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Research Paper

Assessing the long-term fluctuations in dry-wet spells over Indian region using CHIRPS rainfall data based on Markov model in GEE cloud platform

INDRANI CHOUDHURY[*1,2] and BIMAL BHATTACHARYA[2]

[1]*Department of Science and Technology, New Delhi*

[2]*Biological and Planetary Sciences Applications Group, EPSA, Space Applications Centre, ISRO, Ahmedabad 380015, Gujarat, India*

**Corresponding author's e-mail: icaug4@yahoo.com*

ABSTRACT

The long-term fluctuations in dry-wet spells were assessed at standard meteorological week (SMW) over India using Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) rainfall data. The weekly sum of rainfall was embedded in Markov Chain Probability Model in Google Earth Engine (GEE) platform to compute initial and conditional probabilities of dry-wet spells during 2009-2020. An effective monsoon window (23rd SMW–39th SMW) was identified where initial probabilities (IPs) of dry (P_d) and wet (P_w) spells intersect at 50% probability level. Significant spatiotemporal variation of IPs was observed with initiation and withdrawal of monsoon over India. The analysis of co-efficient of variation (CV) showed low CV (<60%) in P_d and high CV (>60%) in P_w in semi-arid and arid regions whereas northern, central and eastern regions observed high CV (>60%) in P_d and low CV (<40%) in P_w. The drought prone and moisture sufficient zones were indentified based on the analysis of long-term frequency distribution of dry-wet spells and trend. Inter-comparison of IPs between CHIRPs with IMD (Indian Meteorological Department) and NOAA CPC (National Oceanic and Atmospheric Administration/Climate Prediction Centre) showed encouraging results. The study provides baseline reference for climate-resilient agricultural crop planning with respect to food security.

Keywords: CHIRPS, Markov Chain Model, dry- wet spells, agricultural planning

The climate change induces alteration in rainfall pattern thus increasing the scope for extreme events such as droughts, floods, unseasonal and extreme rainfall that has an adverse impact on agriculture threatening food security. Therefore, knowledge on the spatiotemporal distribution of rainfall pattern based on its long-term variability and frequency distribution are prime necessity for minimizing agricultural risk for sustainable agricultural production (Pradhan *et al.*, 2020). Various agricultural operations viz. field preparation, sowing/planting of crops, fertilizer application, scheduling of irrigation etc. requires detailed information of rainfall distribution, onset and withdrawal of rainy season, periods of dry and wet spells. Moreover, the knowledge on the sequence of dry and wet spells at weekly scale corresponding to the sensitive crop phenological stages and its critical undertstanding are important to reduce mid-season stresses and its adverse effects on crop yield. This provides precise information for better crop-water management practice for successful crop planning (Pandharinath, 1991). Earlier studies focused on the rainfall variability pattern and its probability distribution for crop planning using Markov Chain Probability Model (MCPM) in various climatic situations (Dabral *et al.*, 2014; Joseph and Tamilmani, 2017; Behera and Subudhi, 2018; Pawar *et al.*, 2019, Makwana *et al.*, 2021). The present study explored a novel approach to evaluate weekly inference of dry-wet spells at spatiotemporal scale using long-term (2009-2020) global rainfall data over Indian region using MCPM embedded in Google Earth Engine (GEE). GEE as cloud computing platform has the significance to process and analyze large volume of global satellite data at hourly to daily scale (https://signup.earthengine.google.com). This present research provides an important feedback for clear zonation of monsoon pattern over India while assessing long-term fluctuations of dry-wet spells for locating drought prone and moisture sufficient zones. This also aids an important input for better and structured insurance claim settlement in rainfall-based crop insurance.

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Table 1: Description of rainfall data products

Rainfall data	Data Source	Spatial resolution	Temporal resolution	Data used
CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data)	https://developers.google.com/earth-engine/datasets/catalog/UCSB-CHG_CHIRPS_DAILY	0.05° × 0.05°	Daily	2009-2020
NOAA CPC (National Oceanic and Atmospheric Administration /Climate Prediction Centre)	ftp.ncep.noaa.gov /pub/cpc/fews/A.Asia	0.10° × 0.10°	Daily	
IMD (Indian Meteorological Department)	IMD archive (imdpune.gov.in)	0.25° × 0.25°	Daily	

MATERIALS AND METHODS

Study area and data used

The study region belongs to India (68–96^0 E, 8–40^{0}N) has wide climatic variability extending over arid, semi-arid, sub-humid and humid regions. There are two main crop-growing seasons such as *kharif* (June to October) influenced by south-west monsoon known as rainfed agriculture and *rabi* (December–April) depends on irrigation as well as rainfall (some parts of India). The study area was categorized in to five broad geographic regions such as northern (Jammu & Kashmir, Himachal Pradesh, Uttaranchal, Punjab, Haryana, Uttar Pradesh), western (Rajasthan, Gujarat, Maharashtra), southern (Karnataka, Kerala, Tamil Nadu, Andhra Pradesh), central (Madhya Pradesh, Chhattisgarh) and eastern (Bihar, Jharkhand, Orissa, West Bengal, Assam, Meghalaya, Arunachal Pradesh, Nagaland, Manipur, Mizoram). Daily rainfall data from three different sources (CHIRPS, NOAACPC and IMD) were used for the analysis (Table 1).

