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

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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 like Gujarat, India. A precise assessment of drought is critical for early warning, mitigation planning, and sustainable management of water resources. This study evaluates annual meteorological drought in Vadodara district over a 30-year period (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 for the classification of drought, wet, and normal years according to the indices. Spatio-temporal concordance analysis was done to analyze the congruence of SPI and RAI in describing drought occurrence. Results indicated a moderate agreement among the indices with consistency of 30% at Kawat to 50% at Pilol and Rampura. Such differences mirror the effect of localized climatic and topographic factors along with methodological differences between RAI and SPI. Although both are useful for detecting drought, their partial agreement highlights the significance of a multi-index approach for increasing the reliability of drought monitoring. The results help improve knowledge of index performance and inform the construction of more reliable regional drought early warning systems and water resource management.

INTRODUCTION

Drought represents one of 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, driven by insufficient precipitation, excessive evapotranspiration, unsustainable water use, or a combination of these factors (Gond et al. 2023). The multifaceted nature of drought means 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, while agricultural scientists define it in terms of soil moisture deficits that impair crop growth. Economists may assess drought through its socioeconomic repercussions, such as food insecurity and economic losses, whereas urban populations experience it as severe water shortages and supply disruptions (Rosalia et al. 2021).

Globally, drought is classified into three major types meteorological, hydrological, and agricultural each with distinct indicators and implications. Meteorological drought, the most fundamental type, is defined by prolonged periods of below-average precipitation. Hydrological drought reflects the subsequent depletion of water resources in rivers, lakes, and aquifers, often lagging behind meteorological drought due to delayed hydrological responses. Agricultural drought, which directly affects food production, is determined by insufficient soil moisture to sustain crops, influenced by rainfall variability, evapotranspiration rates, and soil water-holding capacity. 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.

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 drought frequency, duration, and severity, particularly in regions already prone to water scarcity. For instance, rising temperatures exacerbate evapotranspiration rates, accelerating soil moisture depletion even in the absence of reduced rainfall. Compound extremes such as concurrent heatwaves and droughts further amplify water stress, posing greater risks to ecosystems and human systems. Consequently, drought indices that integrate both precipitation and temperature data are increasingly recognized as more 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 like RDI showed high prediction accuracy, SPI remained robust for long-term precipitation trends. SPI's adaptability across different climatic conditions makes it a reliable tool for monitoring drought in diverse environments. (Gonçalves et al. 2023) compared five drought indices, including SPI and RDI, in Brazil's semi-arid basins. Their analysis found SPI to be the most suitable for hydrological monitoring due to its effectiveness in identifying drought episodes and capturing drought duration and severity. Similarly, (Worku 2024) used SPI and SPEI to analyze spatiotemporal drought in Ethiopia's Borana region, highlighting SPI's utility in seasonal drought detection.

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

In Southeast Asia, (Nuryadi 2023) 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 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 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 SPI due to its statistical standardization and ability to assess drought across multiple temporal scales.

A few studies integrate remote sensing with SPI. (Sirisena et al. 2022) used SPI along with NDVI and soil moisture data in the Narmada Basin, India, to assess agricultural drought. SPI's integration 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 current study adds a novel dimension by conducting a spatio-temporal 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 works that typically focus on a single index or larger regional scales, this study simultaneously evaluates 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 reveal partial agreement between the indices, with values ranging from 30% to 50%. Pilol and Rampura stations showed the highest agreement, while Kawat had the lowest. These discrepancies are attributed to methodological differences; SPI standardizes rainfall over time, while RAI simply classifies anomalies. The spatial variability of agreement highlights the influence of local topography and rainfall distribution on index performance.

2. STUDY AREA AND DATA COLLECTION:

The present study is conducted in Vadodara district, located in the state of Gujarat, India. Covering an area of approximately 7,794 km², Vadodara is the third-largest city in the state and lies between latitudes 21°49'N to 22°49'N and longitudes 72°05'E to 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 about 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 also 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 and relevant case for such studies. For the present analysis, daily rainfall data along with maximum and minimum temperature were collected from the State Data Water Centre, Gandhinagar, and the Meteorological Department of Anand Agricultural University, Anand, covering 11 different stations across the Vadodara district over a 30-year period (1991-2021). Missing records were estimated using the Inverse Distance Weighting (IDW) method and the Simple Arithmetic Average method. Furthermore, trend analysis of the hydro-climatic variables was carried out using the non-parametric Mann–Kendall test and Sen’s slope estimator.

