[35] derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor onboard the Aqua satellite were used. A common time period of 2003–2015, based on availability of these four satellite-based datasets, was considered in this study.

As precipitation (P) and soil moisture (SM) datasets are available at 0.25° latitude/longitude resolution, MODIS-derived LST and NDVI datasets were resampled at the same spatial resolution. Three non-parametric drought indices namely, SPI, standardized soil moisture index (SSI), and multivariate standardized drought index (MSDI) were used to assess the meteorological and agricultural droughts[16,17] over India. These indices range from –0.50 to –0.79 corresponding to abnormally dry, –0.80 to –1.29 corresponding to moderate drought, –1.30 to –1.59 corresponding to extreme drought, and –2.0 or less corresponding to exceptional drought conditions. Moreover, four single condition drought indices including precipitation condition index (PCI), soil moisture condition index ($SMCI$), temperature condition index (TCI), and vegetation condition index (VCI) defined by eqs (1)–(4) were used in this study.

$$PCI = \frac{P - P_{\min}}{P_{\max} - P_{\min}}, \tag{1}$$

$$SMCI = \frac{SM - SM_{min}}{SM_{max} - SM_{min}}, \quad (2)$$

$$TCI = \frac{LST_{max} - LST}{LST_{max} - LST_{min}}, \quad (3)$$

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}. \quad (4)$$

The subscripts 'min' and 'max' stand for the minimum and maximum magnitude of the respective variables at a specific grid location. These indices range between 0 and 1, and are effective in characterizing the different aspects of droughts[13,19]. The magnitude of 0–0.1 of these four indices corresponds to extreme drought, 0.1–0.2 to severe drought, 0.2–0.3 to moderate drought, 0.3–0.4 to mild drought and 0.4–0.5 to abnormally dry condition.

The IMD reported 12% and 14% deficits in all-India summer monsoon rainfall (AISMR) for 2014 and 2015, respectively based on rain gauge observations. The deficit in AISMR is computed from the long-term mean and a deficit in AISMR of 10% or more is considered as a meteorological drought. Figure 1 shows the standardized monsoon rainfall anomaly over India for 2014 and 2015 using gauge-based gridded observations[27]. These anomalies are computed from the long-term mean of 1971–2015 and divided by the standard deviation. It can be seen that rainfall anomaly is not homogenous even at meteorological sub-divisional scale. It is essentially due to high spatio-temporal variability of the monsoon rainfall. The Indo-Gangetic plain shows anomalously deficit monsoon rainfall during both years. The monsoon rainfall over this region is vital for agricultural production. Most of the southwest monsoon rainfall occurs over the Indo-Gangetic plain, central India, Western Ghats and north-east India. The northern, western and south-eastern parts of India received very less monsoon rainfall during both years. Some meteorological sub-divisions such as East Uttar Pradesh, West Uttar Pradesh, Haryana, Punjab, Madhya Maharashtra, and Marathwada received more than 30% deficit in monsoon rainfall during 2014 and 2015. Hence, deficit in monsoon rainfall over the rainfed regions had rather larger impacts on crop yield. The arid regions of northwestern India received exceptionally heavy rainfall during the monsoon season of 2015, which caused flooding over these regions. As the losses due to successive droughts are cumulatative[24], the Indian monsoon droughts of 2014 and 2015 led to substantial socio-economic losses especially over southwest India and Indo-Gangetic Plain regions[25,26].