Markov chain probability model

The theory of MCPM (Pandharinath, 1991; Dash and Senapati, 1992) describes long-term frequency behaviour of two states, i.e. dry and wet spell probabilities that are mutually exclusive and completely exhaustive. The model calculates the initial and conditional probabilities of dry and wet spells in a given standard meteorological week (SMW). The initial rainfall probability is the probability that a particular week of the year is dry (or wet) under the assumption that the weather of the previous week (dry or wet) is not taken into account. A conditional rainfall probability is the probability that a particular week of the year is dry or wet under the assumption that, the weather of the previous week (dry or wet) is taken into account. It indicates the probability of changes in weather from one week to the next week. The computation of initial and conditional probabilities are given below:

Initial Probabilities: $$P_d = \frac{F_d}{n};\ P_w = \frac{F_w}{n}; \quad (1)$$

Conditional Probabilities: $$P_{dd} = \frac{F_{dd}}{F_d};\ P_{ww} = \frac{F_{ww}}{F_w}; \quad (2)$$

$$P_{wd}=1-P_{dd},\ P_{dw}=1-P_{ww}; \quad (3)$$

Where P_d and P_w are the probabilities of the dry and wet weeks, respectively; F_d and F_w are the number of observed dry weeks and wet weeks respectively; n is the number of years of data used; P_{dd} and P_{ww} are the probabilities of dry week preceded by another dry week, wet week preceded by another wet week, respectively; F_{dd} and F_{ww} are the number of dry weeks preceded by another dry week, wet week preceded by another wet week respectively; P_{wd} and P_{dw} are the probabilities of wet week preceded by another dry week and vice versa.

Processing of rainfall data and computation of rainfall probabilities

The time series of daily CHIRPS rainfall data products (2009-2020) were extracted from the GEE data catalogue (i.e., ee.ImageCollection) and were processed using GEE platform through JavaScript API. The functions available in GEE platform ("Map.", "filterDate", "reduce", ".clip", ".print", ".expression", "Export.") were used to import, filter, process and map to compute dry and wet spells probabilities. The daily rainfall data were converted in to weekly sum of rainfall (1st to 52nd weeks) based on the SMW (http://www.icar-crida.res.in). A threshold-based approach was embedded in GEE platform based on the MCPM to compute the initial and conditional probabilities of dry spell (less than 20 mm in a week) and wet spell (20 mm or more rainfall in a week). Similar method was implemented for the daily rainfall data of both NOAA CPC and IMD (2009–2020) for the computation of initial probabilities of dry and wet spells using "Band Math" option in ENVI-image processing software.

Computation of spatial variability and duration of dry-wet spells within monsoon window

The spatial variability of dry and wet spell probabilities was assessed through coefficient of variation (CV) as given below:

$$Coefficient\ of\ variation\ (CV_{dry\ spell/wet\ spell}) = \frac{100\times\sigma}{\bar{X}} \quad (4)$$

where σ is the standard deviation of dry spell/wet spell probability and $\bar{X}$ is the mean of dry spell/wet spell during June-September (JJAS).

The sum of the frequency of each of dry spell (N_d), wet spell (N_w), two consecutive dry spells (N_{dd}) and two consecutive wet spells (N_{ww}) were computed during JJAS from 2009 to 2020. The mean frequency of duration of spells (N_d, N_w, N_{dd}, N_{ww}) were computed as below:

$$Mean\ frequency\ of\ N_d/N_w/N_{dd}\ /\ N_{ww} = \frac{\sum_1^n\left(\sum_{June}^{September} N_d/N_w/N_{dd}/N_{ww}\right)}{n} \quad (5)$$

where is $\sum_{June}^{September} N_d/N_w/N_{dd}/N_{ww}$ is the sum of the observed N_d, N_w, N_{dd} and N_{ww} respectively, during June-September ; n is the number of years of data used;

Trend analysis

The non-parametric Mann-Kendell (MK) test (Mann 1945, Kendell 1975) was used to detect the monotonic trend in dry and wet spells during JJAS from 2009 to 2020. The null hypothesis, indicated by H_0 (no trend) was tested against the alternative hypothesis, H_1 (monotonic trend increasing/decreasing trend). The MK "Z' statistics computed for different states were compared with the tabulated Z-statistics (critical Z-values for various significance levels) at 90% and 95%, level of significance. The trend is said to be significantly decreasing (or increasing) if sample Z is negative (or positive) and absolute Z is greater than the tabulated value at a given level of significance.

Inter-comparison of initial rainfall probabilities estimated from three rainfall products

The initial rainfall probabilities computed from CHIRPS were compared with that of NOAA CPC and IMD using four quantitative statistical parameters i.e. Pearson correlation coefficient (R), coefficient of determination (R^2), root mean square deviation (RMSD) and mean absolute percent deviation (MAPD).

