



# Spatio-Temporal Agreement Between Standardized Precipitation Index (SPI) and Rainfall Anomaly Index (RAI) for Drought Monitoring: A Case Study of Vadodara District, Gujarat

Nirav V. Shah<sup>1,2,†</sup> , Akil V. Memon<sup>1,3</sup> , Pranavkumar D. Bhangaonkar<sup>4</sup>  and Yogesh S. Patel<sup>1</sup> 

<sup>1</sup>Department of Civil Engineering, Sankalchand Patel College of Engineering, Sankalchand Patel University, Visnagar, Gujarat, India

<sup>2</sup>Department of Food Engineering, College of Food Processing Technology and Bio Energy, Anand Agricultural University, Anand, Gujarat, India

<sup>3</sup>College of Agricultural Engineering and Technology, Anand Agricultural University, Godhra, Gujarat, India

<sup>4</sup>Department of Civil Engineering, Neotech Faculty of Diploma Engineering, Vadodara, Gujarat, India

†Corresponding author: Nirav V. Shah; nvshah@aau.in

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## ABSTRACT

Drought is among the most ruinous natural disasters, and its frequency and severity are likely to rise because of climate change, especially in susceptible areas such as Gujarat, India. A precise assessment of drought is critical for early warning, mitigation planning, and sustainable water resource management. This study evaluated annual meteorological drought in the Vadodara district over 30 years (1991–2021) using daily rainfall data obtained from the State Data Water Center (SDWC), Gandhinagar, and Anand Agricultural University. The assessment employs two widely recognized indices: the Standardized Precipitation Index (SPI) and the Rainfall Anomaly Index (RAI). Eleven meteorological stations at the district level were used to classify drought, wet, and normal years based on these indices. A spatiotemporal concordance analysis was performed to analyze the congruence of the SPI and RAI in describing drought occurrence. The results indicated moderate agreement among the indices, with a consistency of 30% at Kawat and 50% at Pilol and Rampura. These differences mirror the effects of localized climatic and topographic factors, along with methodological differences between the RAI and SPI. Although both are useful for detecting droughts, their partial agreement highlights the significance of a multi-index approach for increasing the reliability of drought monitoring. The results help improve the knowledge of index performance and inform the construction of more reliable regional drought early warning systems and water resource management.

## INTRODUCTION

Droughts are among the most complex and devastating natural hazards, with far-reaching consequences for water security, agricultural productivity, ecosystems, and socioeconomic stability. Unlike other natural disasters that manifest abruptly, drought develops gradually, making its onset difficult to detect and its impacts challenging to mitigate. It arises from prolonged imbalances in the hydrological cycle, which are driven by insufficient precipitation, excessive evapotranspiration, unsustainable water use, or a combination of these factors (Kartal et al. 2023). The multifaceted nature of drought means that its definition varies across disciplines: meteorologists characterize it as a significant departure from normal precipitation levels, hydrologists associate it with diminished streamflow, declining reservoir storage, or falling groundwater tables, and agricultural scientists define it in terms of soil moisture deficits that impair crop growth (Rahmalina et al. 2023). Economists may assess droughts through their socioeconomic repercussions, such as food insecurity and economic losses, whereas urban populations experience them as severe water shortages and supply disruptions (Bakanoğullari et al. 2020).

Globally, drought is classified into three major types: meteorological, hydrological, and agricultural, each with distinct indicators and implications. Meteorological droughts, the most fundamental type, are defined by prolonged periods of below-average precipitation. Hydrological droughts reflect the subsequent depletion of water resources in rivers, lakes, and aquifers, often lagging behind meteorological droughts because of delayed hydrological responses (Aktürk et al. 2022). Agricultural drought, which directly affects food production, is determined by insufficient soil moisture to sustain crops and is influenced by rainfall variability, evapotranspiration rates, and soil water-holding capacity (Mombriani 2023). While traditional drought indices predominantly rely on precipitation data, emerging research emphasizes the need to incorporate additional climatic variables, particularly temperature, to enhance drought monitoring under changing climate conditions in the future.

According to the latest assessments by the Intergovernmental Panel on Climate Change (IPCC), climate variability is intensifying, with significant regional disparities in precipitation patterns and temperature trends. These shifts are expected to alter the frequency, duration, and severity of droughts, particularly in regions that are already prone to water scarcity. For instance, rising temperatures exacerbate evapotranspiration rates, accelerating soil moisture depletion, even in the absence of reduced rainfall (Staudinger et al. 2014). Compound extremes, such as concurrent heatwaves and droughts, further amplify water stress, posing greater risks to ecosystems and human systems (Mohanta et al. 2020). Consequently, drought indices that integrate both precipitation and temperature data are increasingly recognized as robust tools for drought assessment in climate change scenarios (Memon et al. 2018).

Surendran et al. (2019) employed the DrinC model to assess drought conditions across humid, semi-arid, and arid regions of India. They concluded that while several indices, such as the RDI, showed high prediction accuracy, the SPI remained robust for long-term precipitation trends. SPI's adaptability across different climatic conditions makes it a reliable tool for monitoring droughts in diverse environments. (Gonçalves et al. 2023) compared five drought indices, including the SPI and RDI, in Brazil's semi-arid basins. Their analysis found that the SPI was the most suitable for hydrological monitoring because of its effectiveness in identifying drought episodes and capturing drought duration and severity. Similarly, Worku (2024) used the SPI and SPEI to analyze spatiotemporal droughts in Ethiopia's Borana region, highlighting the SPI's utility of the SPI in seasonal drought detection.

In the Indian context, multiple studies have supported the efficacy of SPI (Sharma et al. 2023). Chand and Dhaliwal (2024) examined the relationship between ENSO events and SPI in Punjab, finding a correlation between strong El Niño years and abnormal rainfall patterns, particularly during the kharif season. Another localized study in Bharuch District, Gujarat (2023), applied the SPI to evaluate drought severity, showing that the SPI can effectively inform water management strategies at the district level. Achite et al. (2022) used the SPI and SRI in Algeria's Wadi Ouahrane Basin to forecast droughts using ARIMA models. The SPI data helped detect seasonal trends and enhance drought preparedness. (Pande et al. 2022) extended the utility of the SPI by combining it with machine learning models, such as ANN and M5P, to forecast meteorological droughts.

In Southeast Asia, Septiani et al. (2022) focused on the Brantas Hulu watershed using SPI-3 and SPI-6 to assess short- and medium-term drought. A strong correlation was observed between the SPI values and reservoir inflows, confirming its operational relevance in watershed-level planning. SPI was also effective in identifying drought trends in Nagaland (Lairenjam & Hangshing 2023) and Karnataka's dry zone (Chauhan et al. 2021), supporting its broad applicability across India.

Although the RAI is less frequently used in recent literature, it remains a useful tool for historical drought analysis. The RAI's straightforward approach, based on ranking precipitation deviations from the mean, allows for easy computation and interpretation. However, newer research often favors the SPI because of its statistical standardization and ability to assess drought across multiple temporal scales.

A few studies have integrated remote sensing with the SPI. Sirisena et al. (2022) used the SPI along with NDVI and soil moisture data in the Narmada Basin, India, to assess agricultural drought. SPI's integration of SPI with satellite-based datasets adds spatial depth to its temporal analysis capabilities. Similarly, Wang et al. (2022) developed an improved daily SPI dataset for mainland China (1961-2018), significantly enhancing drought monitoring accuracy (Dakhil et al. 2024).

This study adds a novel dimension by conducting a spatiotemporal comparison of drought classifications using both the Standardized Precipitation Index (SPI) and the Rainfall Anomaly Index (RAI) across 11 meteorological stations in Vadodara district for the period 1991–2021. Unlike earlier studies that typically focus on a single index or larger regional scales, this study simultaneously evaluates the SPI and RAI at the station level, quantifies the degree of agreement between them, and explores the influence of local

topography and rainfall variability on index performance. The results revealed partial agreement between the indices, with values ranging from 30% to 50%. Pilol and Rampura stations showed the highest agreement, whereas Kawat had the lowest. These discrepancies are attributed to methodological differences; the SPI standardizes rainfall over time, whereas the RAI simply classifies anomalies. The spatial variability of agreement highlights the influence of local topography and rainfall distribution on the index performance.