Figure 2 illustrates the 4-month SPI, SSI and MSDI for the monsoon seasons of 2014 and 2015 over India exclusively derived from satellite-based datasets. These three standardized indices were computed using monthly precipitation and soil moisture datasets for the 13-year period. The deficit in rainfall is well-depicted by the satellite-derived SPI for both the monsoon years. However, the larger area of the country was under the influence of meteorological drought in 2014 as compared to 2015. About 47% of the country showed meteorological drought (SPI ≤ –0.5) in 2014, whereas about 15% area of the country was under the influence of meteorological drought in 2015. SPI is a state-of-the-art drought index, utilized by several operational agencies, to assess the onset, severity and persistence of meteorological drought. However, SSI does not show any considerable deficit in soil moisture across the country especially in 2015. About 19% area of the country showed agricultural drought (SSI ≤ –0.5) in 2014, whereas only 8% of area was under the influence of agricultural drought. This shows that although India was under the influence of meteorological drought during the consecutive monsoon years, there was no agricultural drought. The meteorological (deficit in precipitation) and agricultural (deficit in soil moisture) droughts do not essentially occur simultaneously. There is generally a considerable time lag between the onsets of both types of droughts.

The MSDI is a non-parametric multivariate drought index which uses both precipitation and soil moisture information and is recognized as a better surrogate for drought detection[17]. MSDI showed about 71% and 30% area of the country under the influence of drought (MSDI≤ –0.5) in 2014 and 2015 respectively. The comparison of spatial patterns of these three indices showed a correlation of 0.13 (0.33) between SPI and SSI, 0.76 (0.78) between SPI and MSDI, and 0.61 (0.77) between SSI and MSDI in the monsoon season of 2014 (2015).

In order to investigate the correspondence among these three drought indices, time-series of 4-month SPI, SSI and MSDI averaged over India are inter-compared for the period 2003–2015 (Figure 3). MSDI reproduced the major Indian drought of 2009 better than SPI and SSI alone. The linear correlation between the 4-month SPI and SSI was found to be 0.71. However, the correlation coefficient of MSDI was 0.93 and 0.91 with SPI and SSI respectively. It clearly shows that MSDI benefits from the relative merits of both precipitation and soil moisture, and performs better than SPI and SSI alone for the monitoring of drought and its severity. It is also to be noted that these drought indices are computed from 13-years (2003–2015) of satellite datasets, which are not adequate to characterize the droughts in climatic perspective.

Furthermore, four single drought condition indices based on satellite datasets were used. Figure 4 presents the PCI, SMCI, TCI, and VCI for the monsoon seasons of 2014 and 2015 over India. Lower magnitude of these indices corresponds to drought condition. PCI, SMCI, and TCI clearly show the deficit in precipitation, soil moisture, and land surface temperature respectively over the country during both the monsoon years. However, VCI does not show notable deficit in NDVI in 2015. It

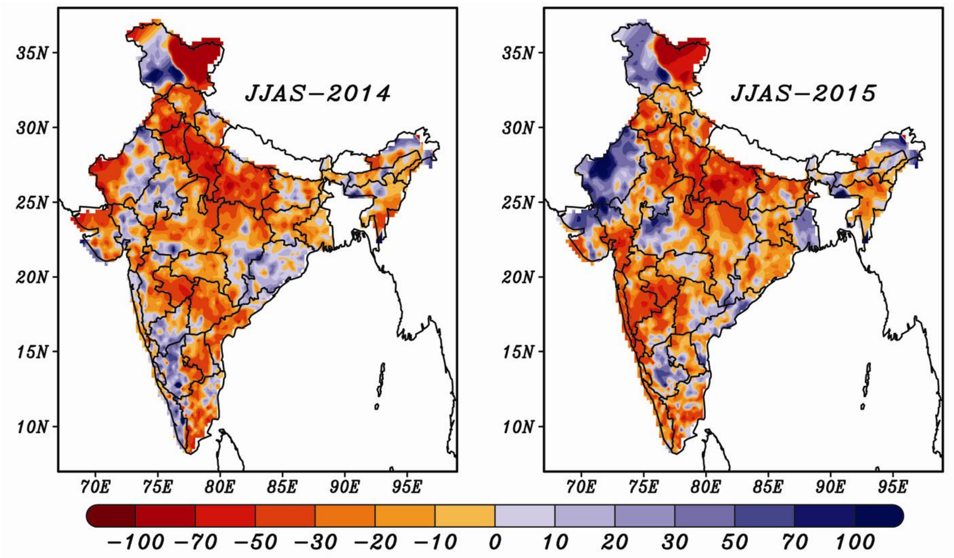

Figure 1. Seasonal standardized monsoon rainfall anomalies (%) over India for 2014 and 2015 using the IMD gauge-based data for 1971–2015.

