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An Integrated Geospatial Techniques and Drought Indices Approach for Assessing Drought Risk in Chitradurga Taluk, Karnataka, India

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Abstract

Drought poses a significant threat to water security, agriculture, and socio-economic stability in semi-arid regions like Chitradurga Taluk, Karnataka, India. This study integrates geospatial techniques and meteorological indices (SPI, NDVI, NDWI, LST) to assess drought risk from 2000 to 2020. Rainfall analysis reveals high variability, with stations like Bahadhurghatta recording extreme fluctuations (270.96 mm in 2010 to zero in subsequent years), while others (e.g., Holalkere) show stability (778.44 mm average). The SPI identifies severe droughts (e.g., 2019, SPI: -2.16) and wet extremes (2011, SPI: 2.00), correlating with agricultural stress. Vegetation health, accessed via NDVI and VCI, indicates severe stress in 2000 (NDVI: -0.3; VCI: 1 to 25) due to low rainfall and high land surface temperature (LST: 47°C), with recovery in 2015 to 2020 (NDVI: 0.41; VCI: 71 to143) as temperatures moderated (LST: 40 to 41°C). Hydrological conditions, evaluated through NDWI, show acute water scarcity in 2000 (NDWI: -0.41) and improved availability in 2015 (NDWI: 0.39). Spatiotemporal analysis highlights the interplay between meteorological deficits, thermal stress, and ecological responses, with geospatial mapping identifying high-risk zones for targeted mitigation. Machine learning and trend analysis further enhance drought prediction by linking drivers like groundwater depletion and land use changes. The study advocates for multi-index drought monitoring to improve early-warning systems and adaptive strategies, supporting sustainable development goals aligned water management. Findings offer a replicable framework for semi-arid regions globally, emphasizing integrated approaches to build resilience against climate extremes.

Keywords: *Drought, Geospatial, Drought Indices, Rainfall, Semi-arid region*

Introduction

Drought is a complex, persistent climatic extreme that undermines water security, agricultural production and socio-economic stability, especially in semi-arid regions such as the Chitradurga Taluk, Karnataka, India (Pradeep et al. 2022; Talukdar and Ali, 2022; Wilhite et al., 2014; Mishra and Singh, 2010). Drought is defined as a natural hazard with long-lasting pattern of precipitation deficits aggravated by climate change (IPCC, 2021; Dogan et al., 2012), Its risk assessment long-term approach requires, combined to represent the multiple consequences, technique which integrate geospatial technologies and meteorological indices (Tarate et al., 2024; Chowdary and Kesarwani, 2023; Hayes et al., 2011; Zargar et al., 2011). Many researchers have recommended geospatial techniques such as geographic information systems (GIS), remote sensing (RS) and global navigation satellite system (GNSS) are efficient in significant drought monitoring and analysis (Das et al., 2021; Palchaudhuri and Biswas, 2020; Hegde and Patil, 2019; Basavaraj Hutti and Nijagunappa, 2012, 2011; Kogan, 1995; Tucker, 1979; Palmer, 1965) animal stress on vegetation NDVI, land surface temperature (LST), and soil moisture (SM) provide accurate spatial-temporal patterns (Zhao et al., 2016; Zhang et al., 2016). Frequently many researchers are used drought severity indices contain the standardized precipitation index (SPI), standardized precipitation evapotranspiration index (SPEI) and palmer drought severity index (PDSI) (Sridhara et al., 2021; Tan et al., 2015; Sruthi et al., 2015; Sumanta et al., 2013; Vicente-Serrano et al., 2010; McKee et al., 1993; Palmer, 1965), but their use in conjunction with geospatial data on the spatial dimension of drought is not yet widespread in semi-arid India (Thomas et al., 2016). The rain-shadow area Chitradurga Taluk is located in the middle of the Karnataka state is prone to drought and, accountable to inconsistent monsoon activities with extreme groundwater withdrawal and land degradation (IMD, 2020; NRSA, 2019; CGWB, 2018), warranting advanced assessment frameworks for these risks.