### Study Area and Data Collection

The present study was conducted in Vadodara district, located in the state of Gujarat, India. Covering an area of approximately 7,794 km<sup>2</sup>, Vadodara is the third-largest city in the state and lies between latitudes 21°49'N and 22°49'N and longitudes 72°05'E and 74°16'E. Geographically, the district is situated between two major river basins, the Narmada and the Mahi, and is traversed by the seasonal Vishwamitri River, which originates from the Pavagadh Hills. The region experiences a semi-arid climate with an average annual rainfall of approximately 930 mm, primarily received during the southwest monsoon season from June to September. This concentrated rainfall often leads to flooding in the Vishwamitri River, despite the presence of modern urban drainage infrastructure. Simultaneously, the district suffers from periodic water scarcity, creating a dual challenge of drought and flood management. Rapid urbanization, coupled

with increasing pressure on water resources, underscores the need for effective and timely drought monitoring, making Vadodara a representative case for such studies. For the present analysis, daily rainfall data along with maximum and minimum temperatures were collected from the State Data Water Center, Gandhinagar, and the Meteorological Department of Anand Agricultural University, Anand, covering 11 different stations across the Vadodara district over 30 years (1991-2021). Missing records were estimated using the Inverse Distance Weighting (IDW) and Simple Arithmetic Average methods. Furthermore, a trend analysis of the hydro-climatic variables was conducted using the non-parametric Mann-Kendall test and Sen's slope estimator. Fig. 1 shows the location of the study area.

## MATERIALS AND METHODS

### Standardized Precipitation Index (SPI)

The SPI, developed by McKee et al. (1993), is a widely used drought index that quantifies precipitation deficits across different timescales. In this study, the SPI was calculated at 3-, 6-, 9-, and 12-month timescales to capture both short- and long-term drought conditions. Table 1 shows the classification of Standardized Precipitation Index (SPI) values.

The computation of the SPI involves the following steps:

1. Long-term monthly precipitation data for each station were fitted to gamma probability distributions.

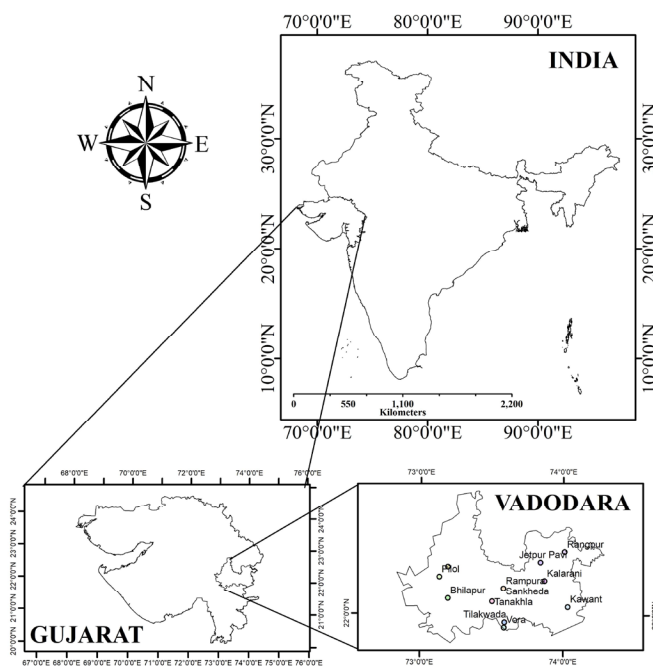


Fig. 1: Study area map of Vadodara district.

Table 1: Classification of SPI Values.

Description	Classification
2 or more	Extremely wet
1.5 to 1.99	Severely wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately dry
-1.5 to -1.99	Severely dry
-2 or less	Extremely dry

2. The cumulative probability was then transformed into a standard normal distribution, resulting in SPI values with a mean of zero and a standard deviation of one.

The SPI is mathematically expressed as

$$SPI = \frac{X_{ij} - \bar{X}}{\sigma} \quad \dots(1)$$

Where,  $X_{ij}$  = precipitation at the  $i^{\text{th}}$  rain gauge and  $j^{\text{th}}$  observation,  $\bar{X}$  = long-term seasonal mean

$\sigma$  = standard deviation. When the value of the SPI reaches -1 or less, a drought occurs. Similarly, when SPI reaches a positive value, a drought ends

### Rainfall Anomaly Index (RAI)

The Rainfall Anomaly Index (RAI), introduced by Van Rooy (1965), is another effective index used to evaluate drought conditions based solely on precipitation deviations from the norm. The RAI standardizes precipitation anomalies against the historical range of extreme rainfall events. The classification of RAI values is presented in Table 2.

Where:

$$RAI = 3 \left[ \frac{N - \bar{N}}{M - \bar{N}} \right], \text{ for positive anomalies} \quad \dots(2)$$

$$RAI = 3 \left[ \frac{N - \bar{N}}{\bar{X} - \bar{N}} \right], \text{ for negative anomalies} \quad \dots(3)$$

RAI values typically range from -3 (extremely dry) to +3 (extremely wet), categorizing precipitation irregularities into ten defined intervals.

To evaluate the station-wise consistency in the SPI and RAI drought classifications, a comparative assessment was conducted using the classification of drought, wet, and normal years (Table 4). The agreement percentage was calculated as the number of years with matching classifications between the SPI and RAI divided by the total number of years observed (Fig. 7).

## RESULTS AND DISCUSSION

The 30-year drought appraisal of the Vadodara district

Table 2: Classification of Rainfall Anomaly Index Intensity.

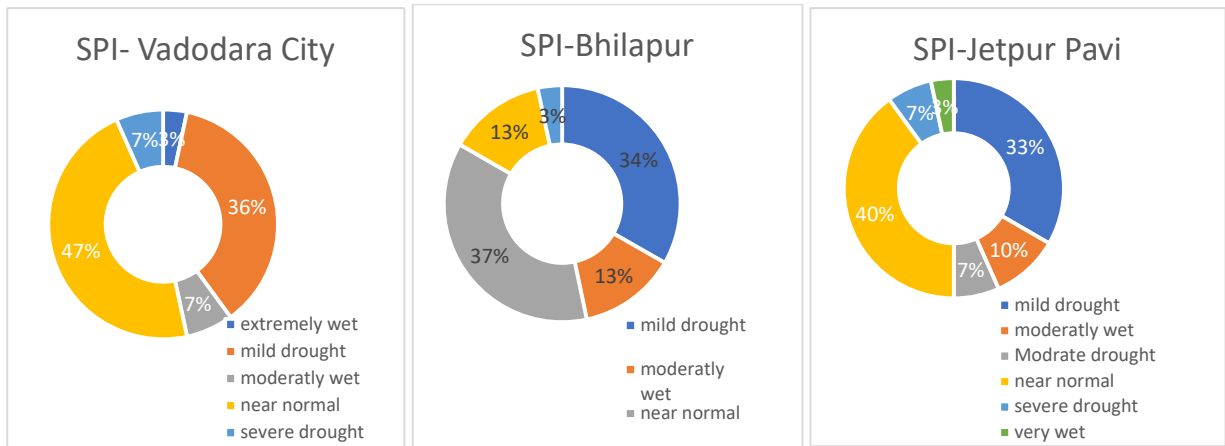
RAI range	Classification
Above 4	Extremely humid
2 to 4	Very humid
0 to 2	Humid
-2 to 0	Dry
-4 to -2	Very dry
Below -4	Extremely dry

based on the Standardized Precipitation Index (SPI) and Rainfall Anomaly Index (RAI) offers essential insights into the spatial and temporal variability of drought patterns. Comparative classification for the years 1991–2021 across 11 stations-Vadodara City, Bhilpura, Jetpur-Pavi, Kalarani, Kawat, Pilol, Rampura, Rangpur, Sanjeli, Sankheda, and Tilakwada-reflects high hydrometeorological contrasts owing to localized climatic differences.