RESULT AND DISCUSSIONS

The 12 year's mean of weekly total rainfall distribution during 1st–52nd SMWs (Fig. 1) showed low weekly total rainfall (<20 mm) till 18th SMW (30thApr–6th May) that increased further and reached to 34 mm at 23rd SMW (4th –10th Jun). A sharp increase in rainfall was observed from 21st SMW (21st–27th May) to 29th SMW (16th–22nd July) with peak at 29th SMW (73.4 mm) followed by decreasing trend till 41st SMW (< 20 mm) (8th–14th Oct) that further continued till 52nd SMW (24th–31st Dec). The state-wise analysis of rainfall probability distributions (P_d and P_w) at spatiotemporal scale indicated an effective monsoon window from 23rd SMW (4th–10th June) to 39th SMW (24th–30th September) over Indian region, at those weeks both P_d and P_w intersect each other at 50% probability level (Fig. 2). Therefore, the mean length of monsoon season was found to be 17 weeks (119 days). Consequently, the emphasis should be given on those crop varieties whose growing cycle is completed within the period matching with water availability period as identified. At the 50% probability level i.e.at 23th SMW, the sowing of rainfed crops could be planned. At higher probability level of P_w (≥70%–≤ 80%) i.e. during 26th to 29th SMW (25th June–22nd July), the risk of sowing rainfed crops are lesser. This period with $P_w \geq 70\%$ is the core monsoon period, during which drought hazard remains low and thus, this could be regarded as the moisture sufficiency period (Sarkar, 1994). The early sowing of rainfed crops with more than 20 mm of weekly rainfall could be set at 17th SMW (23rd – 29th Apr) (Sattar *et al.*, 2018).

Temporal analysis of dry spell (P_d) and wet spell (P_w) probabilities in India

The temporal pattern of P_d (Fig. 3a) in 52 SMWs computed from CHIRPS data showed high P_d (>80%–100%) till 13th SMW (26th Mar–1stApr) over Indian region. In eastern region, beyond 13th SMW, the P_d was found decreasing till 32nd SMW (6th–12th Aug) where P_d at its lowest value (<10%) and remained lowest (<30%) till 39th SMW as compared to other regions. According to IMD, a north-south trough from East Uttar Pradesh to Northwest Bay of Bengal, coupled with strong and moist southwesterly winds blowing in from the Bay of Bengal, collectively creates wet conditions over eastern regions particularly in northeast India during this period (https://weather.com/en-IN/india/news/news/2022-04-01-heavy-rains-to-lash-northeast-assam-arunachal-from-april-1-5). In Southern region, high P_d (>80%) was observed till 13th SMW followed by decrease in P_d till 32nd SMW with few ups and down in between. The central regions showed the highest P_d (>95%), the northern and western regions showed high P_d (>85%) till 21st SMW. Beyond 21st SMW, decrease in P_d was observed till 31st SMW (30th Jul –5th Aug) in the central regions where P_d at its lowest value (≈12%). Similarly, P_d was also found decreasing in both northern (P_d≈17%) and western regions (P_d≈ 28%) till 33rd SMW (13th – 19th Aug). The P_d was found decreasing (<50%) from 22nd to 25th SMW (28th May – 24thJun) onwards in eastern, central, southern and western regions covering more than 75% area of the country indicating initiation of summer monsoon in those areas. The P_d across the country was observed to be gradually increasing from Northwestern India to other parts of the country from 35th SMW (27th Aug–1st Sep) onwards due to the withdrawal of the Southwest monsoon. During 45th SMW (5th –11th Nov) onwards, the P_d was found to be very high (>80%) in major parts of the country except Southern Peninsular India viz. major parts of Tamil Nadu, Kerala and Coastal Andhra Pradesh due to the receipt of Northeast monsoon rainfall. During 50th to 52nd SMW (10th –31st Dec), the P_d over entire Indian region was found to be more than 90% except Southern Peninsular India.

The temporal distribution of P_w (Fig. 3b) estimated from CHIRPS data in 52 SMWs represents the progress of summer monsoon over India. From 13th SMW onwards, the P_w was found increasing in the eastern region that remained highest among the other regions throughout the monsoon period. High P_w (>50%) was observed in the southern and eastern regions during 22nd SMW (20th May–3rd Jun) to 43rd SMW (22nd–28th Oct) and 21st SMW to 40th SMW (1st–7th Oct), respectively. The central region showed high P_w (>50%) from 24th SMW (11th–17th Jun) to 37th SMW (10th – 16th Sep), whereas northern and western regions showed high P_w (>50%) from 25th SMW (18th –24th Jun) to 36th SMW (3rd–9th Sep). Therefore, the initiation of monsoon ranges from 22nd–25th SMW throughout Indian region. Till first week of August (31st SMW), high P_w (>80%) was observed in the entire eastern, northern and central regions whereas southern and western regions showed low P_w (<55%).