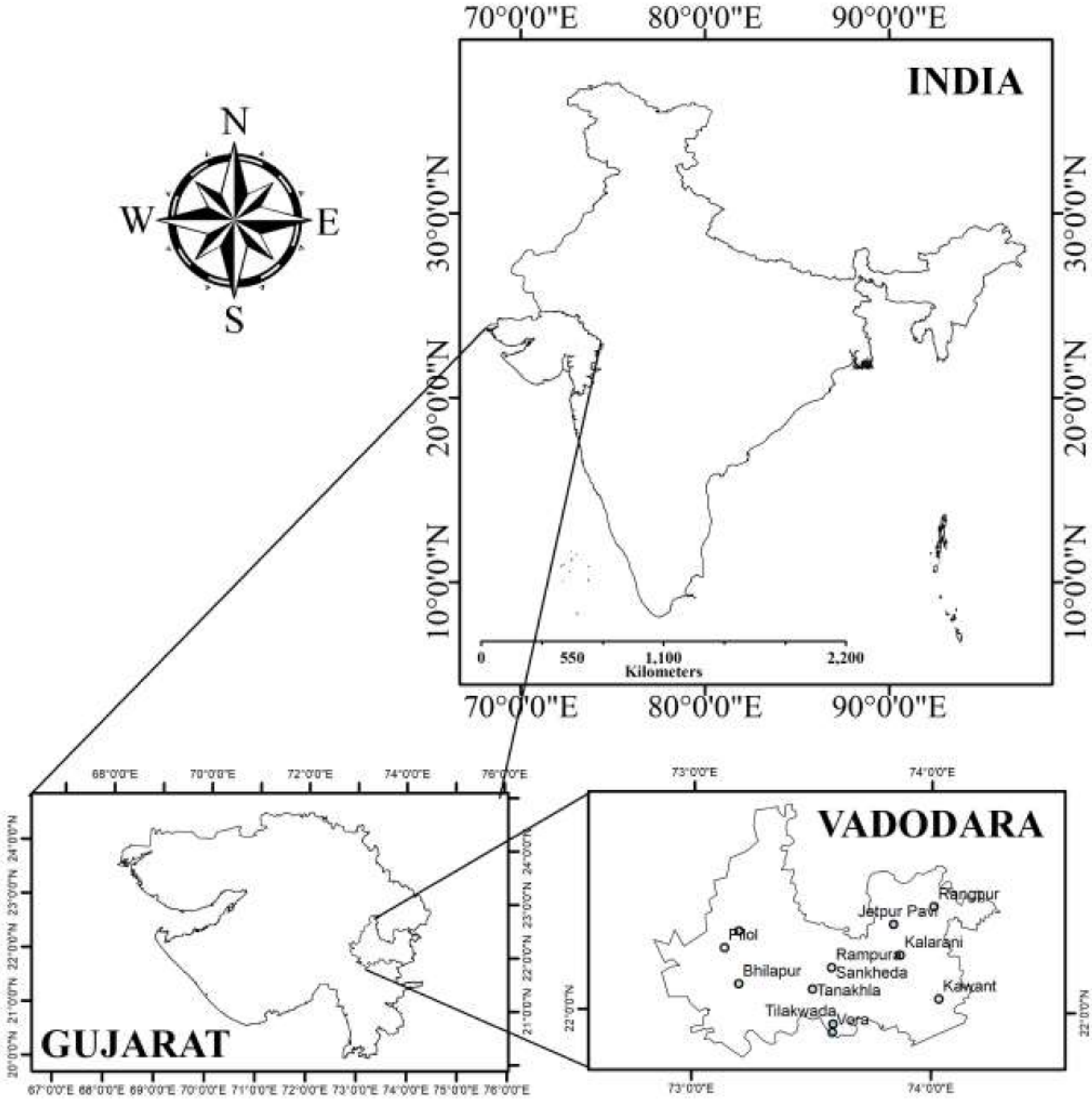


Fig.1: Study area map of Vadodara district

3. MATERIALS AND METHODS

3.1. Standardized Precipitation Index (SPI)

The SPI, developed by McKee et al. (1993), is a widely used drought index that quantifies precipitation deficits across different time scales. In this study, SPI was calculated at 3-, 6-, 9-, and 12-month timescales to capture both short-term and long-term drought conditions.

The computation of SPI involves the following steps:

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

$$\boldsymbol{SPI} = \frac{X_{ij}-\bar{X}}{\sigma} \qquad \ldots(1)$$

Where, $\boldsymbol{X_{ij}}$= precipitation at ith rain gauge and jth observation, $\boldsymbol{\bar{X}}$ = long term seasonal mean

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

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

3.2. 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 the precipitation anomaly against the historical range of extreme rainfall events.

Where:

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

$$RAI = 3\left[\frac{N-\bar{N}}{\bar{X}-\bar{N}}\right], for\ negative\ anormalies \qquad \ldots(3)$$

RAI values typically range from -3 (extremely dry) to +3 (extremely wet), categorizing precipitation irregularities into 10 defined intervals.

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

Source: Freitas(2005) adapted by Araujo et al. (2009)

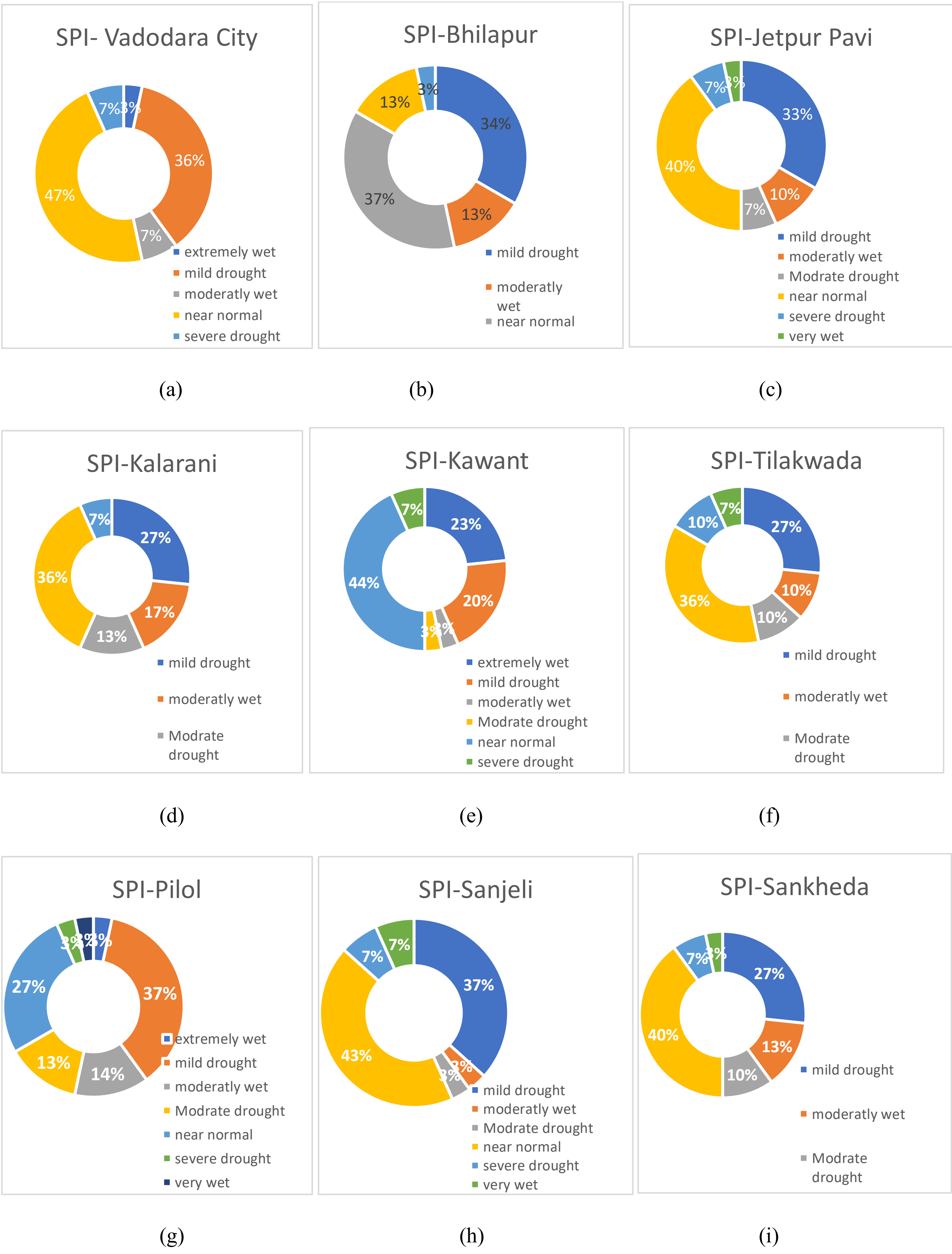
To evaluate station-wise consistency in SPI and RAI drought classifications, a comparative assessment was conducted using the classification of drought, wet, and normal years (Table 4). The agreement percentage was calculated as the number of years with matching classification between SPI and RAI divided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

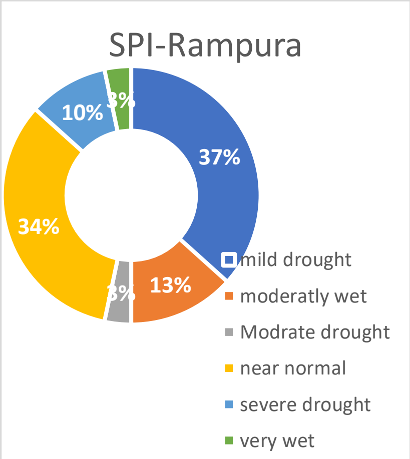
4. RESULTS AND DISCUSSION

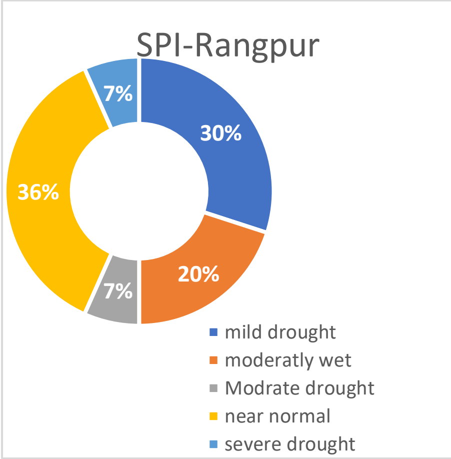
The 30-year drought appraisal of Vadodara district based on the Standardized Precipitation Index (SPI) and Rainfall Anomaly Index (RAI) offers essential insights into the spatial and temporal variability of drought patterns. Comparative classification for the years 1991–2021 across 11 stations—Vadodara City, Bhilpura, Jetpur-Pavi, Kalarani, Kawat, Pilol, Rampura, Rangpur, Sanjeli, Sankheda, and Tilakwada—reflects high hydrometeorological contrasts due to localized climatic differences.