Years such as 2000-01, 2001-02, and 2009-10 were marked by extensive and severe drought conditions. As shown in Fig. 4, both the SPI and RAI consistently reported “severe drought” or “mild drought” across almost all stations, validating a district-wide hydrological deficit likely resulting from monsoonal failure. In 2000-01, for example, all 11 stations reported “moderate” to “severe drought” under both indices, indicating high agreement. Similarly, 2001-02 demonstrated widespread dry conditions, with the SPI providing a more consistent identification of prolonged drought, reinforcing its reliability as a long-term drought indicator.

The highlighted drought years of 2000-01, 2001-02, and 2009-10 can be further interpreted in the context of large-scale climatic drivers such as the El Niño Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD). The 2009–10 drought coincided with a well-documented El Niño event, which typically weakens the Indian summer monsoon, thereby supporting the severe rainfall deficits observed across the Vadodara district in both SPI and RAI. In contrast, 2000-01 and 2001-02 occurred during the neutral or transition phases of ENSO, with mixed IOD signals that alternated between weak positive and negative phases. This suggests that the widespread drought during these years cannot be solely explained by global teleconnections and may have been exacerbated by regional-scale monsoon breaks, local sea surface temperature anomalies, and land-atmosphere feedback. The divergence in drivers emphasizes that while El Niño events provide a clear mechanism for monsoon weakening, many severe droughts arise from the complex interplay between global teleconnections and regional climatic variability.

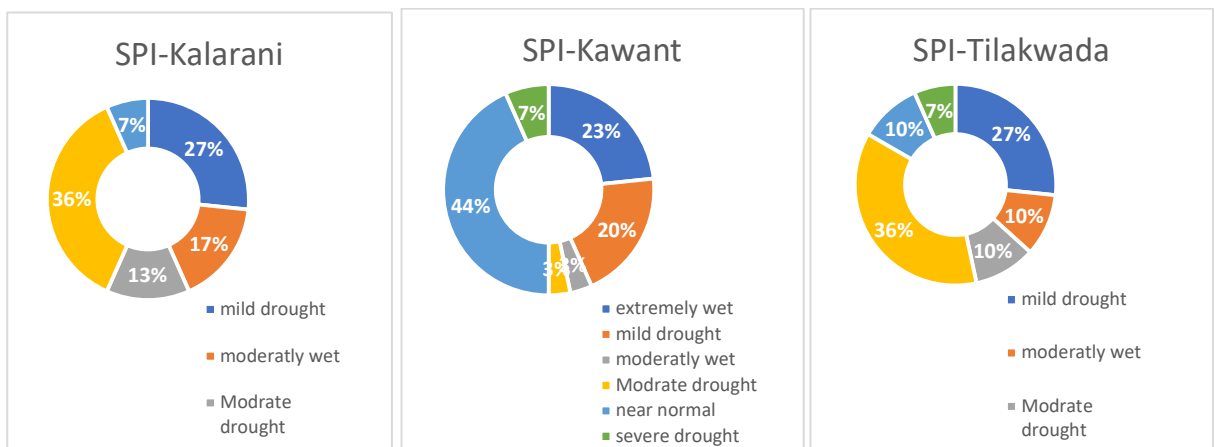
In contrast, the years 1996–97, 2006-07, 2013-14, and 2014-15 recorded extremely wet to above-normal conditions.



(a)

(b)

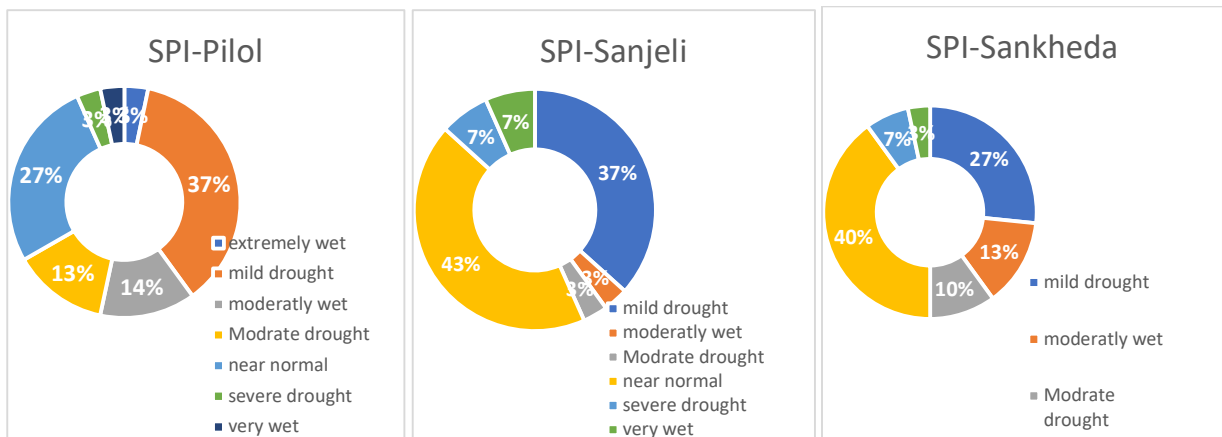
(c)



(d)

(e)

(f)



(g)

(h)

(i)

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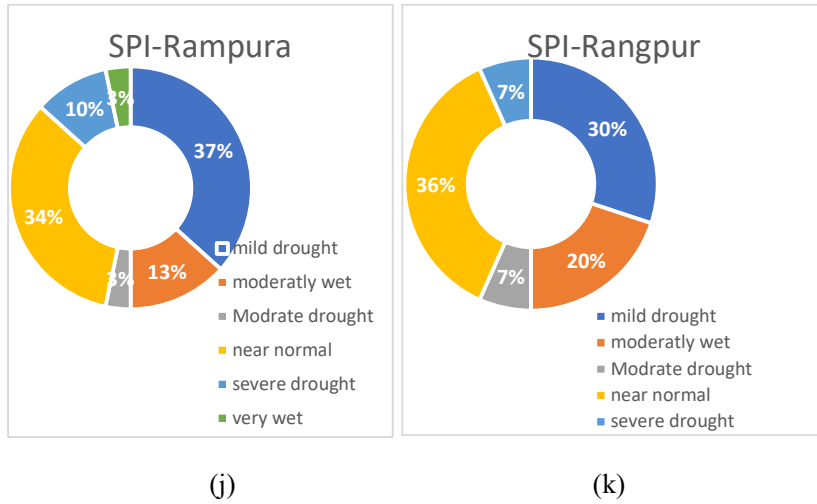


Fig. 2: (a-k) Percentage distribution of drought classifications (SPI) at individual meteorological stations in Vadodara district (1991–2021).