Earlier studies demonstrate that the integration of satellite-derived indices (e.g., MODIS NDVI, NDWI, Landsat LST) with ground-based meteorological products can provide information to improve drought early-warning systems (Agha Kouchak et al., 2015; Jain et al., 2020). However, large inconsistency remains in region on both sides of implementations in particular connecting with drought indices to socio-economic susceptibility and land use alterations (UNDRR, 2019; Turner et al., 2007). This study aims to fill these gaps by providing an integrated approach that combines multi-sensor RS data (Landsat 8 OLI, Sentinel-2), GIS based spatial analytics and drought indices (SPI, SPEI) to derive drought risk at the micro-watershed scales (Jain et al., 2020). The methods involves using machine learning algorithms (Random Forest, SVM) to find drought drivers (Ganguli & Reddy, 2014) and the Mann-Kendall test (Mann, 1945; Kendall, 1975) of trend, providing an applicable model for semi-arid areas worldwide. Make use of the drought intensity and crop yield data (UNCCD, 2022; FAO, 2021) and groundwater levels (from GSDA, 2020), this study offers actionable insights for policymakers to preference irrigation investments and execute to improve the water management approach (Beithou et al., 2022; World Bank, 2018; NWP, 2012). The research study also initiates a new arrangement to assess the drought impact based on target objective from the sustainable development goals in 2030. The study appearance associations with sustainable development goals (UN, 2015) and provide for the environmental robust planning growing literature (Mall et al., 2021; Huggi et al., 2020; Kavy et al., 2006).

The Study Area

The study area is in the Chitradurga district of Karnataka, India, specifically in Chitradurga Taluk, which covers an area of about 1,388 km^2 between latitudes 14°00' to 15°00' N and longitudes 76°00' to 77°00' E. It has a semi-arid climate, with erratic pattern of an average annual 600 mm rainfall predominantly from the southwest monsoon (June–September) so that it is prone to recurrent droughts (Singh et al., 2004). The terrain is mostly undulating, rocky, and characterized by shallow, poor soils, as it belongs to the Deccan Plateau's arid zone, limiting the ability of the soil to retain moisture, and thus agricultural productivity. The primary land utilization patterns comprise non-irrigated farming (predominantly sorghum, millet varieties, and legumes), sparse woodland areas, and unproductive terrain. Limited irrigation is available from water bodies such as the Vanivilas Sagar reservoir and subterranean water resources. In the context of geological studies, the presence of granite and gneiss formations plays a crucial role in determining the replenishment and accessibility of underground water resources within the region. These rock types significantly influence the processes of groundwater recharge and its subsequent availability in the area under consideration. The region's flora primarily consists of drought-tolerant species, including spiny shrubs and deciduous trees adapted to arid conditions. The area exhibits diverse soil compositions, ranging from reddish sandy loams to dark clay-rich soils, each possessing distinct water retention properties and agricultural suitability (Shankar et al., 2017). These variations in soil characteristics influence the potential for different crop cultivations across the landscape (Kavy et al., 2006). Chitradurga, an area historically vulnerable to extreme weather events such as drought has been facing the severe consequences of acute drought exacerbated due to effects of climate variability, over-