Years like 2000–01, 2001–02, and 2009–10 were marked by extensive and severe drought conditions. As shown in Figure 4, both 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 SPI providing 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 the 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 Vadodara district in both SPI and RAI. In contrast, 2000–01 and 2001–02 occurred during 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 feedbacks. The divergence in drivers emphasizes that while El Niño events provide a clear mechanism for monsoon weakening, many severe droughts arise from a complex interplay between global teleconnections and regional climatic variability.

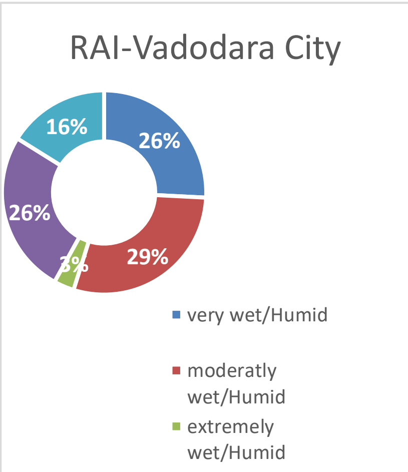

SPI- Vadodara City
36%
47%
7%
7%
3%
extremely wet
mild drought
moderatly wet
near normal
severe drought
(a)
SPI-Bhilapur
34%
13%
37%
13%
3%
mild drought
moderatly wet
near normal
(b)
SPI-Jetpur Pavi
33%
10%
7%
40%
7%
3%
mild drought
moderatly wet
Modrate drought
near normal
severe drought
very wet
(c)
SPI-Kalarani
27%
17%
13%
36%
7%
mild drought
moderatly wet
Modrate drought
(d)
SPI-Kawant
23%
20%
44%
7%
extremely wet
mild drought
moderatly wet
Modrate drought
near normal
severe drought
(e)
SPI-Tilakwada
27%
10%
10%
36%
10%
7%
mild drought
moderatly wet
Modrate drought
(f)
SPI-Pilol
37%
14%
13%
27%
extremely wet
mild drought
moderatly wet
Modrate drought
near normal
severe drought
very wet
(g)
SPI-Sanjeli
37%
43%
7%
7%
mild drought
moderatly wet
Modrate drought
near normal
severe drought
very wet
(h)
SPI-Sankheda
27%
13%
10%
40%
7%
3%
mild drought
moderatly wet
Modrate drought
(i)

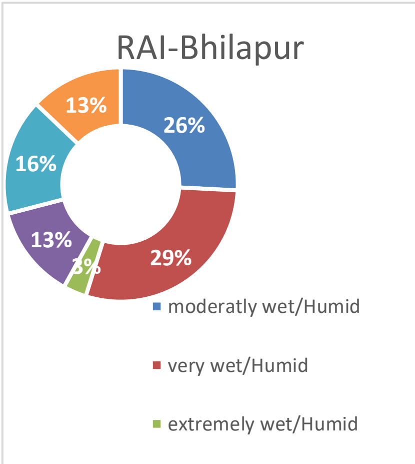


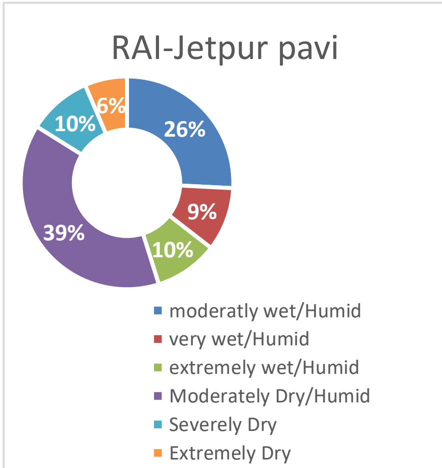


(j) (k)

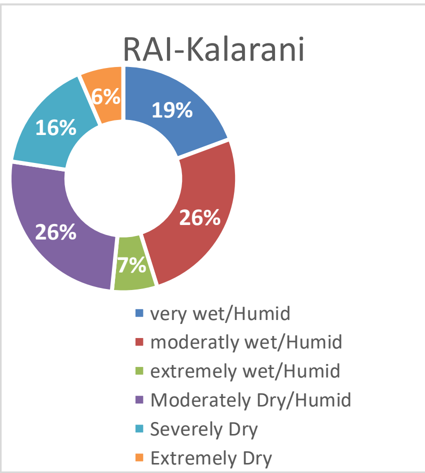
Fig. 2: (a -k) Percentage distribution of drought classifications (SPI) at individual meteorological stations in Vadodara district (1991–2021)

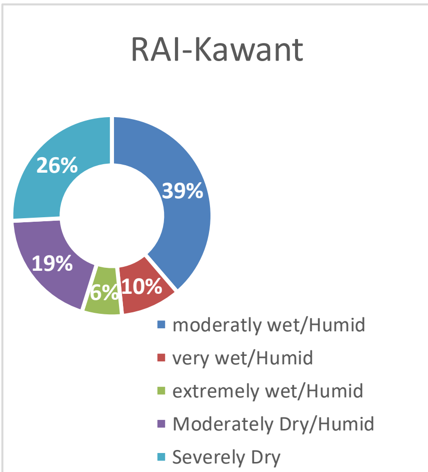


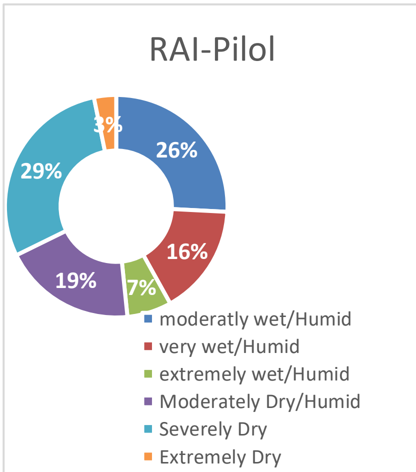




(a) (b) (c)







(d) (e) (f)