During 29th SMW, the overall P_w was found to be the highest during monsoon season in India. During 27th–34th SMW (2nd Jul–26th Aug), a consistent high P_w was observed in most parts of the country. This leads to the assured water supply that makes condition favorable for transplanting of *kharif* rice in the first week of July in the rainfed rice-growing areas. Moreover, the residual soil moisture in the lowland areas can further be utilized for growing of second crop under rainfed conditions. Beyond mid-August, the P_w was found decreasing indicating withdrawal of summer monsoon

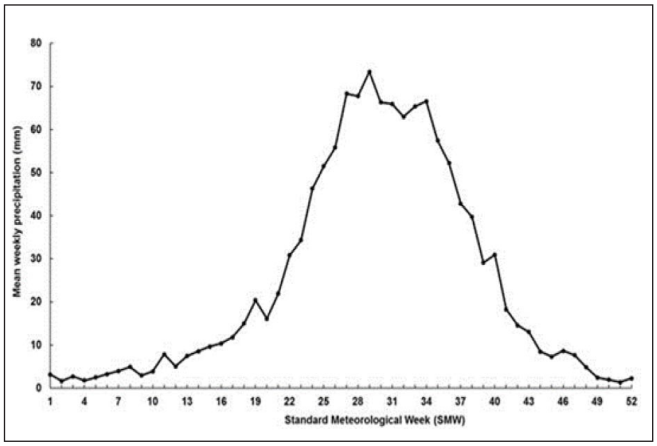

Fig. 1: Mean weekly rainfall distribution of India using CHIRPS rainfall data (2009-2020)

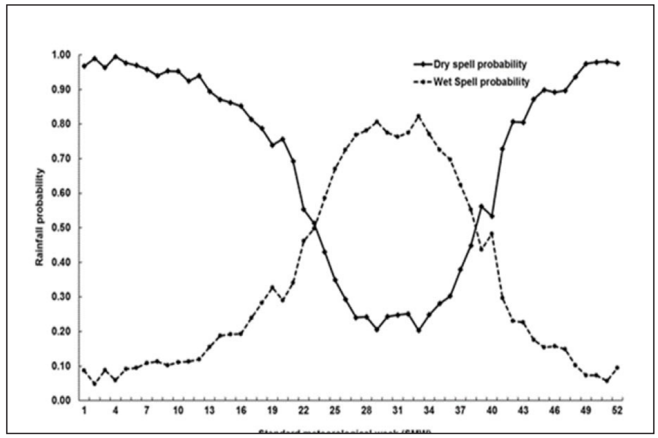

Fig 2: CHIRPS estimated dry and wet spell rainfall probability distribution over India

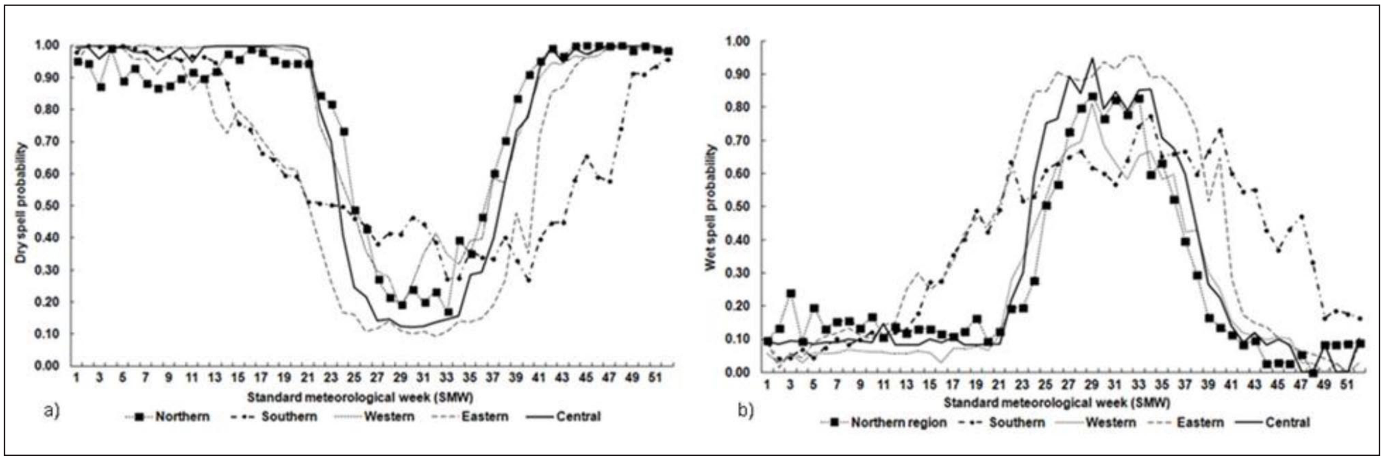

Fig. 3: Initial probability of rainfall based on Markov chain model (2009-2020) over India using CHIRPS rainfall data, a) dry spell probability; b) wet spell probability