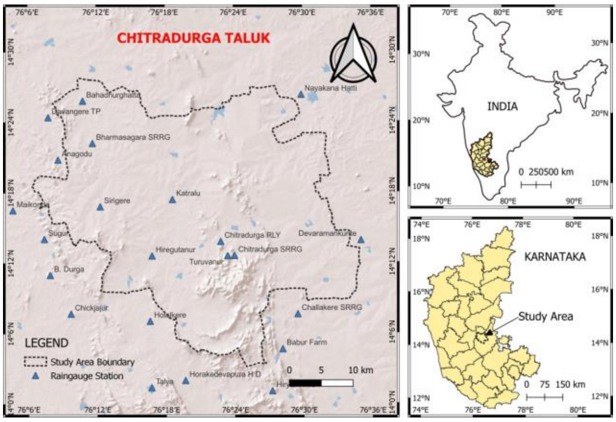

Fig.1. Location map of Chitradurga Taluk, Karnataka, India

extraction of groundwater and unsustainable agriculture practices, with significant socio-economic implications manifested through crop failures, sustainable loss of available water and rural distress (Huggi et al., 2020). This study combines geospatial methods (i.e., remote sensing and GIS) with drought indices (i.e., Standardized Precipitation Index (SPI), Normalized Difference Vegetation Index (NDVI), and Soil Moisture Index (SMI)) to evaluate spatiotemporal drought patterns, vulnerability, and risk. Our research methodology involves conducting a geospatial examination of data acquired from multiple satellite sources, including Landsat and MODIS platforms, as well as precipitation estimates such as CHIRPS. To ensure the accuracy of our findings, we will utilize terrestrial meteorological and hydrological measurements for output validation. The study, which is based on the integration of these methods, will use climate data to prepare a holistic drought risk assessment framework that will also guide policies, such as adoption of water-efficient irrigation practices, drought-resilient cropping systems and create an early warning system in the regions. This study would contribute to the sustainable management of resources in semi-arid areas, which are susceptible to recurring climate extremes and face uncertainties related to future climate change. The findings would aid in addressing the challenges posed by biennial climate fluctuations and potential long-term climate shifts in these vulnerable regions.

Materials and Methodology

The study employs an integrated geospatial and drought indices approach to assess drought risk in Chitradurga Taluk, Karnataka, a semi-arid region prone to recurrent droughts due to erratic rainfall and high agricultural dependence (Lakshmi et al., 2020; Mishra & Singh, 2010). The methodology involves four key steps: (1) *Data collection*, where multi-source datasets are acquired, including remote sensing data (Landsat LST and NDVI), meteorological data (IMD rainfall records, 2010–2020), and ancillary data (Soil maps from NBSS&LUP, LULC from NRSC) (Pandey et al., 2022); (2) *Drought indices computation*, where Standardized Precipitation Index (SPI) (McKee et al., 1993; Wu et al., 2001; Vicente et a., 2010) is calculated at 12 month scales using rainfall anomalies SPI = (Xi-Xm) / σ and transforming cumulative probability to Z-scores using piecewise approximation are classified into extremely wet (2.00 >), very wet (1.50 to 1.90), moderately wet (1.00 to 1.49), normal (-0.99 to 0.99), moderately dry (-1.00 to -1.49), severely dry (-1.50 to -1.99), and extremely dry (< -2.00) drought (Mall and Sonkar, 2021; Lloyd-Hughes and Saunders, 2002 and WMO, 2012). Vegetation Condition Index (VCI) (Kogan, 1995) derived from NDVI to assess crop stress, and Temperature Condition Index (TCI) (Karnieli et al., 2006) were derived from NDVI (VCI = NDVIi − NDVImin NDVImax − NDVImin × 100 *VCI* = *NDVImax* − *NDVImin NDVIi* − *NDVImin* × 100) to capture crop and thermal stress (Kogan, 1995; Karnieli et al., 2006). From LST (TCI = LSTmax − LSTi LSTmax − LSTmin × 100 *TCI* = *LSTmax* − *LSTmin LSTmax* − *LSTi* × 100) to quantify thermal stress; (3) *Geospatial analysis*, where GIS tools (ArcGIS 10.8, QGIS) are used for spatial interpolation (Kriging) of rainfall, NDVI trend analysis and weighted overlay analysis (50% SPI, 30% VCI, 20% LST) to generate a composite drought risk map [Drought Risk = (0.5 × SPI) + (0.3 × VCI) + (0.2 × LST) Drought Risk = (0.5 × SPI) + (0.3 × VCI) + (0.2 × LST)] map (Wilhite & Glantz, 1985); and (4) *Validation*, where results are cross-verified with historical drought records against Kappa coefficient $\kappa > 0.75$ and ground surveys (24 field points, 2020). Statistical validation correlated SPI with reservoir levels ($r = 0.72$, $p < 0.01$), ensuring robustness (Zargar et al., 2011).

Data Analysis and Discussions

1. Rainfall Analysis

The comprehensive study on the spatial and temporal distribution of rainfall in Chitradurga Taluk, utilizing geospatial techniques and drought indices to evaluate drought risk (Sanjay, 2022; Thomas et al., 2016; Tan et al., 2015; Shahabfar and Eitzinger, 2013; Naresh et al., 2012). The analysis is based on rainfall data collected from 24 rain gauge stations across the region, spanning from 2010 to 2020, with each station's annual rainfall recorded alongside its geographical coordinates (latitude and longitude) as shown in the table.