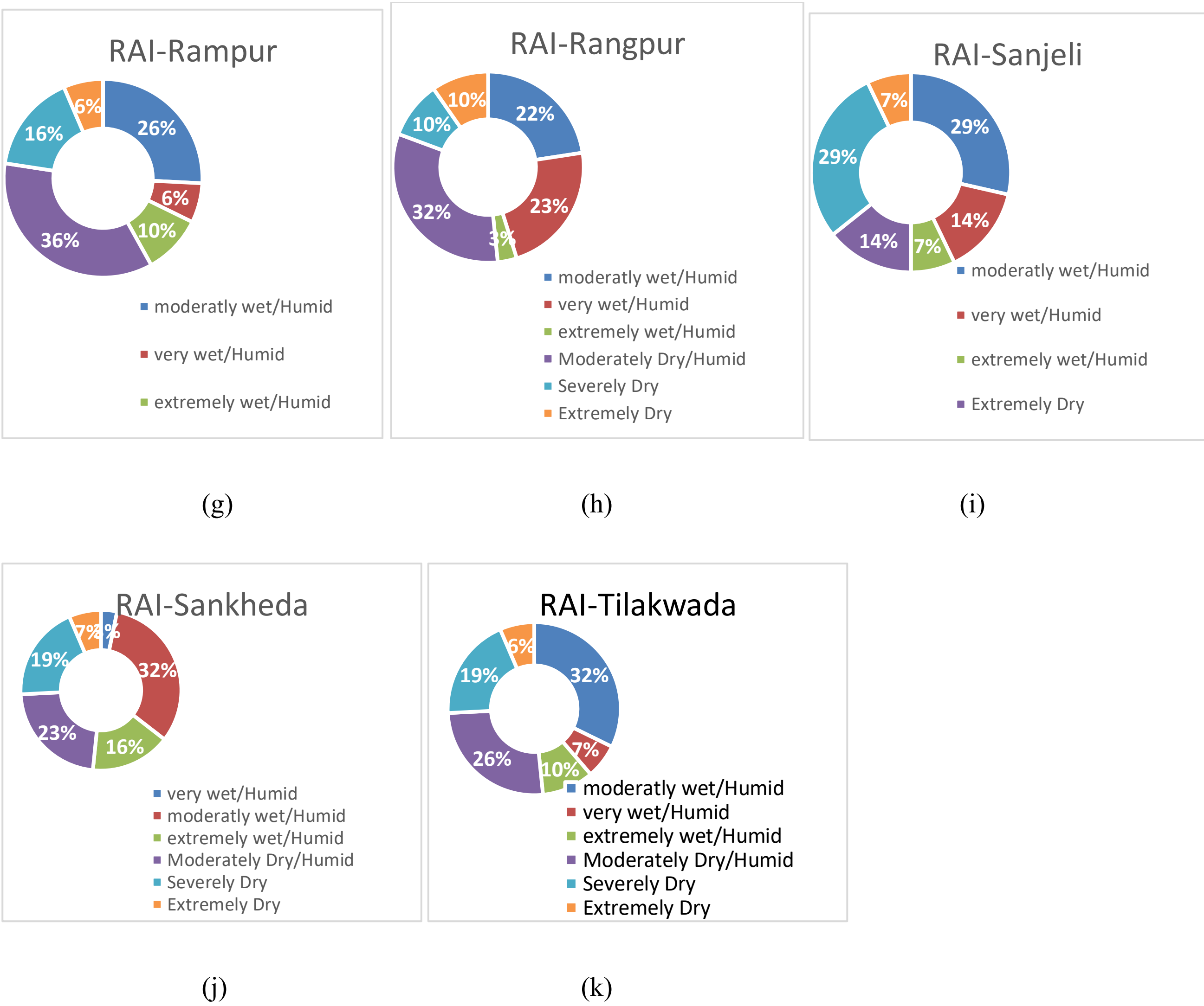
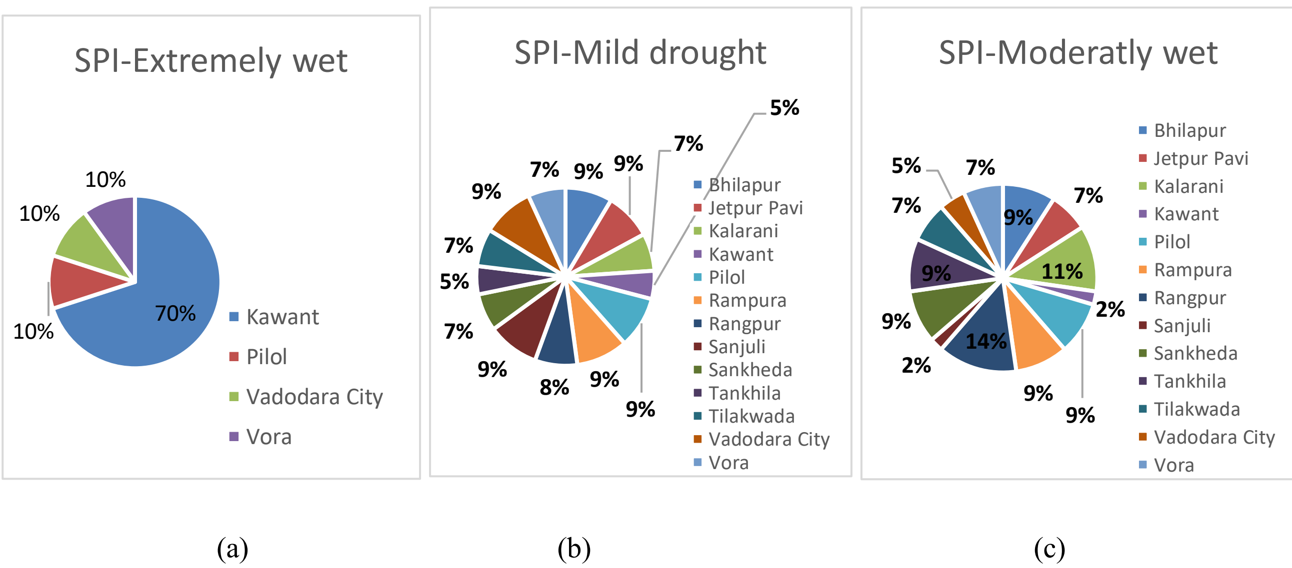
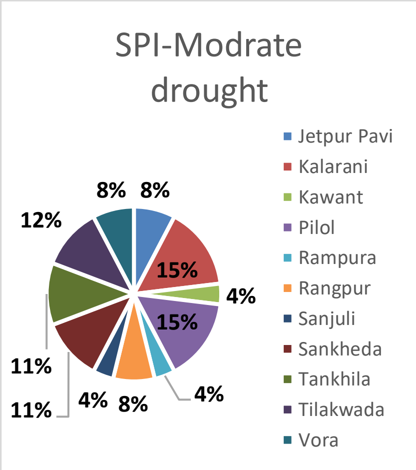
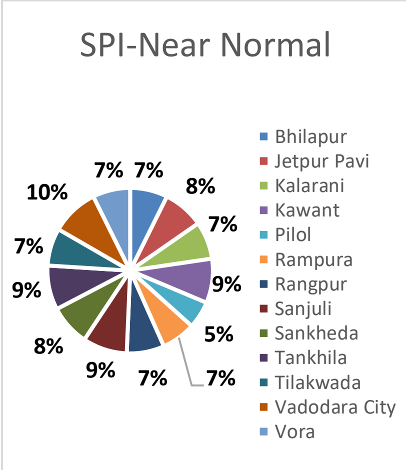


Fig. 3: (a-k) Percentage distribution of drought classifications (RAI) at individual meteorological stations in Vadodara district (1991–2021)

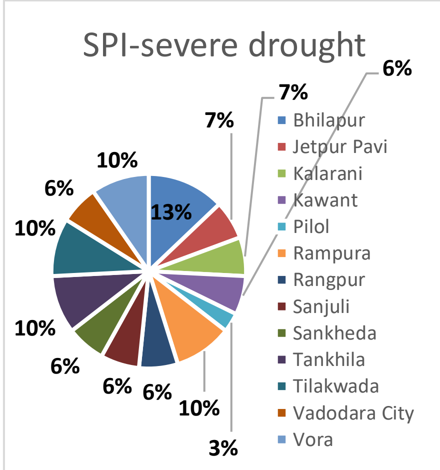



SPI-Modrate drought
Jetpur Pavi
Kalarani
Kawant
Pilol
Rampura
Rangpur
Sanjuli
Sankheda
Tankhila
Tilakwada
Vora
8% 8% 15% 4% 15% 4% 8% 4% 11% 11% 12%