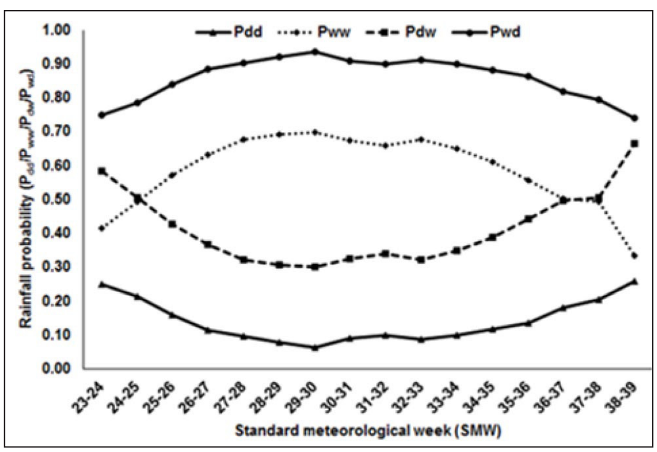

Fig. 4: CHIRPS estimated conditional probabilities of rainfall over India.

in the western, central and eastern parts of India. The withdrawal of summer monsoon was found starting around the 35th SMW onwards (27th Aug–1st Sep) over west Rajasthan and Gujarat that was found approaching towards central and northern parts around last week of September to first week of October (https://www.tropmet.res.in/~kolli/MOL/Monsoon/year2016/Monsoon-2016.pdf) followed by other parts of India from October onwards. In those regions, the decrease of P_w was found associated with the steady increase of P_d. The withdrawal of summer monsoon is generally linked with the sharp increase in convective activity along with the dry periods of the inter-seasonal oscillation (Syroka and Toumi, 2004; Das *et al*., 2020). A typical monsoon pattern was observed in the southern region of India where the P_w rarely reached more than 80%. However, in rest of the regions, the P_w started decreasing from 39th SMW (24th-30th Sep) onwards indicating withdrawal of monsoon rainfall from most parts of India and the beginning of northeast monsoon in the southern India. The temporal occurrence of conditional probabilities (P_{dd}, P_{ww}, P_{dw}, P_{wd}) over Indian region (Fig. 4) showed low P_{dd} (<30%) throughout the monsoon period (23rd–39th SMW) whereas P_{ww} (>40%–<70%) showed increasing trend following the similar pattern of P_w but the values were found lower. The highest P_{ww} was observed during 29th–30th SMW. The start of the monsoon withdrawal symptoms can be captured well by observing the decreasing trends of both P_w (Fig. 2) and P_{ww} (Fig. 4), beyond 33rd SMW over India. Both P_{dw} and P_{wd} showed similar pattern as that of P_{dd} and P_{ww} respectively, but the values were found larger in former conditional probabilities.

The satellite-based weekly variation of rainfall probabilities demonstrated over Indian region can be used for detecting the peak periods of weather adversities in weather sensitive regions. The

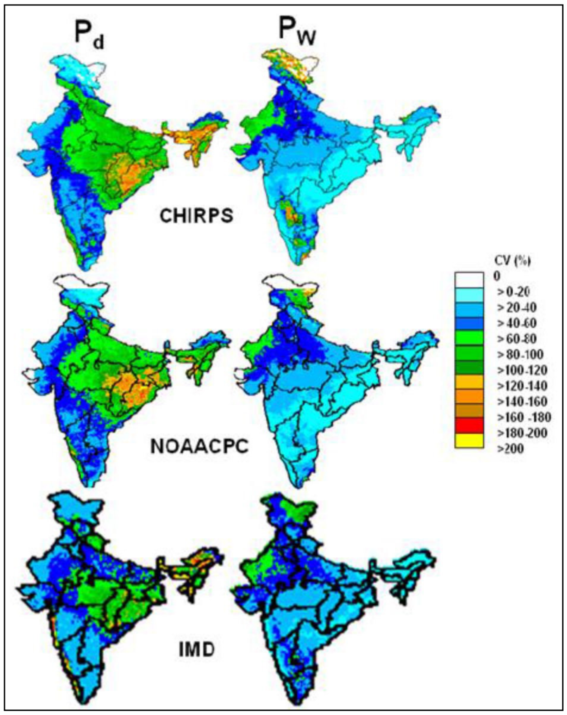

Fig. 5: Co-efficient of variation of Pd and Pw over India during JJAS a) Pd of CHIRPS; b) Pd of NOAA CPC; c) Pd of IMD; d) Pw of CHIRPS; e) Pw of NOAA CPC; f) Pw of IMD;