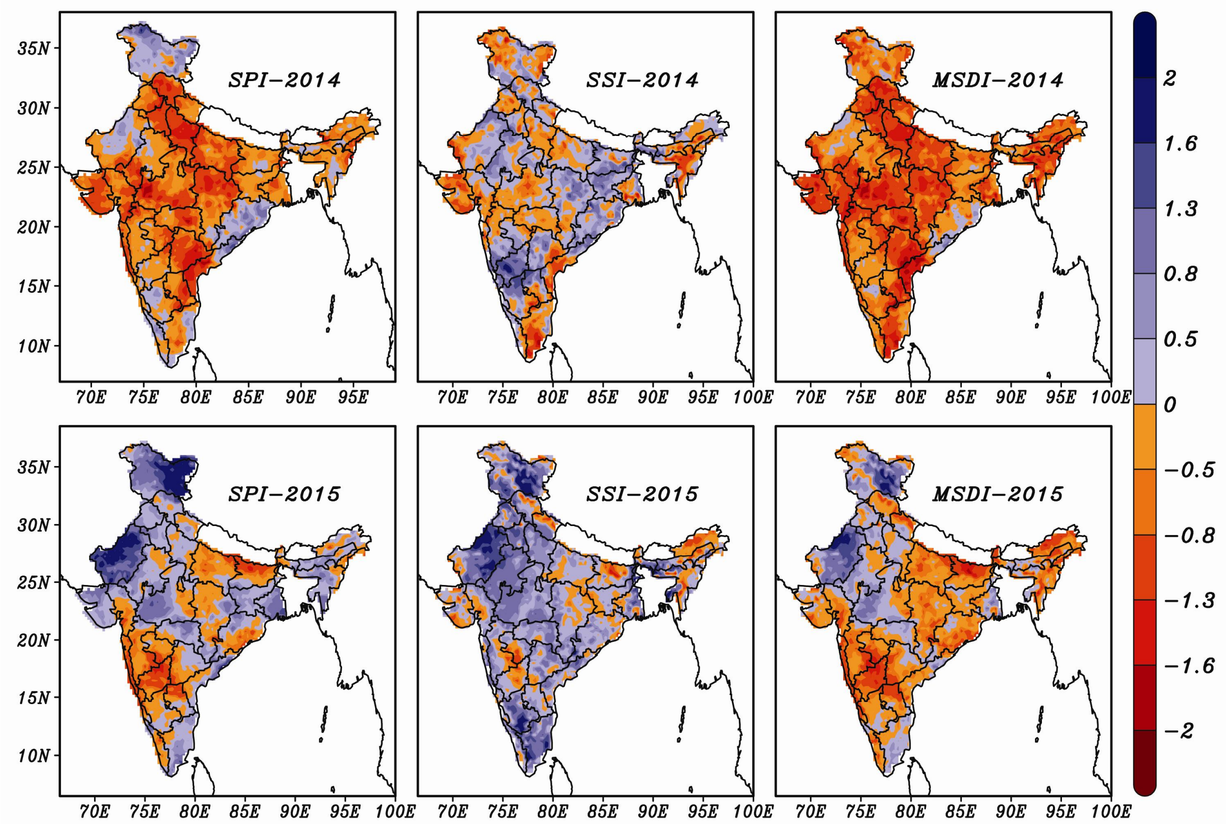

Figure 2. Spatial distributions of 4-month SPI, SSI and MSDI over India for the monsoon seasons of 2014 and 2015 using multi-satellite datasets.