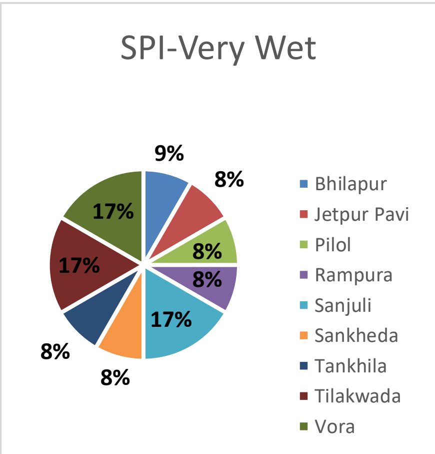
(d)


SPI-Near Normal
Bhilapur
Jetpur Pavi
Kalarani
Kawant
Pilol
Rampura
Rangpur
Sanjuli
Sankheda
Tankhila
Tilakwada
Vadodara City
Vora
7% 7% 8% 7% 9% 5% 7% 7% 9% 8% 9% 7% 10%

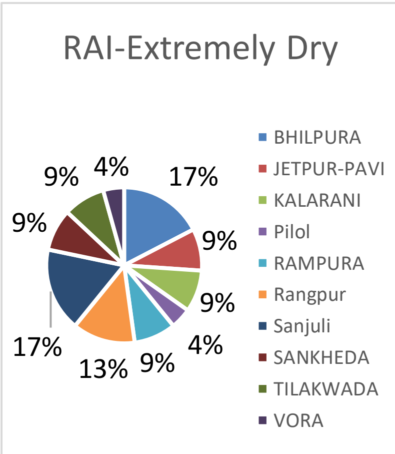
(e)


SPI-severe drought
Bhilapur
Jetpur Pavi
Kalarani
Kawant
Pilol
Rampura
Rangpur
Sanjuli
Sankheda
Tankhila
Tilakwada
Vadodara City
Vora
13% 7% 7% 6% 3% 10% 6% 6% 6% 10% 10% 6% 10%

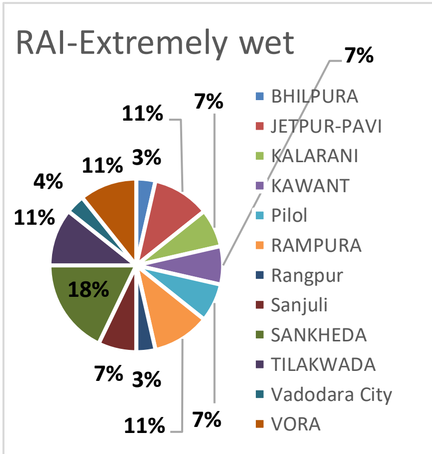
(f)


SPI-Very Wet
Bhilapur
Jetpur Pavi
Pilol
Rampura
Sanjuli
Sankheda
Tankhila
Tilakwada
Vora
9% 8% 8% 8% 17% 8% 8% 17% 17%

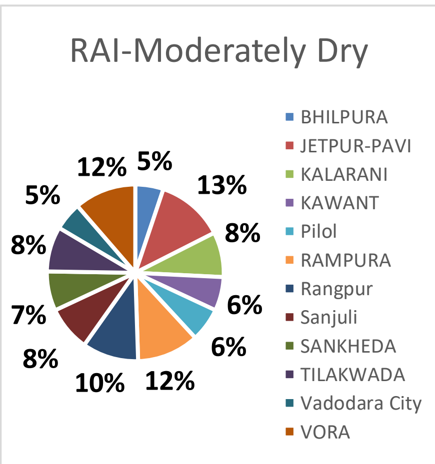
(g)


RAI-Extremely Dry
BHILPURA
JETPUR-PAVI
KALARANI
Pilol
RAMPURA
Rangpur
Sanjuli
SANKHEDA
TILAKWADA
VORA
17% 9% 9% 4% 9% 13% 17% 9% 9% 4%

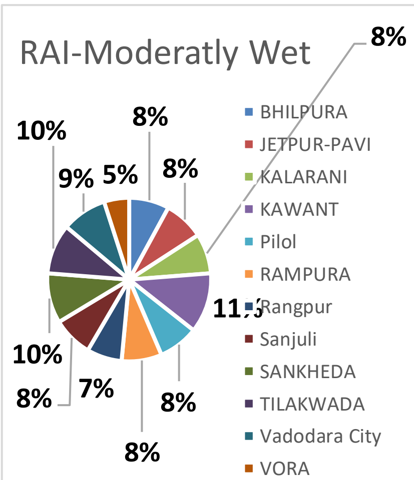
(h)


RAI-Extremely wet
BHILPURA
JETPUR-PAVI
KALARANI
KAWANT
Pilol
RAMPURA
Rangpur
Sanjuli
SANKHEDA
TILAKWADA
Vadodara City
VORA
3% 11% 7% 7% 7% 11% 3% 7% 18% 11% 4% 11%

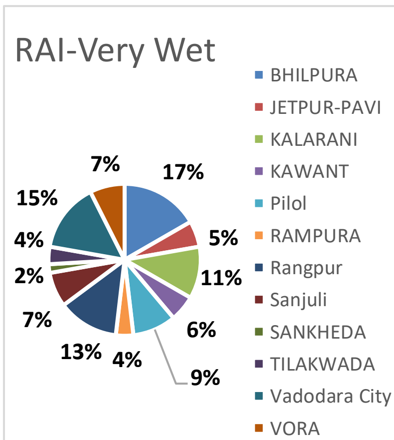
(i)


RAI-Moderately Dry
BHILPURA
JETPUR-PAVI
KALARANI
KAWANT
Pilol
RAMPURA
Rangpur
Sanjuli
SANKHEDA
TILAKWADA
Vadodara City
VORA
5% 13% 8% 6% 6% 12% 10% 8% 7% 8% 5% 12%

(j)


RAI-Moderatly Wet
BHILPURA
JETPUR-PAVI
KALARANI
KAWANT
Pilol
RAMPURA
Rangpur
Sanjuli
SANKHEDA
TILAKWADA
Vadodara City
VORA
8% 8% 8% 11% 8% 8% 7% 8% 10% 10% 9% 5%