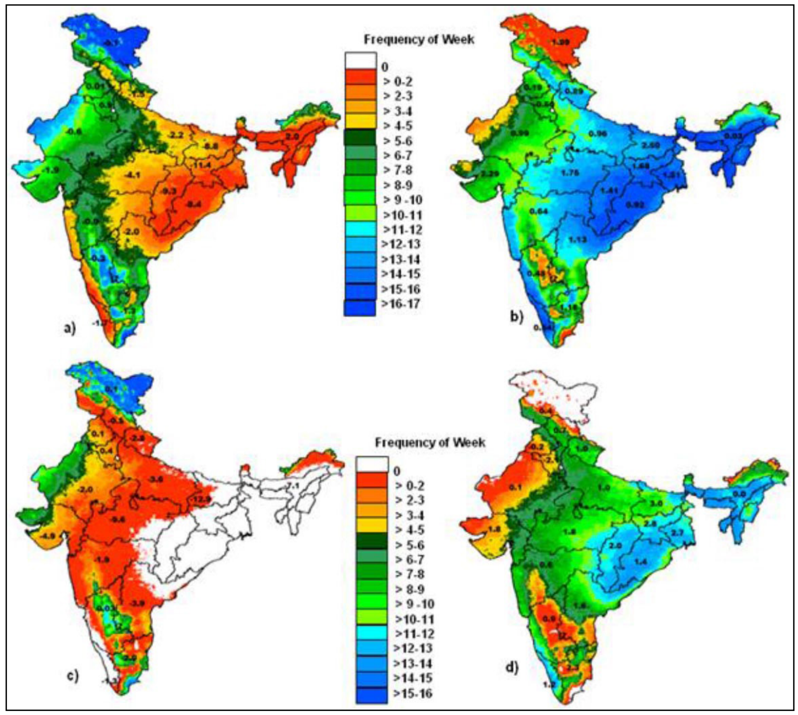

Fig. 6: Average frequency (2009-2020) of dry and wet spells during JJAS over India with percent increasing (+ve) and decreasing (-ve) trend; a) Dry spell; b) Wet spell ; c) Dry spell followed by dry spell; d) Wet spell followed by wet spell

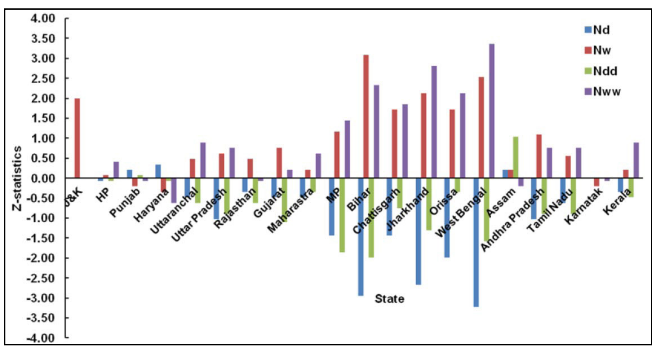

Fig. 7: State-wise computed Z-statistics of frequency of duration of dry and wet spells

regions with high probability of dry spells during monsoon season require an immediate adoption of appropriate location-based crop-water management strategy to save crops from drought. In addition, weekly sequences of dry and wet spell probabilities aided an important input in generating accurate and faster claim settlement in case of rainfall-based crop insurance at weekly scale.

Evaluation of spatial variability and duration of dry and wet spells within monsoon window

The wide variability of P_d and P_w over Indian region was captured well through the analysis of CV during 23rd-39th SMW (Fig. 5). Almost similar pattern of variability of P_d and P_w was observed when comparing amongst CHIRPS, NOAA CPC and IMD but small changes in the CV values in IMD estimated P_d and P_w might be attributed to its coarser resolution data. Low variability (CV<60%) in P_d was observed in the arid and semi-arid regions as compared to the central, eastern, northern and northeastern regions where high variability (CV> 80%) in P_d was observed. On the contrary, low variability (CV<40%) in P_w was observed in the central, eastern, northern and northeastern regions. This is an important input for the selection of crop variety matching the water availability in different locations, as well as scheduling of irrigation coinciding the critical crop growing stages to avoid mid-season water stress particularly in the drought prone areas. Hence, the cropping plan should be tailored on a rational basis with available rainfall resource to enhance agricultural production. The spatial distribution of the average (2009-2020) frequency of dry and wet spells during JJAS along with increasing (+ve sign) and decreasing (-ve sign) trend is depicted in Fig. 6. Regions with highest frequency of dry spell (>10 weeks) was observed in the western, northern (Punjab, Haryana, parts of western Uttar Pradesh), central (Madhya Pradesh) and southern regions (Karnataka, parts of Andhra Pradesh, Tamil Nadu). On the contrary, the highest frequency of wet spell (>11 weeks) was observed in the entire eastern parts of India, major parts of Himachal Pradesh, Uttaranchal, Uttar Pradesh, Andhra Pradesh and Kerala. The frequency of duration of two consecutive weeks of dry spell showed high frequency (>6 to 12 weeks) in western Rajasthan and Gujarat, Karnataka and Tamil Nadu whereas Jammu and Kashmir was observed with more than 13 weeks. The highest frequency (>11 weeks) of two consecutive weeks of wet spell was observed in major parts of Assam, West Bengal, Orissa, Chhattisgarh and Jharkhand. Therefore, the regions with highest frequency of dry spells are the most probable regions for the occurrence of drought during monsoon season.