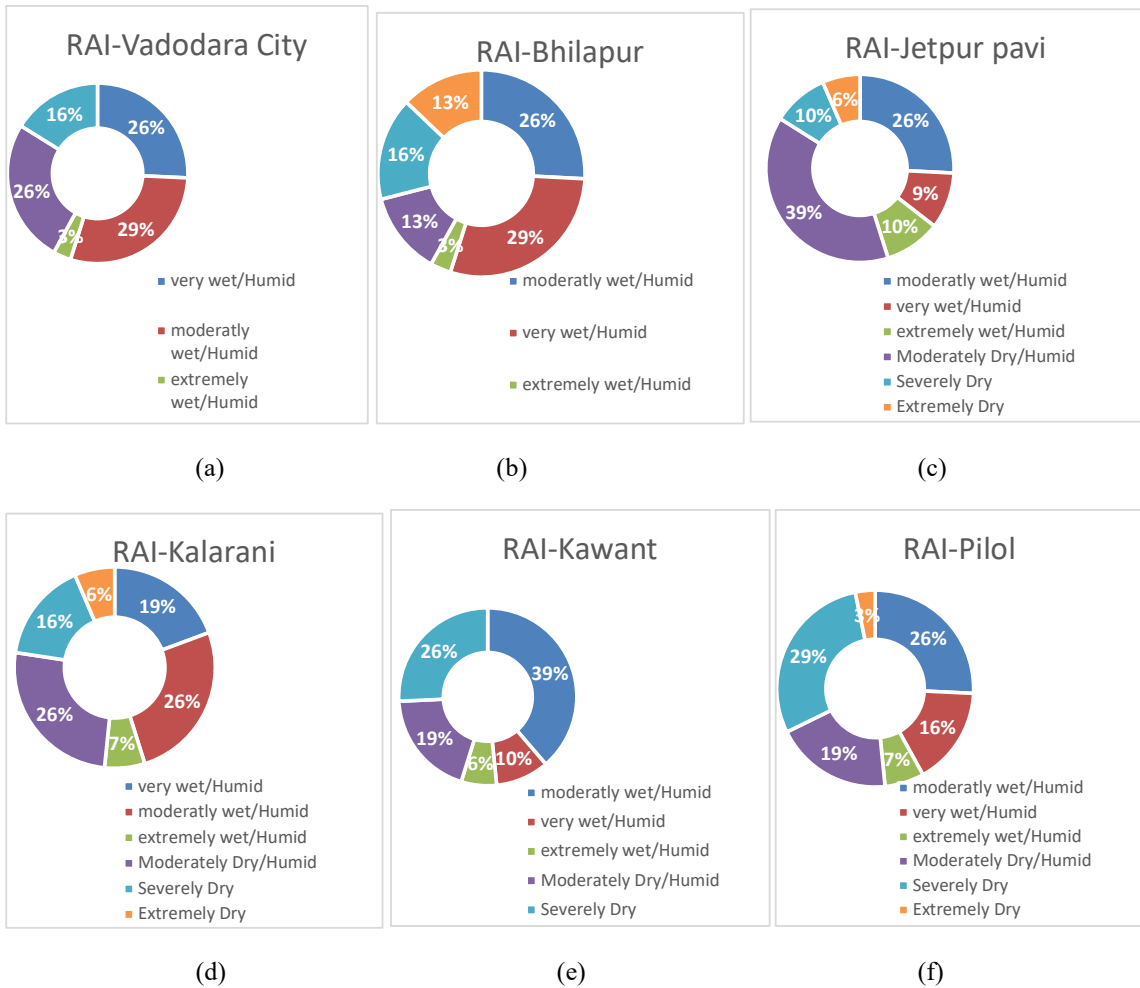


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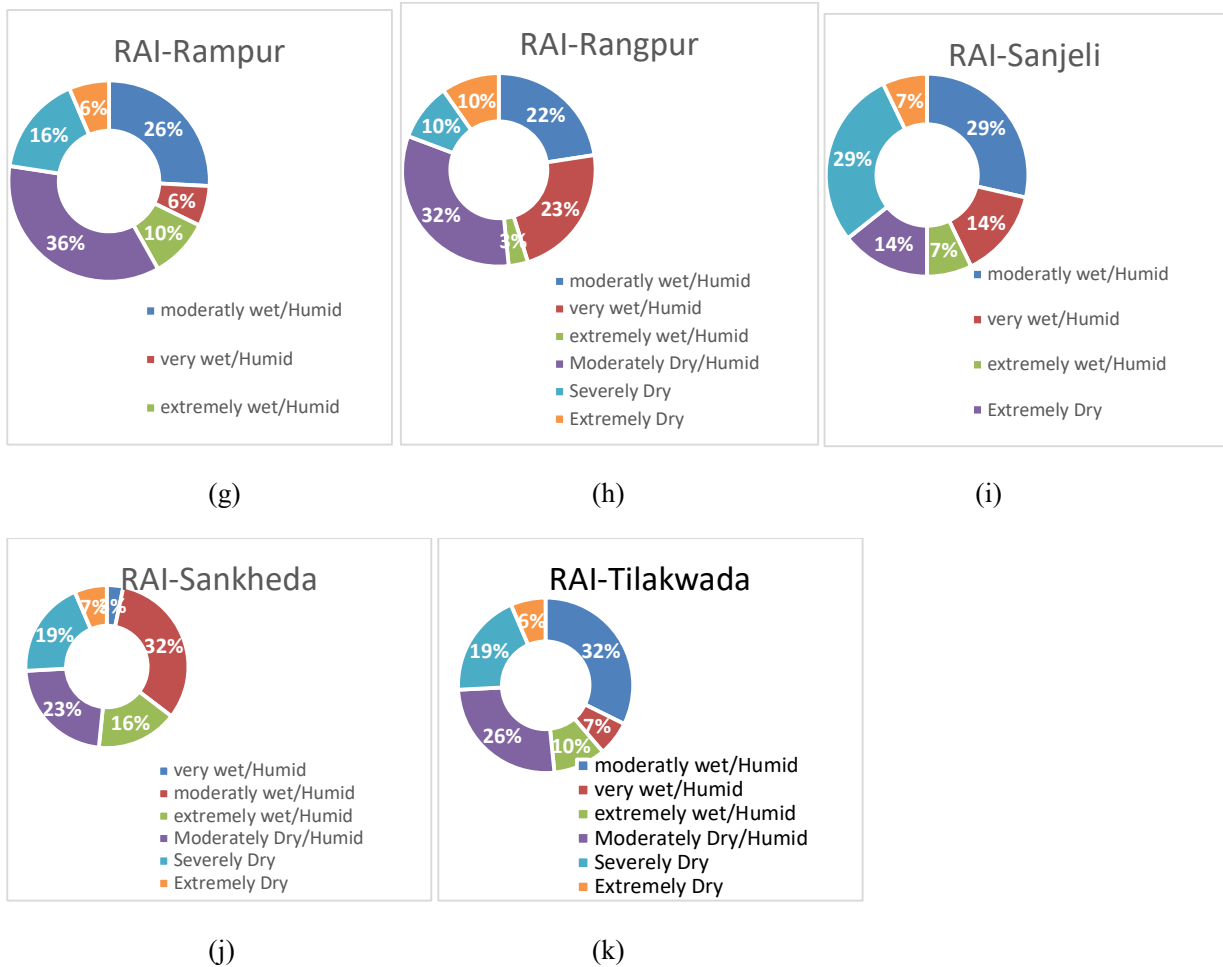


Fig. 3: (a-k) Percentage distribution of drought classifications (RAI) at individual meteorological stations in Vadodara district (1991–2021).

In 1996-97, the SPI and RAI indicated “extremely wet” conditions at over 70% of the stations, particularly at Tilakwada, Kalarani, and Kawat (Fig. 4). These years likely corresponded to strong monsoon events or large-scale climatic drivers, such as ENSO or the Indian Ocean Dipole, which affected rainfall patterns. The spatial variation in drought frequency and intensity is illustrated in Figs. 2 and 3, showing station-wise drought occurrence identified by SPI and RAI, respectively. A higher frequency of droughts was observed at Rampura, Rangpur, Jetpur-Pavi, and Pilol, particularly during the 1995-2010 period. Table 3 illustrates the spatio-temporal variation of drought conditions in Vadodara District using SPI and RAI indices from 1991 to 2021.

These regions may experience lower mean annual rainfall or elevated evapotranspiration, making them prone to agricultural and hydrological droughts. In contrast, Tilakwada, Sankheda, and Kawat recorded more wet years,

especially under the RAI, as shown in Fig. 6(b). For example, RAI showed “very wet” to “extremely wet” conditions in 2003-04 and 2013-14, while SPI still indicated “mild drought” or “near normal.” This suggests that the RAI is more sensitive to short-term rainfall anomalies, particularly those influenced by local topography, in orographically active areas such as Sankheda.

The comparative performances of the SPI and RAI highlight both the consistency and disparity in drought classification. The SPI, a standardized probabilistic index, effectively captures long-term drought accumulation, whereas the RAI responds quickly to short-term rainfall deviations, introducing greater variability. As shown in Fig. 5, this divergence is evident in years such as 2003-04, 2013-14, and 2019-20, when SPI classified conditions as “near normal” or “mild drought,” but RAI indicated “extremely wet” conditions.