was recently noticed that VCI could be strongly influenced by atmospheric changes and is not supposed to be a good choice for drought monitoring especially in the humid regions[19]. Moreover, TCI and SMCI should be ignored in drought monitoring over arid and dense vegetated regions respectively. It shows that the droughts of 2014 and 2015 were a combined consequence of anomalous precipitation, soil moisture, and land surface temperature. However, the areal extent of drought was smaller in 2015 as compared to 2014. The results clearly

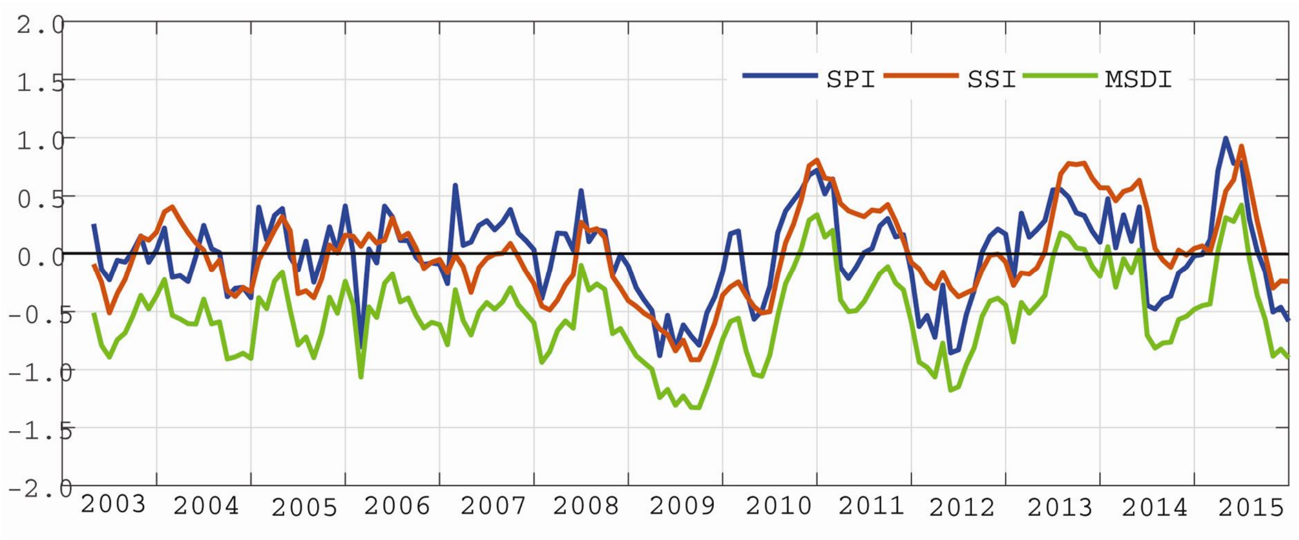

Figure 3. Monthly variations of 4-month SPI, SSI and MSDI averaged over India for the period of 2003 to 2015 using multi-satellite datasets.