The state wise analysis of Z-score of MK test (Fig.7) showed significant decreasing trend of dry spell in Bihar (-8.8%), Jharkhand (-11.4%), Orissa (-8.4%) and West Bengal (-12.9%) whereas Bihar (2.50%), Chhattisgarh (1.4%), Jharkhand (1.68%),

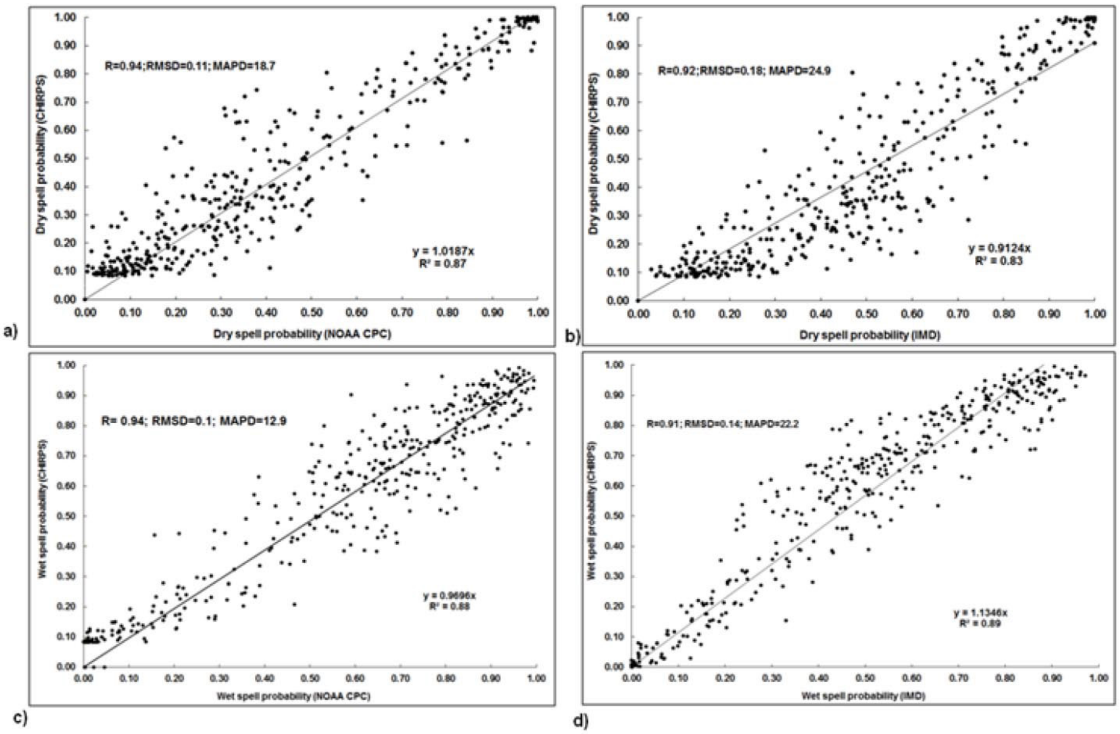

Fig. 8: Comparison of CHIRPS rainfall probability with NOAA CPC and IMD over Indian regions; a) Dry spell probability of CHIRPS vs NOAA CPC; b) Dry spell probability of CHIRPS vs IMD; c) Wet spell probability of CHIRPS vs NOAA CPC; d) Wet spell probability of CHIRPS vs IMD.

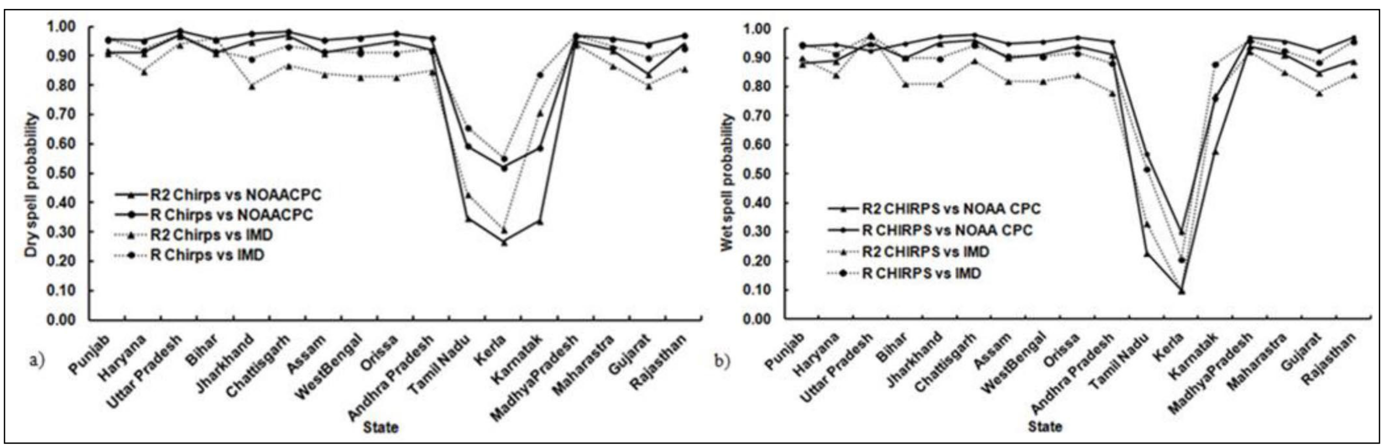

Fig. 9: State-wise comparison of rainfall probabilities among CHIRPS, NOAA CPC and IMD; a) Dry spell probability; b) Wet spell probability