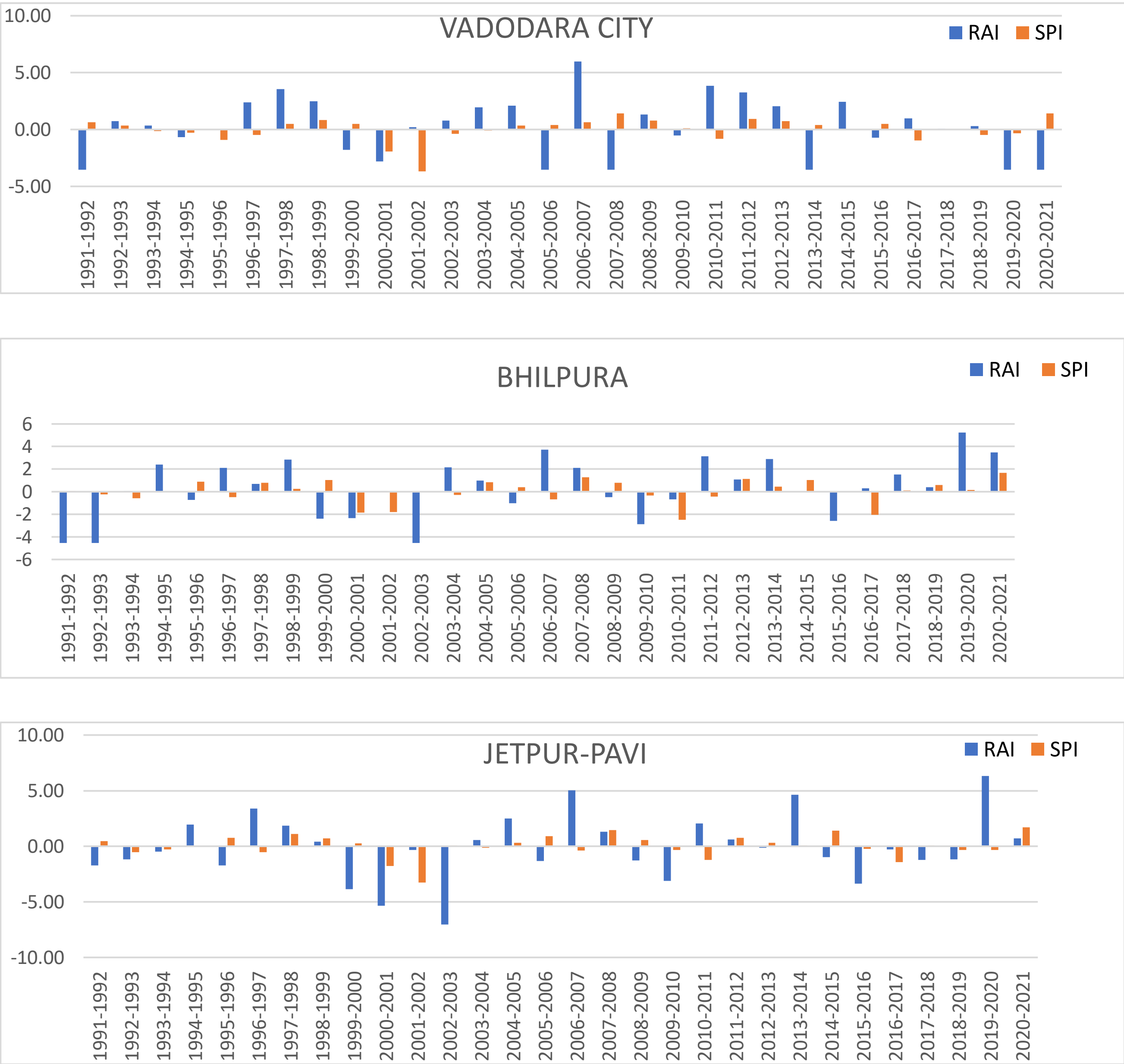
(k)

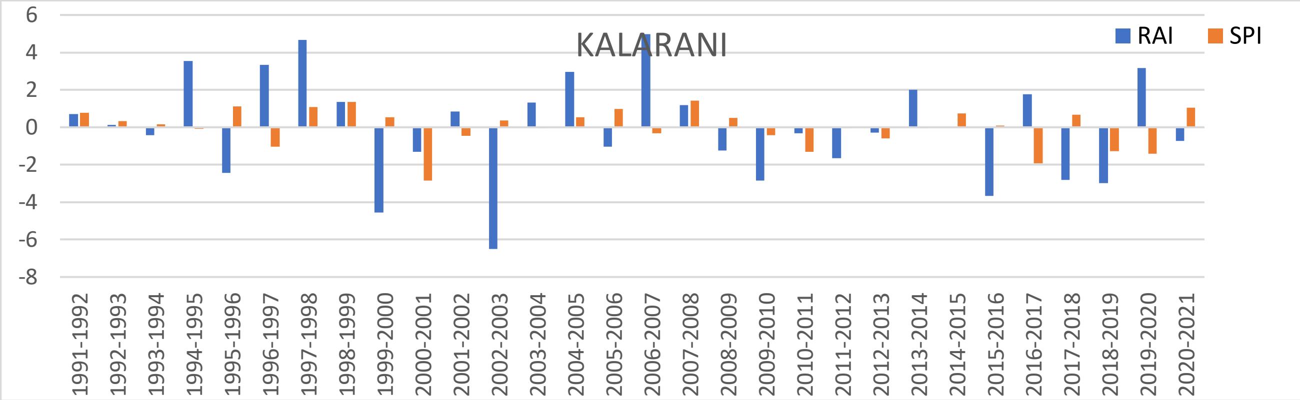

RAI-Very Wet
BHILPURA
JETPUR-PAVI
KALARANI
KAWANT
Pilol
RAMPURA
Rangpur
Sanjuli
SANKHEDA
TILAKWADA
Vadodara City
VORA
17% 5% 11% 6% 9% 4% 13% 7% 2% 4% 15% 7%

(l)

Fig. 4: (a-l) Percentage Annual Classification of Meteorological Drought Using SPI and RAI Indices Across Vadodara District (1991–2021)

On the contrary, years such as 1996–97, 2006–07, 2013–14, and 2014–15 recorded extremely wet to above-normal conditions. In 1996–97, SPI and RAI indicated “extremely wet” conditions at over 70% of stations, particularly at Tilakwada, Kalarani, and Kawat (Figure 4). These years likely corresponded to strong monsoon events or large-scale climatic drivers like ENSO or the Indian Ocean Dipole, affecting rainfall patterns. The spatial variation in drought frequency and intensity is illustrated in Figures 2 and 3, showing station-wise drought occurrence identified by SPI and RAI respectively. Higher frequency of drought was observed at Rampura, Rangpur, Jetpur-Pavi, and Pilol, particularly during the 1995–2010 period.