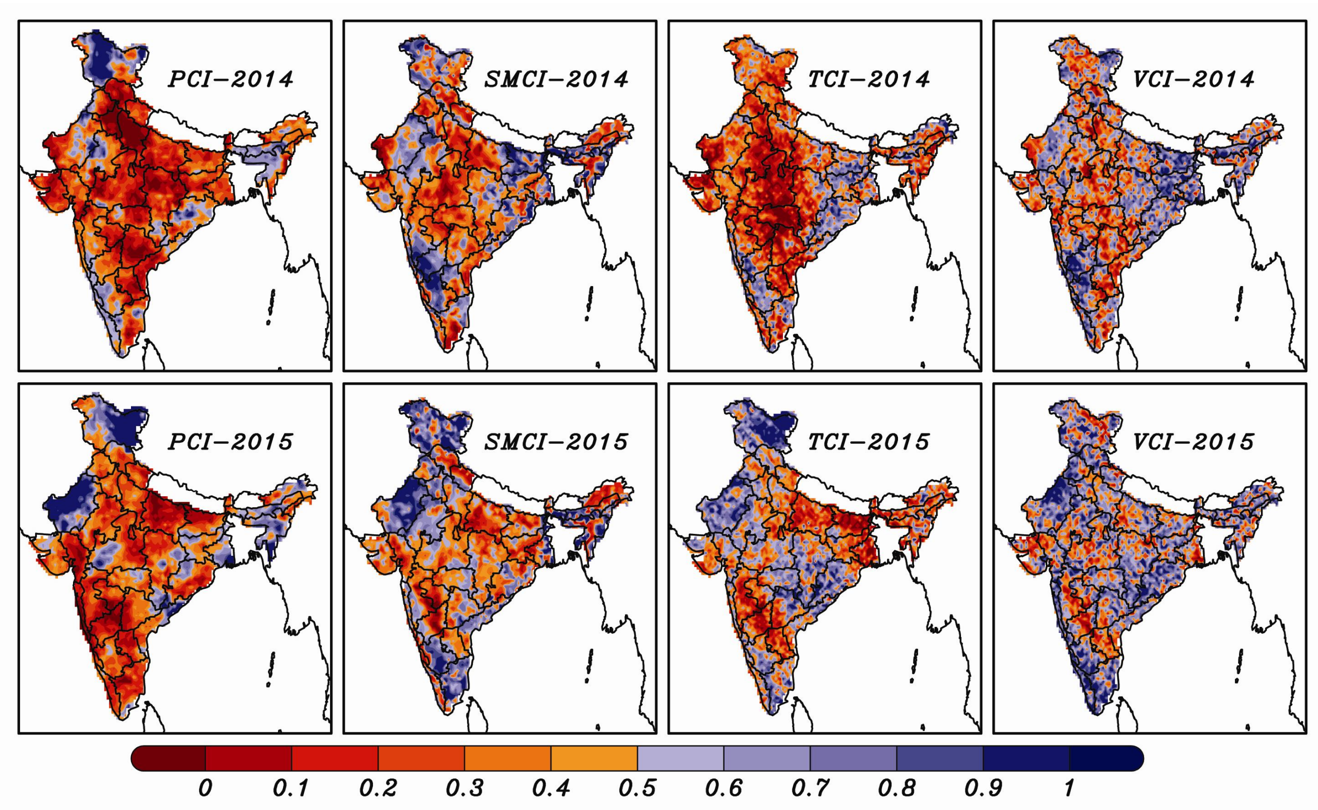

Figure 4. Spatial distributions of PCI, SMCI, TCI and VCI over India for the monsoon seasons of 2014 and 2015 using satellite-derived datasets.

show that remote sensing datasets are capable of detecting various aspects of droughts. The use of different satellite-derived datasets along with ground-based observations would essentially provide a better tool to characterize drought types and its severity comprehensively. However, an operational assessment of droughts over India needs to be done based on a combination of drought indices.

In this study, consecutive Indian monsoon droughts of 2014 and 2015 were assessed using several indices derived from multiple satellite datasets. These droughts were reasonably depicted from the satellite-based precipitation, soil moisture and LST observations. MSDI is a better indicator than SPI and SSI alone for drought detection and monitoring. Following the launch of INSAT-3D satellite in 2013, rainfall estimation from IMSRA was further improved and high-resolution rainfall estimates are now available over India on a regular basis[20]. This operational rainfall product could be utilized for monitoring meteorological drought over India at sub-divisional scale with reasonable accuracy. In general, remote sensing satellite datasets provide immense opportunity to assess different types of drought and their severity using a composite of indices. However, a temporal record of high-resolution satellite data is not sufficient to assess the climatological perspective of droughts. Hence, there is a need for development of high-resolution, long-term, global climate datasets by the synergistic use of multiple satellite observations and numerical model simulations to comprehensively study the drought characteristics and underlying climatic and ecological impacts. Furthermore, numerical modelling of the Indian monsoon has improved quite rapidly at sub-daily to seasonal scale in the last decade due to substantial advancement in observation systems, computing facilities, data assimilation approaches and model physics[36,37]. There is also a need to develop a framework for probabilistic drought prediction over India for early warning and preparedness for drought management.