Table 1. Rainfall data across study area from 2010 to 2020

#	Long	Lat	Rainguage Station	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean
1	76.18	14.43	Bahadhurghatta	270.96	136.92	0	0	0	0	0	0	0	675	890.4	179.28
2	76.194	14.37	Bharmasagara SRRG	942.96	382.92	639	842.4	1045.92	696.96	504	465.48	504	659.04	891.2	681.48
3	76.4	14.21	Chitradurga SRRG	1167	408	603	840.96	1078.92	625.92	738.96	666.48	738.96	742.56	891.12	759.72
4	76.28	14.21	Hiregutanur	1017	528.96	604.92	722.4	936	529.92	117	130.92	117	547.08	949.2	566.16
5	76.31	14.29	Katralu	687	183.96	741.96	789.48	837	558.96	270.96	421.44	270.96	731.52	891.12	607.68
6	76.205	14.28	Sirigere	1119	1013.4	907.92	1000.44	1092.96	747.96	462	532.44	462	77.52	920.16	770.52
7	76.39	14.21	Turuvanur	910.92	211.92	490.92	660.36	829.92	676.92	249	391.44	249	741.6	949.2	553.848
8	76.38	14.23	Chitradurga RLY	1209.96	288.96	690.96	897.96	1104.96	625.92	0	0	0	0	949.2	524.28
9	76.652	14.06	Challakere SRRG	762.96	180	640.92	627.96	615	529.92	274.92	298.92	274.92	630.72	938.64	529.32
10	76.739	14.232	Devaramarikunte	736.92	217.92	399	465.96	532.92	561	237.96	240.96	237.96	591.24	938.64	469.68
11	76.545	14.469	Nayakanahatti	702.96	343.92	600.96	613.44	625.92	600.96	252.96	316.44	252.96	635.52	891.12	542.88
12	76.644	13.95	Babbur form	789	330.96	504	651.96	799.92	816.96	303.96	375.96	303.96	693.24	938.64	604.68
13	76.62	13.94	Hiriyur HMS	847.92	366.96	495	640.92	786.96	969.96	0	0	0	760.92	936	580.92
14	76.047	14.099	Sugur	864	231.96	396	423.48	450.96	693.96	222.96	251.4	222.96	589.92	900	482.232
15	76.162	14.128	Chickjajur	1077	402	480.6	683.28	885.96	1056	288	107.76	288	762	949.2	650.52
16	76.177	14.052	Holalkere	1449	552.96	633	750	867	775.92	456.96	584.88	456.96	831	949.2	778.44
17	76.328	14.033	Horakedevapura	1167.96	651	588	843.48	1098.96	885.96	432	659.4	432	913.32	939.84	824.16
18	76.132	14.183	B. Durga	1065	505.92	648	876	1104	799.92	351	432.96	351	732	949.2	725.28
19	76.279	14.023	Talya	1026.96	507	604.92	743.88	882.96	822	501	672	501	871.44	900	761.28
20	76.388	13.889	Madadakere	312	162	229.92	340.44	450.96	693	295.92	592.92	295.92	919.56	949.2	530.52
21	75.884	14.415	Davanagere TP	1035	547.92	516	706.44	897	636.96	568.92	638.4	568.92	1026.36	1344.7	784.08
22	75.919	14.467	Davanagere Rly	936.96	352.92	468.96	623.88	778.92	411	484.92	569.4	484.92	999.36	1344.7	693.12
23	76.045	14.395	Anagodu	645	385.92	546	658.44	771	672	483	489	483	693	891.12	611.76
24	76.078	14.275	Maikonda	1185	618	555.96	775.92	996	549.96	384	471.96	384	725.16	890.4	701.04
Mean				913.685	396.35	541.08	674.145	811.255	664.085	328.35	387.94	328.35	689.545	957.59	

The data reveals significant variability in rainfall patterns, both spatially and temporally, with some stations experiencing extreme fluctuations such as Bahadhurghatta, which recorded 270.96 mm in 2010 but zero rainfall in subsequent years until a sharp increase to 890.4 mm in 2020, highlighting the region's susceptibility to erratic weather. The average rainfall across all stations over the decade was approximately 913.685 mm, but this masks the stark disparities between stations, such as Bharmasagara SRRG (681.48 mm) and Chitradurga SRRG (759.72 mm), which received relatively consistent rainfall, versus stations like Hiregutanur (566.16 mm) and

Madadakere (530.52 mm), which faced more pronounced dry spells. The study employs geospatial techniques to map these variations, classifying the region into five distinct categories very low, low, moderate, high, and very high rainfall zones to better visualize and assess drought risk. This classification is critical for understanding the spatial distribution of drought vulnerability, as areas with consistently low or erratic rainfall, such as Bahadhurghatta and Madadakere, are at higher risk of drought compared to regions like Holalkere (778.44 mm) and Horakedevapura HD (824.16 mm), which exhibit more stable and higher rainfall are shown in the spatial distribution maps figure 2.