KALARANI
RAI
SPI
6
4
2
0
-2
-4
-6
-8
1991-1992
1992-1993
1993-1994
1994-1995
1995-1996
1996-1997
1997-1998
1998-1999
1999-2000
2000-2001
2001-2002
2002-2003
2003-2004
2004-2005
2005-2006
2006-2007
2007-2008
2008-2009
2009-2010
2010-2011
2011-2012
2012-2013
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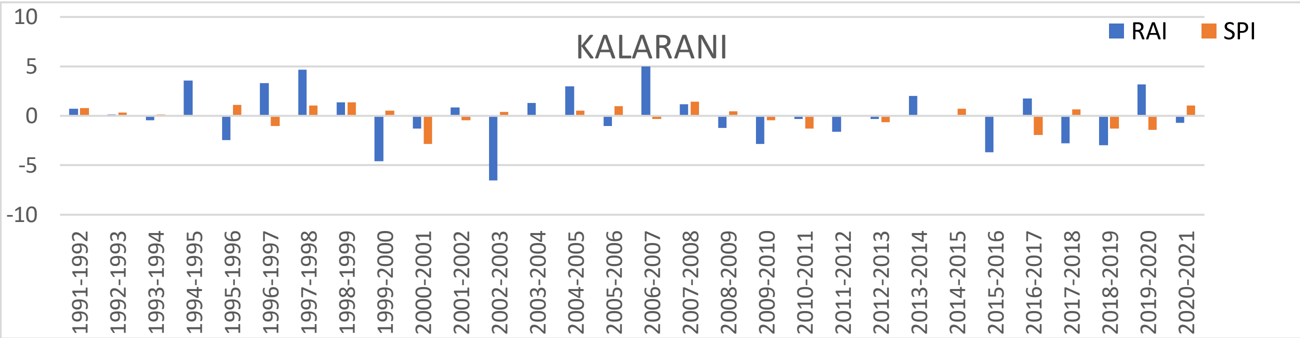
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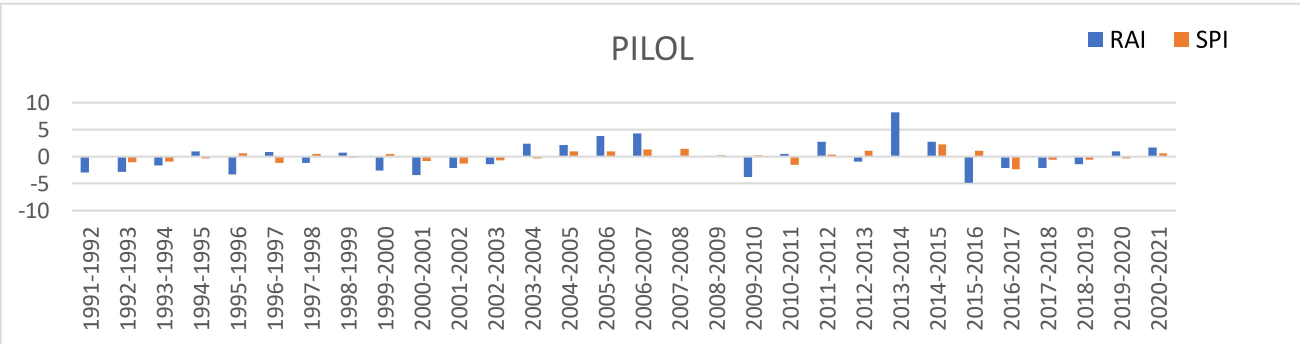
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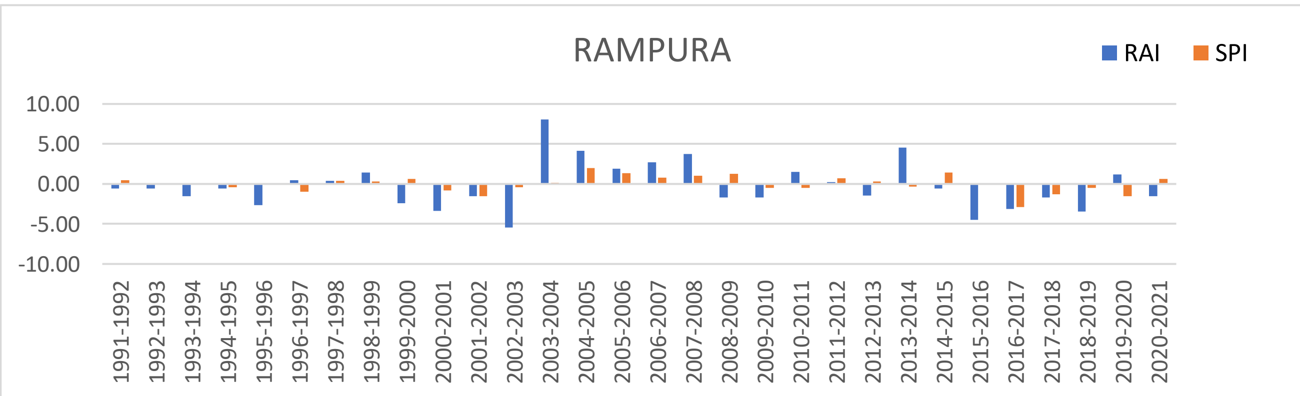
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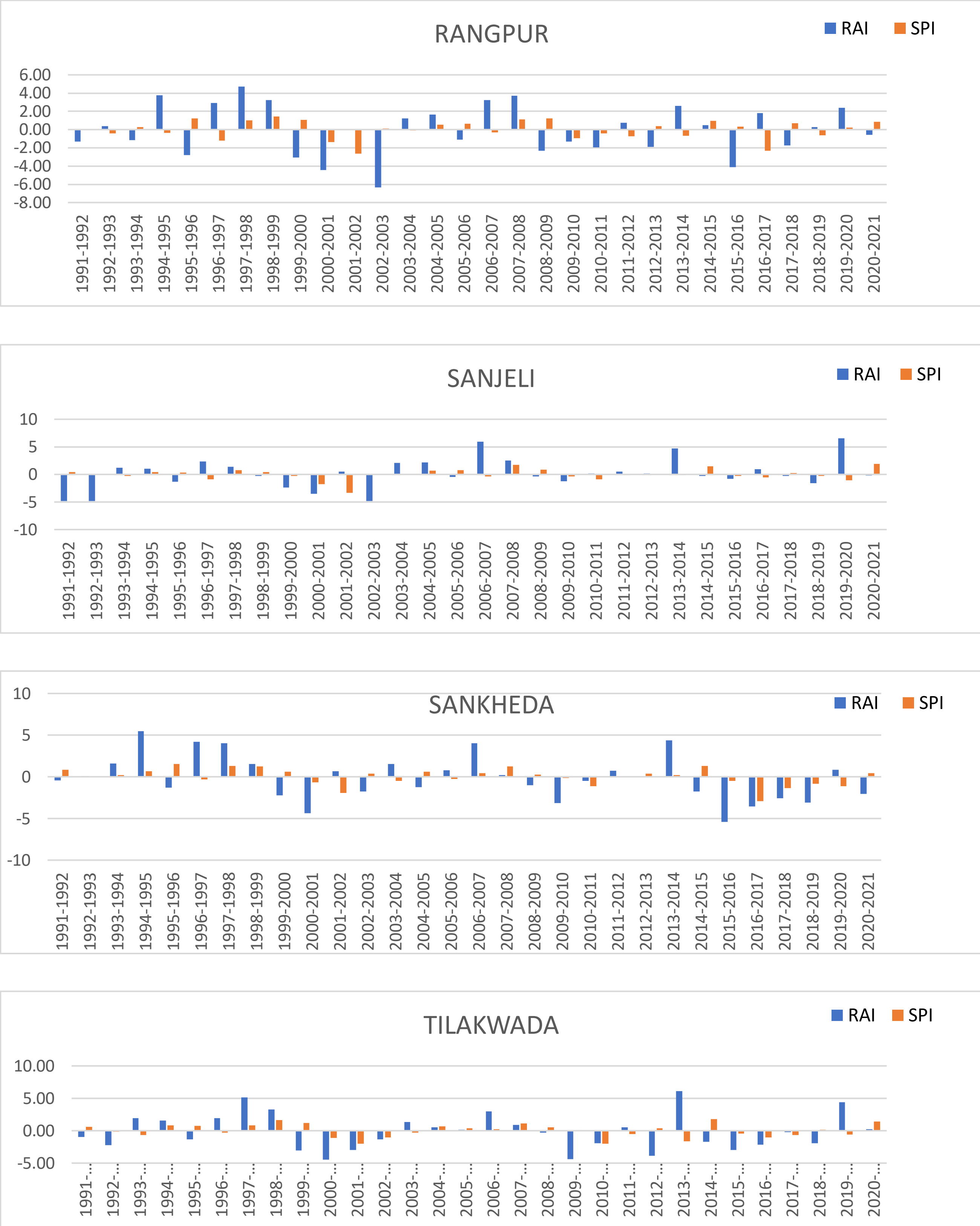


Fig. 5: Comparison between SPI and RAI for different scale

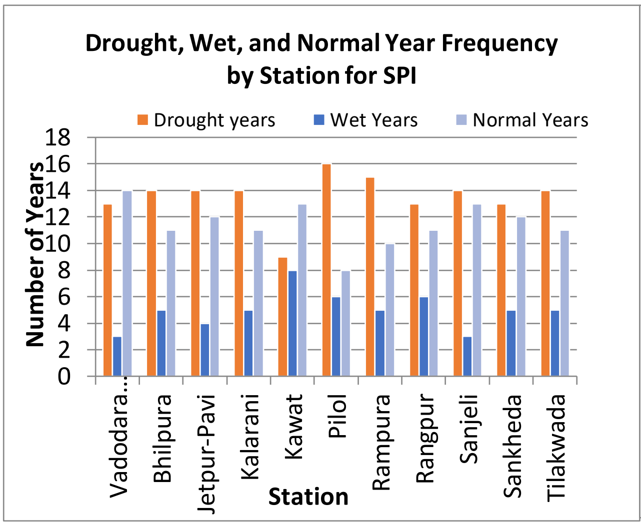
Table:3 Spatio-Temporal Drought Classification Using SPI and RAI Indices Across Vadodara District (1991–2021)