1. Dai, A., Increasing drought under global warming in observations and models. *Nat. Clim. Change*, 2013, **3**, 52–58; doi:10.1038/nclimate1633.
2. Mishra, A. and Liu, S. C., Changes in precipitation pattern and risk of drought over India in the context of global warming. *J. Geophys. Res. Atmos.*, 2014, **119**, 7833–7841; doi:10.1002/2014JD021471.
3. Mallya, G., Mishra, V., Niyogi, D., Tripathi, S. and Govindaraju, R. S., Trends and variability of droughts over the Indian monsoon region. *Weather Clim. Extrem.*, 2016, **12**, 43–68; doi:10.1016/j.wace.2016.01.002.
4. Salvi, K. and Ghosh, S., Projections of extreme dry and wet spells in the 21st century India using stationary and non-stationary standardized precipitation indices. *Clim. Change*, 2016, **139**, 667–681; doi:10.1007/s10584-016-1824-9.
5. Lehner, F., Coasts, S., Stocker, T. F., Pendergrass, A. G., Sanderson, B. M., Raible, C. C. and Smerdon, J. E., Projected drought risk in 1.5°C and 2°C warming climates. *Geophys. Res. Lett.*, 2017, **44**, 7419–7428; doi:10.1002/2017GL074117.
6. Panda, D. K., AghaKouchak, A. and Ambast, S. K., Increasing heat waves and warm spells in India, observed from a multi-aspect framework. *J. Geophys. Res. Atmos.*, 2017, **122**, 3837–3858; doi:10.1002/2016JD026292.
7. Jain, V. K., Pandey, R. P. and Jain, M. K., Spatio-temporal assessment of vulnerability to drought. *Nat. Hazards*, 2015, **76**, 443–469; doi:10.1007/s11069-014-1502-z.
8. Patel, S., Prakash, S. and Bhatt, B., An assessment of Kalpana-1 rainfall product for drought monitoring over India at meteorological sub-division scale. *Water Int.*, 2015, **40**, 689–702; doi:10.1080/02508060.2015.1072784.
9. Pai, D. S., Guhathakurta, P., Kulkarni, A. and Rajeevan, M. N., Variability of meteorological droughts over India. In *Observed Climate Variability and Change Over the Indian Region* (eds Rajeevan, M. N. and Nayak, S.), Springer Geology, 2017, pp. 73–87; doi:10.1007/978-981-2531-0_5.
10. Pai, D. S., Sridhar, L., Guhathakurta, P. and Hatwar, H. R., District-wide drought climatology of the southwest monsoon season over India based on standardized precipitation index (SPI). *Nat. Hazards*, 2011, **59**(3), 1797–1813; doi:10.1007/s11069-011-9867-8.
11. Kiran Kumar, A. S., Tools from the Indian space programme for observing and forecasting extreme weather events – retrospect and prospect. *Mausam*, 2016, **67**(1), 77–92.
12. Navalgund, R. R. and Singh, R. P., Climate change studies using space based observation. *J. Indian Soc. Remote Sensing*, 2011, **39**(3), 281–295; doi:10.1007/s12524-011-0092-4.
13. Kogan, F. N., Global drought watch from space. *Bull. Am. Meteorol. Soc.*, 1997, **78**, 621–636.
14. Mishra, A. K. and Singh, V. P., A review of drought concepts. *J. Hydrol.*, 2010, **391**, 202–216; doi:10.1016/j.jhydrol.2010.07.012.
15. AghaKouchak, A., Farahmand, A., Teixeira, J., Wardlow, B. D., Melton, F. S., Anderson, M. C. and Hain, C. R., Remote sensing of drought: progress, challenges and opportunities. *Rev. Geophys.*, 2015, **53**, 452–480; doi:10.1002/2014RG000456.
16. Farahmand, A. and AghaKouchak, A., A generalized framework for deriving nonparametric standardized drought indicators. *Adv. Water Resour.*, 2015, **76**, 140–145; doi:10.1016/j.advwatres.2014.11.012.
17. Hao, Z. and AghaKouchak, A., A nonparametric multivariate multi-index drought monitoring framework. *J. Hydrometeorol.*, 2014, **15**, 89–101; doi:10.1175/JHM-D-12-0160.1.
18. Zhao, M., Geruo, A., Velicogna, I. and Kimball, J. S., A global gridded dataset of GRACE drought severity index for 2002–14: comparison with PDSI and SPEI and a case study of the Australia millennium drought. *J. Hydrometeorol*., 2017, **18**(8), 2117–2129; doi:10.1175/JHM-D-16-0182.1.
19. Zhang, L., Jiao, W., Zhang, H., Huang, C. and Tong, Q., Studying drought phenomena in the Continental United States in 2011 and 2012 using various drought indices. *Remote Sens. Environ*., 2017, **190**, 96–106; doi:10.1016/j.rse.2016.12.010.
20. Gairola, R. M., Prakash, S., Bushair, M. T. and Pal, P. K., Rainfall estimation from Kalpana-1 satellite data over Indian land and oceanic regions. *Curr. Sci.*, 2014, **107**(8), 1275–1282.
21. Mahesh, C., Prakash, S., Gairola, R. M., Shah, S. and Pal, P. K., Meteorological sub-divisional scale rainfall monitoring using Kalpana-1 VHRR measurements. *Geogr. Res.*, 2014, **52**(3), 328–336; doi:10.1111/1745-5871.12068.
22. Aadhar, S. and Mishra, V., High-resolution near real-time drought monitoring in South Asia. *Sci. Data*, 2017, **4**, 170145; doi:10.1038/sdata.2017.145.
23. Ray, S. S., Sesha Sai, M. V. R. and Chattopadhyay, N., Agricultural drought assessment: operational approaches in India with special emphasis on 2012. In *High-Impact Weather Events over the SAARC Region* (eds Ray, K. *et al.*), Springer, Cham, 2015, pp. 349–364; doi:10.1007/978-3-319-10217-7_24.
24. Sesha Sai, M. V. R., Murthy, C. S., Chandrasekar, K., Jeyaseelan, A. T., Diwakar, P. G. and Dadhwal, V. K., Agricultural drought: assessment and monitoring. *Mausam*, 2016, **67**(1), 131–142.
25. Kulkarni, A., Gadgil, S. and Patwardhan, S., Monsoon variability, the 2015 Marathwada drought and rainfed agriculture. *Curr. Sci.*, 2016, **111**, 1182–1193; doi:10.18520/cs/v111/i7/1182-1193.
26. Mishra, V., Aadhar, S., Asoka, A., Pai, S. and Kumar, R., On the frequency of the 2015 monsoon season drought in the Indo-Gangetic Plain. *Geophys. Res. Lett.*, 2016, **43**, 12102–12112; doi:10.1002/2016GL071407.
27. Pai, D. S., Sridhar, L., Rajeevan, M., Sreejith, O. P., Satbhai, N. S. and Mukhopadhyay, B., Development of a new high spatial resolution (0.25° × 0.25°) long period (1901–2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam*, 2014, **65**, 1–18.