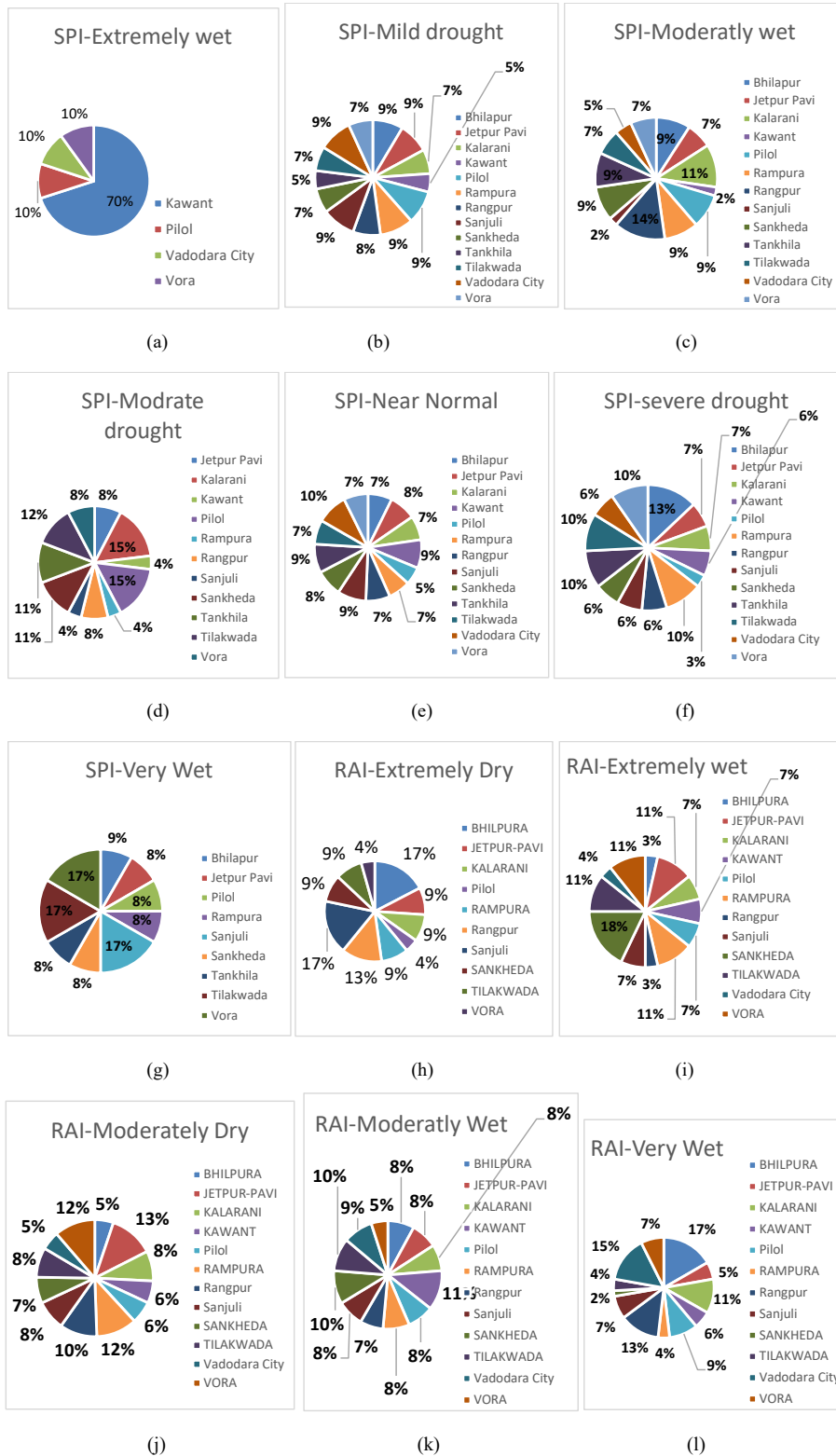


Fig. 4: (a-l) Percentage annual classification of meteorological drought using SPI and RAI Indices across Vadodara District (1991–2021).

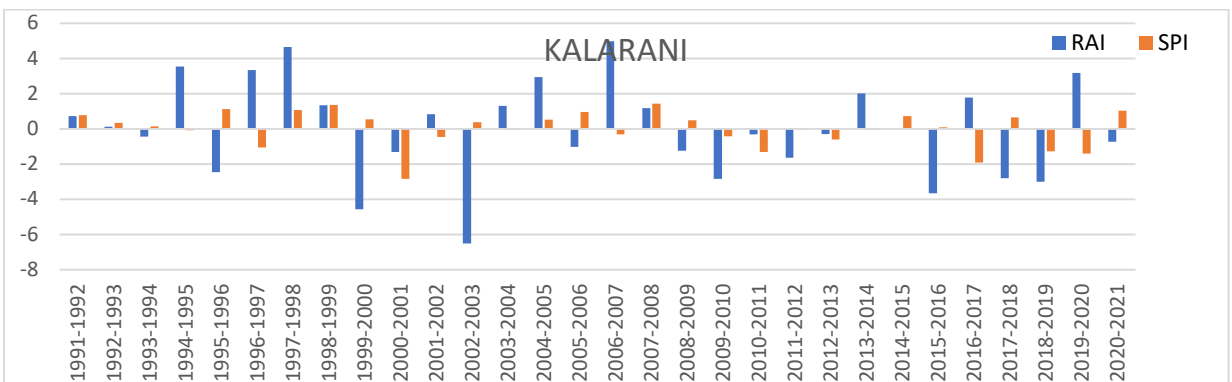
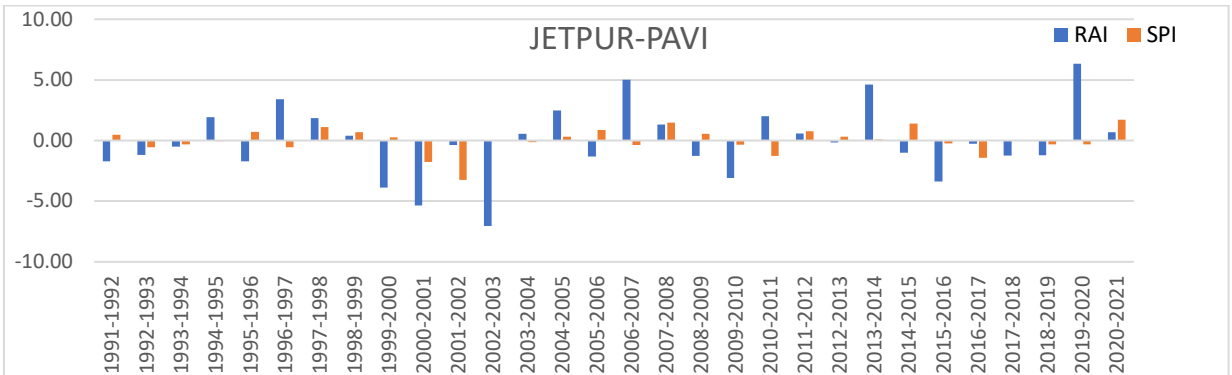
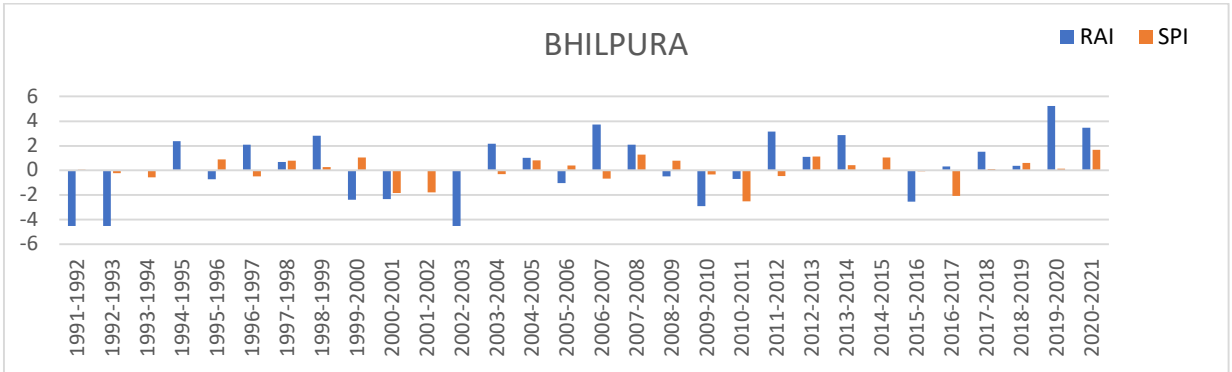
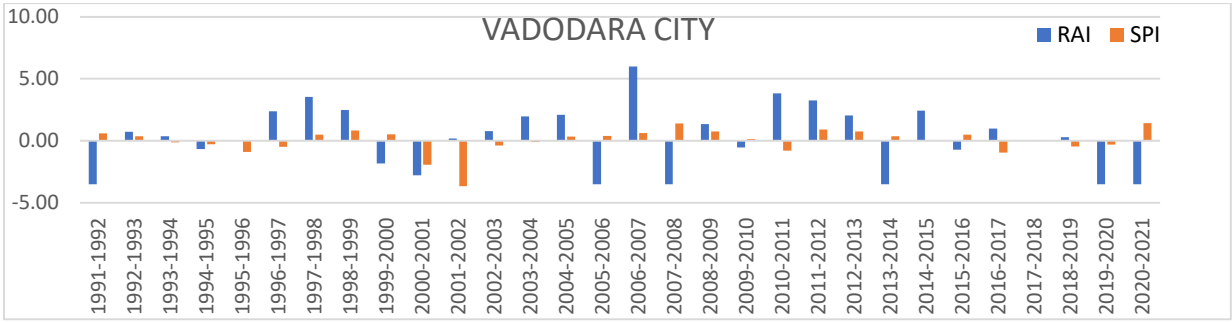