	VADODARA CITY		BHILPURA		JETPUR-PAVI		KALARANI		KAWAT		PILOL		RAMPURA		RANGPUR		SANJELI		SANKHEDA		TILAKWADA	
YEAR	**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	NN	NN	MD	MD	SD	NN	MD	NN	MOD	NN	SD	NN	MD	NN	MD
1992-1993	NN	NN	MD	SD	MD	MOD	NN	NN	MD	MD	MOD	SD	MD	MD	MD	NN	NN	SD	NN	NN	MD	SD
1993-1994	MD	NN	MD	NN	MD	MD	NN	MD	MD	NN	MD	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	MW	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	MW	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	SD	MOD	MOD	SD	MD	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	SD	MD	SD	NN	SD	NN	SD	SD
2002-2003	MD	NN	MD	SD	NN	SD	NN	SD	NN	SD	MD	MOD	MD	SD	NN	SD	NN	SD	NN	SD	MOD	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	MW	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	MD	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	MW	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	MD	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	EW	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	NN	SD	EW	SD	MW	SD	MD	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	SD	VW	MD	NN	SD	SD	MOD	SD
2017-2018	MD	NN	NN	VW	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	MOD	SD	NN	MD	MD	MOD	MD	SD	MD	NN	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

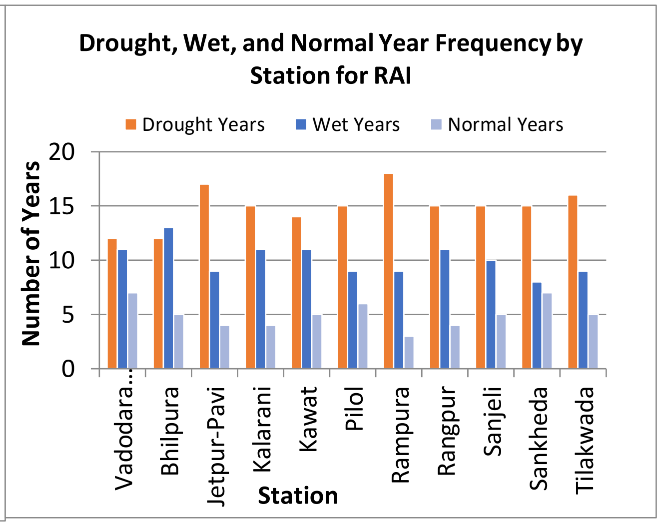
NN= Nearly Normal, MD=Mild Drought, MOD= Moderately Drought, SD=Severe Drought, MW=Moderately Wet, VW=Very Wet EW=Extremely Wet

Table 4: Comparison of Drought, Wet, and Normal Year Counts and Index Agreement by Station

	SPI			RAI			Agreement	Agreement
Station's	**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



(a)



(b)

Fig. 6 (a) & (b) Drought, Wet and Normal year frequency by station for SPI and RAI

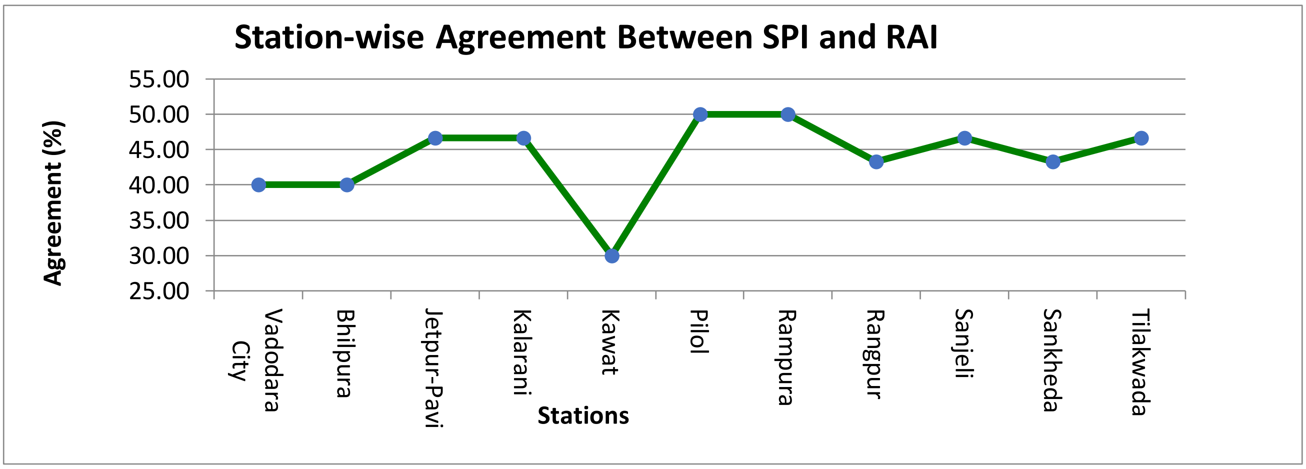


Fig.7 Station-wise agreement between SPI and RAI

These regions may experience lower mean annual rainfall or elevated evapotranspiration, making them prone to agricultural and hydrological drought. In contrast, Tilakwada, Sankheda, and Kawat recorded more wet years, especially under RAI, as seen in Figure 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 RAI’s higher sensitivity to short-term rainfall anomalies, particularly influenced by local topography in orographically active areas like Sankheda.

The comparative performance of SPI and RAI highlights both consistencies and disparities in drought classification. SPI, being a standardized probabilistic index, effectively captures long-term drought accumulation, while RAI responds quickly to short-term rainfall deviations, introducing greater variability. As shown in Figure 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.

The combined use of both indices is advantageous. While SPI provides a stable long-term perspective, 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 drought in 16 to 18 years, highlighting their vulnerability. In contrast, Tilakwada and Sankheda experienced drought in less than 10 years, with more than 12 wet years, indicating a relative hydrological advantage. The frequency analysis (Figure 6) underlines 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 Figure 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 classified consistently under both indices, possibly due to more stable local rainfall patterns.
- Jetpur-Pavi, Kalarani, Sanjeli, and Tilakwada showed 46.67% agreement, signifying substantial yet partial 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 variations.

- The lowest agreement (30%) was found at Kawat, reflecting significant divergence, likely influenced by SPI's multi-time-scale sensitivity versus RAI's reliance on monthly anomalies.

5. CONCLUSIONS

The comparative analysis of drought classification using Standardized Precipitation Index (SPI) and Rainfall Anomaly Index (RAI) across eleven stations in Vadodara district from 1991 to 2021 reveals important insights into the spatial and temporal variability of drought assessment methodologies. The 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. Results indicated a moderate agreement overall, with agreement percentages ranging from 30% to 50% across stations. Stations like Pilol and Rampura showed the highest agreement (50%), suggesting stronger coherence between 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 differing sensitivities of the indices. The SPI, being 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. Furthermore, wet and normal year classifications also varied considerably between the two indices, particularly in stations with high rainfall variability. The 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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Conflicts of Interest: The authors declare that they have no conflicts of interests

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