28. Huffman, G. J., Adler, R. F., Bolvin, D. T. and Nelkin, E. J., The TRMM multi-satellite precipitation analysis (TMPA). In *Satellite Applications for Surface Hydrology* (eds Hossain, F. and Gebremichael, M.), Springer, 2010, pp. 3–22.
29. Prakash, S., Mitra, A. K., Momin, I. M., Gairola, R. M., Pai, D. S., Rajagopal, E. N. and Basu, S., A review of recent evaluations of TRMM multisatellite precipitation analysis (TMPA) research products against ground-based observations over Indian land and oceanic regions. *Mausam*, 2015, **66**, 355–366.
30. Prakash, S., Mitra, A. K., Gairola, R. M., Norouzi, H. and Pai, D. S., Status of high-resolution multi-satellite precipitation products across India. In *Remote Sensing of Aerosols, Clouds, and Precipitation* (eds Islam, T. *et al.*), Elsevier, 2018, pp. 301–314; doi:10.1016/B978-0-12-810437-8.00014-1.
31. Prakash, S., Mitra, A. K., Pai, D. S. and AghaKouchak, A., From TRMM to GPM: how well can heavy rainfall be detected from space? *Adv. Water Resour.*, 2016, **88**, 1–7; doi:10.1016/j.advwatres.2015.11.008.
32. Dorigo, W. *et al.*, ESA CCI soil moisture for improved Earth system understanding: State-of-the art and future directions. *Remote Sensing Environ.*, 2017, **203**, 185–215; doi:10.1016/j.rse.2017.07.001.
33. Reichle, R. H., Koster, R. D., De Lannoy, G. J. M., Forman, B. A., Liu, Q., Mahanama, S. P. P. and Toure, A., Assessment and enhancement of MERRA land surface hydrology estimates. *J. Clim.*, 2011, **24**, 6322–6338; doi:10.1175/JCLI-D-10-05033.1.
34. Wan, Z., MYD11C3 MODIS/aqua land surface temperature/emissivity monthly L3 global 0.05deg CMG V006, *NASA EOSDIS Land Processes DAAC*, 2015; doi:10.5067/modis/myd11c3.006.
35. Didan, K., MYD13C2 MODIS/Aqua vegetation indices monthly L3 global 0.05deg CMG V006. *NASA EOSDIS Land Processes DAAC*, 2015; doi:10.5067/modis/myd13c2.006.
36. Gadgil, S. and Srinivasan, J., Monsoon prediction: are dynamical models getting better than statistical models? *Curr. Sci.*, 2012, **103**(3), 257–259.
37. Mitra, A. K. *et al.*, Prediction of monsoon using a seamless coupled modelling system. *Curr. Sci.*, 2013, **104**(10), 1369–1379.