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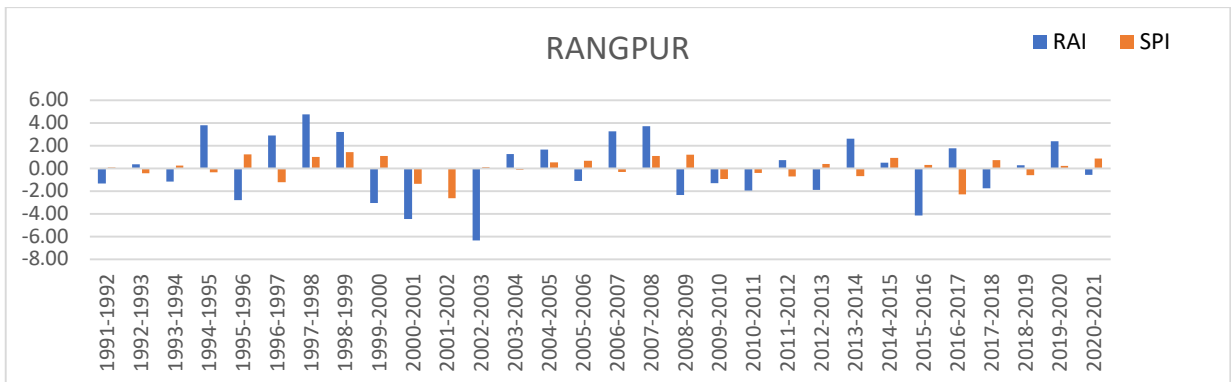
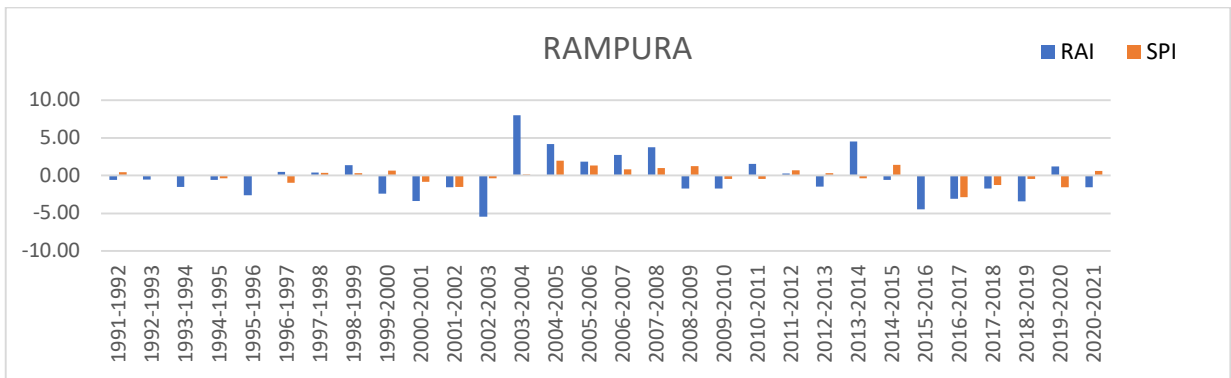
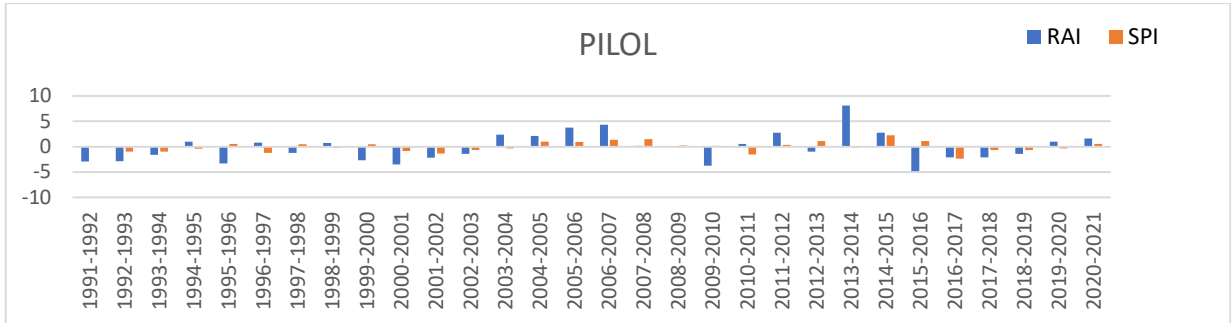
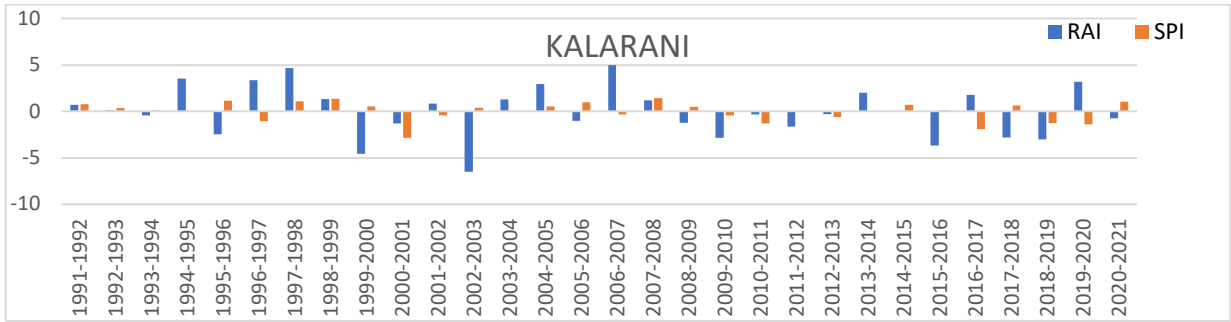