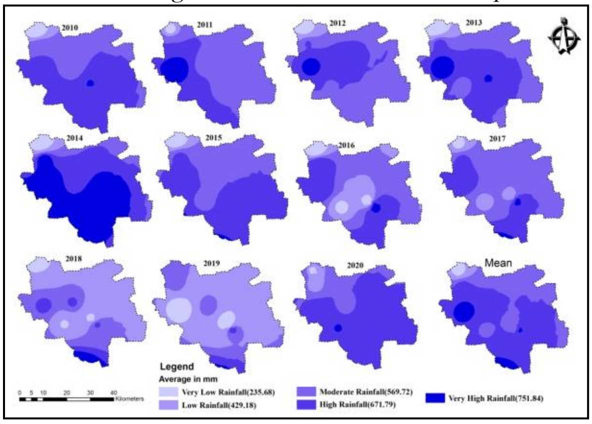

Fig.2. Spatial distribution of rainfall trends from 2010 to 2020

2. Standardized Precipitation Index (SPI) Analysis

The study provides a detailed examination of drought conditions in the region using the SPI, a widely recognized metric for quantifying precipitation deficits over multiple time scales (Paulo et al., 2012). The study spans from 2010 to 2020 and analyzes data from 24 locations across Chitradurga Taluk, revealing significant spatial and temporal variations in drought severity are shown in the table 2. The SPI values, which classify drought intensity into seven categories are shown in the table 3 and ranging from "extremely dry" (SPI ≤ -2.16) to "extremely wet" (SPI ≥ 2.1) highlight extreme conditions such as the severely dry year of 2019 in Bahadurghatta (SPI: -2.16) and Chitradurga RLY (SPI: -1.87 in 2015), as well as wetter periods like 2011 and 2015 in Chikkajajur and Sirigere (SPI: 1.11 to 2.00).

Table 2. Spatial and temporal variations of study area across the 24 stations

RG Station / Year	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Bahadhurghatta	-1.27	-0.84	-0.29	-0.12	-0.07	-1.87	-0.05	-0.32	-0.05	-0.05	-0.08
Bharmasagara SRRG	0.06	-0.04	0.05	0.03	0.02	0.09	0.03	0.06	0.03	-0.10	-0.08
Chitradurga SRRG	0.50	0.04	0.03	0.03	0.02	-0.11	0.07	0.23	0.07	0.17	-0.08
Hiregutanur	0.20	0.43	0.03	0.01	0.01	-0.38	-0.03	-0.21	-0.03	-0.45	-0.01
Katralu	-0.45	-0.69	0.11	0.02	0.00	-0.30	-0.01	0.03	-0.01	0.13	-0.08
Sirigere	0.41	2.00	0.20	0.06	0.03	0.24	0.02	0.12	0.02	-1.92	-0.05
Turuvanur	-0.01	-0.60	-0.03	0.00	0.00	0.04	-0.01	0.00	-0.01	0.16	-0.01
Chitradurga RLY	0.59	-0.35	0.08	0.04	0.03	-0.11	-0.05	-0.32	-0.05	-2.16	-0.01
Challakere SRRG	-0.30	-0.70	0.05	-0.01	-0.02	-0.38	-0.01	-0.07	-0.01	-0.18	-0.02
Devaramarikunte	-0.35	-0.58	-0.08	-0.04	-0.03	-0.29	-0.01	-0.12	-0.01	-0.31	-0.02
Nayakanahatti	-0.42	-0.17	0.03	-0.01	-0.02	-0.18	-0.01	-0.06	-0.01	-0.17	-0.08
Babbur form	-0.25	-0.21	-0.02	0.00	0.00	0.43	0.00	-0.01	0.00	0.01	-0.02
Hiriyur HMS	-0.13	-0.10	-0.02	-0.01	0.00	0.86	-0.05	-0.32	-0.05	0.22	-0.03
Sugur	-0.10	-0.53	-0.08	-0.04	-0.03	0.08	-0.02	-0.11	-0.02	-0.31	-0.07
Chickjajur	0.32	0.02	-0.03	0.00	0.01	1.11	-0.01	-0.23	-0.01	0.23	-0.01
holalkere	1.06	0.51	0.05	0.01	0.01	0.32	0.02	0.16	0.02	0.44	-0.01
Horakedevapura	0.50	0.83	0.03	0.03	0.03	0.63	0.02	0.23	0.02	0.70	-0.02
B. Durga	0.30	0.36	0.06	0.04	0.03	0.38	0.00	0.04	0.00	0.13	-0.01
Talya	0.22	0.36	0.03	0.01	0.01	0.45	0.03	0.24	0.03	0.57	-0.07
Madadakere	-1.19	-0.76	-0.17	-0.06	-0.03	0.08	-0.01	0.17	-0.01	0.72	-0.01
Davanagere TP	0.24	0.49	-0.01	0.01	0.01	-0.08	0.04	0.21	0.04	1.05	0.48
Davanagere Rly	0.05	-0.14	-0.04	-0.01	0.00	-0.71	0.03	0.15	0.03	0.97	0.48
Anagodu	-0.53	-0.03	0.00	0.00	0.00	0.02	0.02	0.08	0.02	0.01	-0.08
Maikonda	0.54	0.72	0.01	0.02	0.02	-0.32	0.01	0.07	0.01	0.11	-0.08