Orissa (0.9%), West Bengal (1.5%), Jammu & Kashmir (1.13%) showed significant increasing trend of wet spell. In case of two consecutive weeks of dry spell, MP (-9.6%) and Bihar (-12.9%) showed significant decreasing trend whereas in case of two consecutive weeks of wet spell, Bihar (3%), Chhattisgarh (2%), Jharkhand (2.8%), Orissa (1.4%) and West Bengal (2.7%) showed significant increasing trend.

Bias evaluation

The comparison of pooled rainfall probabilities (all states together) between CHIRPS and NOAA CPC (P_d; R=0.94; $P_{w;}$ R=0.94), CHIRPS and IMD (P_d; R=0.92; $P_{w;}$ R=0.91) showed good match (Fig. 8).

The state-wise comparison (Fig. 9) showed good measure of association over entire Indian region except for the states like Kerala, Tamil Nadu and Karnataka. An earlier study (Saicharan and Rangaswamy, 2023) had reported that the CHIRPS data performed well in the central part of India, whereas the data was found less suitable for the Southern part of India. This can be attributed to uncertainty in the dataset because of merging CHIRPS and rain-gauge station data using inverse distance weighting. The uncertainty might be due to the scattered distribution of rain gauges (Funk *et al.*, 2015). In addition, complex orography is another region for less suitability of the CHIRPS data in the southern part of India. Similarly, rain-gauge based extrapolated IMD data might also induce certain level of uncertainty (Mishra and Rafiq, 2019).

Table 2: District level comparison of dry spell of CHIRPS rainfall with IMD and NOAA CPC

State	CHIRPS vs NOAA CPC			CHIRPS vs IMD		
	Dry spell probability			Dry spell probability		
	R	RMSD	MAPD	R	RMSD	MAPD
Uttar Pradesh	0.91	0.11	24.71	0.82	0.21	38.39
West Bengal	0.59	0.09	47.86	0.56	0.18	57.82
Tamil Nadu	0.67	0.21	27.68	0.65	0.22	29.35
Maharashtra	0.75	0.12	29.32	0.70	0.16	32.24
Gujarat	0.67	0.16	27.02	0.73	0.15	23.95
	Wet spell probability			Wet spell probability		
Uttar Pradesh	0.90	0.21	13.80	0.83	0.12	32.83
West Bengal	0.56	0.18	16.72	0.52	0.19	19.08
Tamil Nadu	0.64	0.21	29.29	0.63	0.23	50.36
Maharashtra	0.74	0.12	13.56	0.66	0.16	23.13
Gujarat	0.74	0.15	23.56	0.77	0.15	24.21

For district level comparison, few representative states (Uttar Pradesh, West Bengal, Tamil Nadu, Maharashtra and Gujarat) were selected (Table 2) which showed good match (R>0.50). The statistical indicators showed best performance in Uttar Pradesh for both dry and wet spells. Due to coarser resolution of IMD and NOAACPC data (larger grid size), the information of more localized rainfall is missing that could be the cause of some discrepancy of the datasets with CHIRPS. It was observed that as the evaluation grid size decreased (state-to-district), the performance of the rainfall data products decreased indicating excellent bias score at the higher grid size. Therefore, it is necessary to analyse the suitability of the datasets at various spatial scales, such as the regional scale, metrological sub-division scale and pixel level for optimum utilization of the datasets. Additionally, the complex topography of India requires orographic correction for further improvement of accuracy among the three rainfall data products.

CONCLUSION

The long-term (2009-2020) evaluation of dry-wet spells using CHIRPS rainfall data played significant role for the implementation of early warning rainfall activities over Indian region. The spatiotemporal assessment of rainfall probabilities were able to delineate a clear zonation of diverse monsoon pattern across the country, identify drought prone and moisture sufficient zones based on the evaluation of CV as well as frequency of duration of the dry-wet spells and its trend analysis. Good match of CHIRPS with NOAACPC and IMD rainfall data increases the scope of using long-term data for climatological studies without any data gap.

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Conflict of Interest: The authors declare that there is no conflict of interest related to this article.

Data availability: Raw data can be downloaded from the cited websites (Table 1). Derived data can be available from the corresponding author (Indrani Choudhury) on request after publication of the research paper.

Author's contributions: **I. Choudhury**: Conceptualization, Methodology, Analysis, Writing, editing., **B.K. Bhattacharya**: Conceptualization, Methodology, discussion, Supervision

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