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Use of molecular-based approach in resolving subspecies ambiguity of the rescued tiger cubs from Arunachal Pradesh, India and their relationship with other population

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Genetic approach is often suggested for resolving taxonomic ambiguities in areas where there have been overlaps in distribution of a species or subspecies. The Northeast part of India is one of the identified biodiversity hotspots, having the junction of Palearctic and Indomalyan realms with dense canopy forests and rugged terrains. The distribution range of two tiger subspecies, i.e. Bengal tiger and northern Indo-Chinese tiger, overlaps with each other in this region. The government authorities rescued three tiger cubs from Angrim Valley Village, Arunachal Pradesh, Northeast India in November 2012. We carried out a comprehensive genetic study on the rescued cubs to elucidate their subspecies status and determine their relationship with the remnant tiger populations. Our findings based on 3661 base pair of mitochondrial DNA sequence spanning across six mitochondrial genes (ND1, ND2, ND5, ND6, 12S rRNA and CytB) and non-coding control region (CR) suggest the Bengal tiger ancestry of the rescued tiger cubs. Further, comparison of mitochondrial haplotype with other Bengal tiger populations reveals that the haplotype reported for the rescued cub is novel and has close affinity to the northeast tiger populations of India. However, detailed population assignment to infer the source of origin was not possible due to lack of genetic data for all Bengal tiger populations. The present study attempts an assessment of tiger status that has resulted in identification of another tiger occupied landscape in India (Dibang Tiger Reserve).

Keywords: Bengal tiger, DNA sequencing, single nucleotide polymorphism, subspecies.

HUMAN-INDUCED environmental changes have deteriorated habitat quality and quantity in different ecosystems worldwide and have driven most of the wildlife towards extinction[1–3]. The larger species experience aggravated effects of human-induced environmental changes as

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