Table 3. Drought intensity

SPI range	Drought intensity class
-1.25 to -0.91	Extremely dry
-0.90 to -0.58	Severely dry
-0.57 to-0.24	Moderately dry
-0.23 to -0.09	Normal
-0.1 to 0.43	Moderately wet
0.42 to 0.78	Very wet
0.77 to 0.11	Extremely Wet

The analysis underscores the erratic nature of rainfall in the region, with some areas experiencing drastic shifts between drought and surplus conditions within short periods. For instance, Sirigere recorded an SPI of 2.00 in 2011 (extremely wet) but plummeted to -1.92 in 2019 (severely dry), illustrating the volatility of climatic patterns. Similarly, Challakere SRRG and Bahadurghatta faced prolonged dry spells, with SPI values consistently below -0.5 in multiple years, indicating chronic water stress. The study employs geospatial techniques to map these SPI trends, enabling a visual representation of drought hotspots and facilitating targeted mitigation strategies. The integration of SPI with geospatial tools allows for a granular assessment of drought risk, identifying vulnerable areas such as Madadakere (moderate dryness, SPI: -1.11) and Holalkere (moderate wetness, SPI: 0.32 in 2015), which require differentiated approaches to water management. The temporal analysis reveals that 2019 was particularly critical, with multiple stations including Challakere, Bahadurghatta, and Chitradurga recording very low rainfall and correspondingly low SPI values, exacerbating agricultural and ecological stress. Conversely, 2011 and 2015 saw pockets of extreme wetness, such as in Horakedevapura HD (SPI: 0.83 in 2011) and Chickjajur (SPI: 1.11 in 2015), which, while beneficial for groundwater recharge, also pose challenges like flooding and soil erosion. The SPI classification system used in the study (Table 2) provides a standardized framework for interpreting these fluctuations, with "moderate dry" (-1.26 to -0.35) and "normal" (-0.34 to -0.11) ranges helping distinguish between manageable deficits and critical emergencies.