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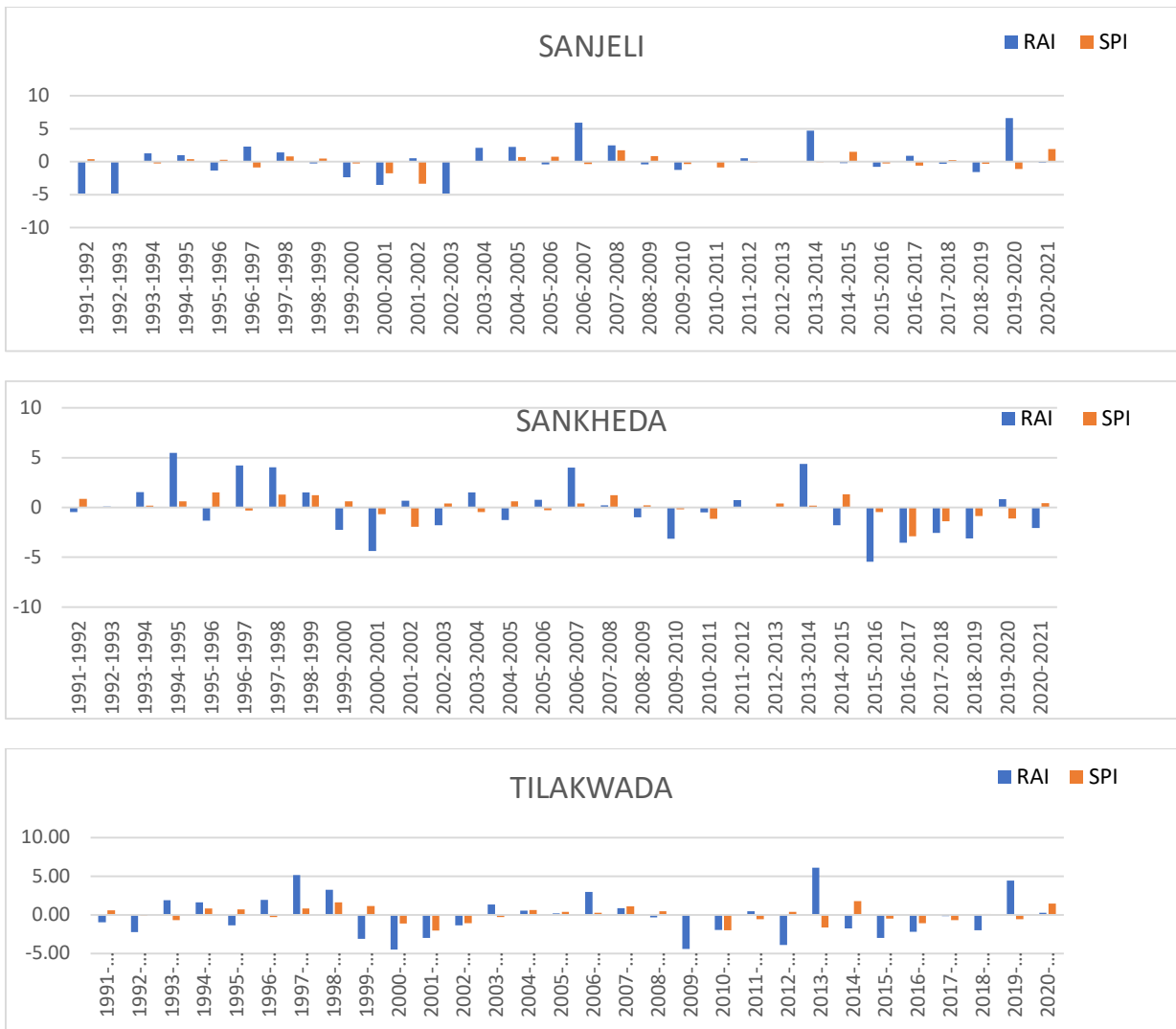


Fig. 5: Comparison between SPI and RAI for different scales.

The combined use of both indices is therefore advantageous. While the SPI provides a stable long-term perspective, the RAI complements this with real-time anomaly detection, and together, they offer a comprehensive drought monitoring framework.

According to Table 4, Vadodara City experienced drought conditions (ranging from light to severe) in 14 out of 30 years, whereas Rampura and Jetpur-Pavi faced droughts in 16 to 18 years, highlighting their vulnerability. In contrast, Tilakwada and Sankheda experienced droughts in less than 10 years, with more than 12 wet years, indicating a relative hydrological advantage. The frequency analysis (Fig. 6) highlights the importance of incorporating site-specific drought histories into localized water management planning.

To evaluate station-wise consistency in SPI and RAI drought classifications, a comparative assessment was conducted using the classification of drought, wet, and normal years (Table 4). The agreement percentage was calculated as the number of years with matching classification between SPI and RAI divided by the total years observed, shown in Fig. 7.

The analysis revealed a moderate level of agreement.

- The highest agreement (50%) was observed at Pilol and Rampura, indicating that half the years were consistently classified under both indices, possibly owing to more stable local rainfall patterns.
- Jetpur-Pavi, Kalarani, Sanjeli, and Tilakwada showed 46.67% agreement, signifying substantial yet partial

Table 3: Spatio-temporal drought classification using SPI and RAI Indices across Vadodara District (1991–2021).

YEAR	VADODARA CITY		BHILPURA		JETPUR-PAVI		KALARANI		KAWAT		PILOL		RAMPURA		RANGPUR		SANJELI		SANKHEDA		TILAKWADA		
	SPI	RAI	SPI	RAI	SPI	RAI	SPI	RAI	SPI	RAI	SPI	RAI	SPI	RAI	SPI	RAI	SPI	RAI	SPI	RAI	SPI	RAI	
1991-1992	NN	SD	NN	SD	NN	SD	NN	SD	NN	SD	NN	SD	NN	SD	NN	SD	NN	SD	NN	SD	NN	MD	
1992-1993	NN	NN	MD	SD	MD	MOD	SD	MOD	SD	MOD	SD	MOD	SD	MD	MD	NN	SD	NN	SD	NN	SD	SD	
1993-1994	MD	NN	MD	NN	MD	MD	NN	MD	NN	MD	SD	SD	NN	SD	NN	MOD	MD	MW	NN	VW	MD	VW	
1994-1995	MD	MD	MD	EW	MD	VW	MD	EW	MD	NN	MD	MW	MD	MD	MD	EW	NN	MW	NN	EW	NN	VW	
1995-1996	MD	MD	NN	MD	NN	SD	MW	SD	NN	MD	NN	SD	MD	SD	MW	SD	NN	MOD	VW	MOD	NN	MOD	
1996-1997	MD	EW	MD	EW	MD	EW	MOD	EW	MD	EW	MOD	NN	MD	NN	MOD	EW	MD	EW	MD	EW	MD	VW	
1997-1998	NN	EW	NN	NN	NN	VW	MW	EW	NN	EW	NN	MOD	NN	NN	MW	EW	NN	MW	MW	EW	NN	EW	
1998-1999	NN	EW	NN	EW	NN	NN	MW	MW	NN	VW	MD	NN	NN	NN	MW	EW	NN	MD	MW	VW	VW	EW	
1999-2000	NN	SD	MW	SD	NN	SD	NN	SD	NN	SD	NN	SD	NN	SD	MW	SD	MD	SD	NN	SD	MW	SD	
2000-2001	SD	SD	SD	SD	SD	SD	MOD	MOD	SD	SD	MOD	SD	MD	SD	MOD	SD	SD	SD	MD	SD	MOD	SD	
2001-2002	SD	NN	SD	NN	SD	MD	MD	NN	SD	VW	MOD	SD	SD	SD	MD	MD	SD	NN	SD	NN	SD	SD	
2002-2003	MD	NN	MD	SD	NN	SD	NN	SD	NN	SD	MOD	MD	MD	SD	NN	SD	NN	SD	NN	SD	SD	MOD	
2003-2004	MD	VW	MD	EW	MD	NN	MD	MW	NN	VW	MD	EW	NN	EW	MD	MW	NN	EW	MD	VW	MD	MW	
2004-2005	NN	EW	NN	EW	NN	EW	NN	EW	NN	EW	MW	EW	VW	EW	NN	VW	NN	EW	NN	MOD	NN	NN	
2005-2006	NN	SD	NN	MOD	NN	MOD	NN	MOD	NN	VW	NN	EW	MW	VW	NN	MOD	NN	MD	MD	NN	NN	NN	
2006-2007	NN	EW	MD	EW	MD	EW	NN	EW	NN	EW	MW	EW	NN	EW	MD	EW	MD	EW	NN	EW	NN	EW	
2007-2008	MW	SD	MW	EW	MW	MW	MW	MW	SD	SD	VW	NN	MW	EW	MW	EW	VW	EW	MW	NN	MW	NN	
2008-2009	NN	MW	NN	MD	NN	MOD	NN	MOD	EW	NN	NN	NN	MW	SD	MW	SD	NN	MD	NN	MD	NN	MD	
2009-2010	NN	MD	MD	SD	MD	SD	NN	SD	NN	SD	NN	SD	MD	SD	MD	MOD	MD	MOD	MD	SD	NN	SD	
2010-2011	MD	EW	SD	MD	MOD	EW	MOD	MD	EW	NN	MOD	NN	MD	VW	MD	SD	MD	NN	MOD	MD	SD	SD	
2011-2012	NN	EW	MD	EW	NN	NN	MD	SD	MD	SD	NN	EW	NN	NN	MD	NN	MD	NN	MD	NN	MD	NN	
2012-2013	NN	EW	MW	MW	NN	MD	MD	MD	SD	SD	MW	MD	NN	MOD	NN	SD	NN	NN	NN	NN	NN	SD	
2013-2014	NN	SD	NN	EW	NN	EW	MD	EW	SD	SD	MD	EW	MD	EW	MD	EW	MD	EW	NN	EW	SD	EW	
2014-2015	EW	EW	MW	MD	MW	MD	NN	NN	EW	SD	EW	EW	MW	MD	NN	NN	MW	MD	MW	SD	VW	SD	
2015-2016	NN	MD	MD	SD	MD	SD	EW	SD	EW	SD	MW	SD	NN	SD	NN	SD	MD	MD	MD	SD	MD	SD	
2016-2017	MD	NN	SD	NN	MOD	MD	SD	VW	EW	MW	SD	SD	SD	SD	VW	VW	MD	NN	SD	SD	MOD	SD	
2017-2018	MD	NN	MD	NN	NN	MOD	NN	SD	NN	NN	MD	SD	MOD	SD	NN	SD	NN	MD	MOD	SD	MD	MD	
2018-2019	MD	NN	NN	NN	MD	MOD	SD	NN	MD	MD	MD	MOD	MD	SD	NN	MD	SD	MD	SD	MD	SD	NN	SD
2019-2020	MD	SD	NN	EW	MD	EW	MOD	EW	MD	EW	MD	NN	SD	MW	NN	EW	MOD	EW	MOD	NN	MD	EW	
2020-2021	MW	SD	VW	EW	VW	NN	MW	MD	EW	MW	NN	VW	NN	SD	NN	MD	VW	MD	NN	SD	MW	NN	

NN= Nearly Normal, MD=Mild Drought, MOD= Moderately Drought, SD=Severe Drought, MW=Moderately Wet, VW=Very Wet, EW=Extremely Wet

Table 4: Comparison of drought, wet, and normal year counts and Index agreement by station.

Station's	SPI			RAI			Agreement	Agreement
	Drought Years	Wet Years	Normal Years	Drought Years	Wet Years	Normal Years	Years	%
Vadodara City	13	3	14	12	11	7	12	40.00
Bhilpura	14	5	11	12	13	5	12	40.00
Jetpur-Pavi	14	4	12	17	9	4	14	46.67
Kalarani	14	5	11	15	11	4	14	46.67
Kawat	9	8	13	14	11	5	9	30.00
Pilol	16	6	8	15	9	6	15	50.00
Rampura	15	5	10	18	9	3	15	50.00
Rangpur	13	6	11	15	11	4	13	43.33
Sanjeli	14	3	13	15	10	5	14	46.67
Sankheda	13	5	12	15	8	7	13	43.33
Tilakwada	14	5	11	16	9	5	14	46.67

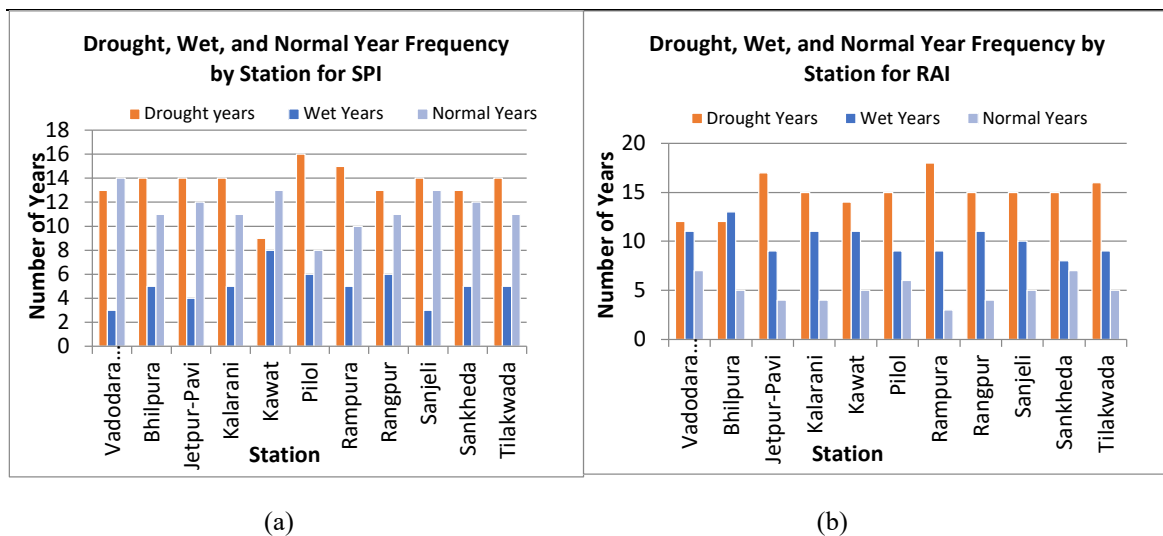


Fig. 6: (a) & (b) Drought, wet and normal year frequency by station for SPI and RAI.

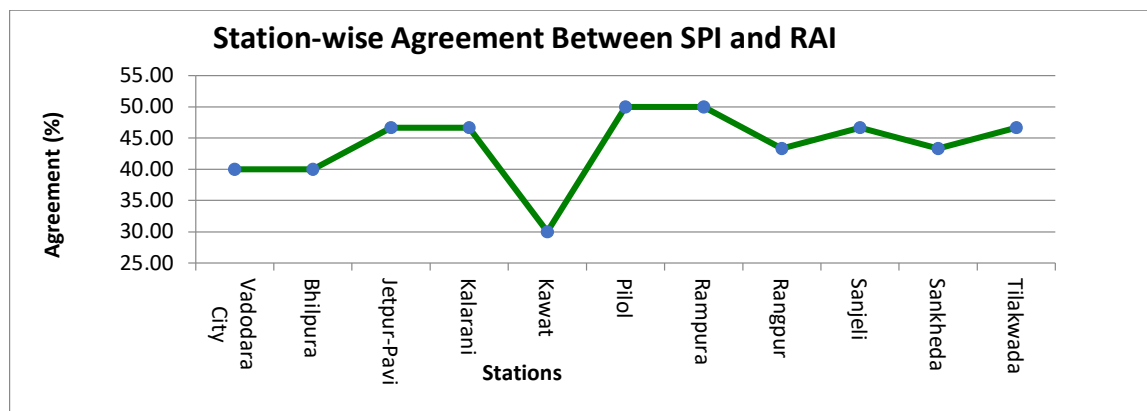


Fig. 7: Station-wise agreement between SPI and RAI.

overlap between SPI and RAI, supporting their joint usage.

- Rangpur and Sankheda followed with 43.33% agreement, and Vadodara City and Bhilpura had only 40% agreement, potentially due to localized rainfall variation.
- The lowest agreement (30%) was found at Kawat, reflecting significant divergence, likely influenced by SPI's multi-time-scale sensitivity of the SPI versus RAI's reliance of the RAI on monthly anomalies.

## CONCLUSIONS

A comparative analysis of drought classification using the Standardized Precipitation Index (SPI) and Rainfall Anomaly Index (RAI) across 11 stations in Vadodara District from 1991 to 2021 revealed important insights into the spatial and temporal variability of drought assessment methodologies. This study quantified drought, wet, and normal years based on both indices and calculated the percentage agreement in drought classification to assess the consistency between SPI and RAI. The results indicated moderate overall agreement, with agreement percentages ranging from 30% to 50% across stations. Stations such as Pilol and Rampura showed the highest agreement (50%), suggesting stronger coherence between the SPI and RAI, potentially due to stable rainfall regimes. In contrast, Kawat exhibited the lowest agreement (30%), indicating significant discrepancies likely caused by local variability or the differing sensitivities of the indices. The SPI, a standardized index that accounts for the temporal distribution of rainfall, sometimes diverged from the RAI, which is more sensitive to long-term averages. This divergence underscores the limitations of single-index drought monitoring and emphasizes the necessity of multi-index approaches for a more accurate and holistic understanding of drought patterns in the region. Furthermore, wet and normal year classifications varied considerably between the two indices, particularly at stations with high rainfall variability. This variation highlights that station-level climatic and topographic differences significantly influence drought detection performance and that regional calibration or hybrid methodologies may be necessary for enhanced accuracy.

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