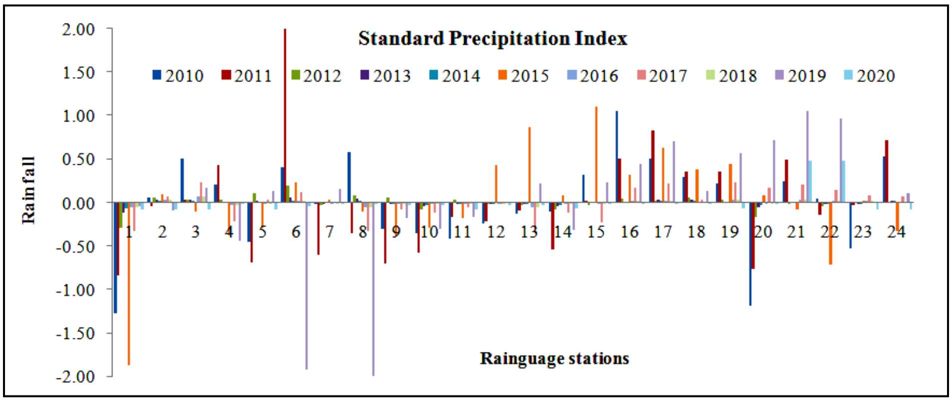

Fig.3. Standardized precipitation index of the study area

The findings emphasize the need for adaptive water governance, as regions like Davanagere TP exhibited resilience with SPI values oscillating near normal ranges (e.g., 0.48 in 2020), while others like Hiregutanur suffered recurrent dryness (SPI: -0.45 in 2019). The study's methodology combining SPI calculations with geospatial mapping enhances the precision of drought monitoring, enabling early warning systems and policy interventions. For example, the identification of "extremely dry" zones in 2019 could prompt the implementation of contingency crop plans or irrigation subsidies, while "extremely wet" areas might prioritize flood control infrastructure. The research also sheds light on the broader climatic trends affecting Chitradurga Taluk, suggesting links to phenomena like El Niño or anthropogenic climate change, which amplify rainfall variability.

3. Normalized Difference Vegetation Index (NDVI)

The presents study of agricultural drought conditions in the region using the NDVI, a key remote sensing tool that quantifies vegetation health by measuring the difference between near-infrared (which vegetation strongly reflects) and red light (which vegetation absorbs). The study leverages Landsat-7 imagery from 2000 and Landsat-8 data from 2015 and 2020 to generate NDVI maps, which reveal significant temporal changes in vegetation cover, serving as a proxy for agricultural drought severity. The NDVI values, ranging from -0.1 (indicating barren or non-vegetated areas) to 1 (representing dense, healthy vegetation), with an average maximum of 0.41, reflect moderate vegetation health in the region, while the minimum value of -0.3 highlights areas of severe vegetation stress, likely due to water scarcity or poor soil conditions.

The comparative analysis of the three years demonstrates a notable improvement in vegetation cover from 2000 to 2015 and 2020, suggesting either climatic variability, such as increased rainfall in later years, or the success of local agricultural interventions like irrigation projects or afforestation efforts. For instance, the 2000 NDVI maps show significantly lower vegetation levels, possibly linked to historical drought events or land degradation, whereas the 2015 and 2020 maps indicate higher NDVI values, signaling recovery or improved land management practices.

The geospatial visualization of these trends are shown in the figure 4 provides a clear, spatially explicit representation of vegetation health, enabling the identification of drought-prone areas, such as those with persistently low NDVI values, and regions of resilience, where vegetation has thrived despite climatic challenges (Praba et al., 2009). This spatial granularity is crucial for targeted policy interventions, as it allows authorities to prioritize resources for areas with chronic vegetation stress, such as implementing water conservation measures or promoting drought-resistant crop varieties (Potop et al., 2012).

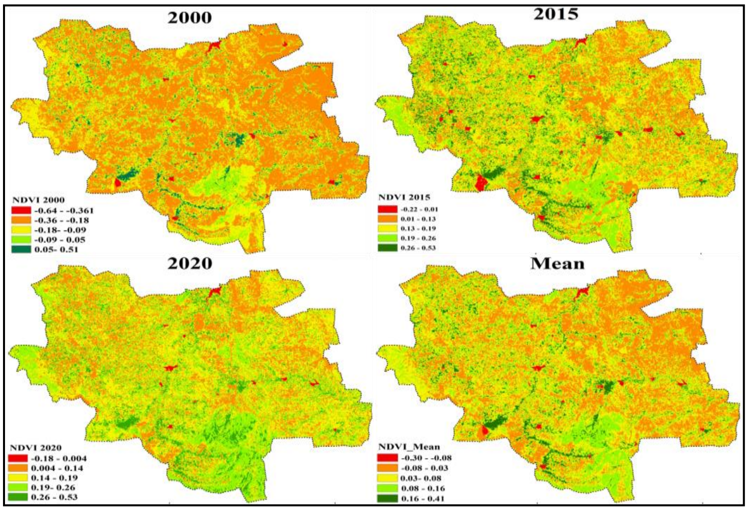

Fig. 4. NDVI trends in 2000, 2015, 2020 and mean

4. Vegetation Condition Index (VCI)

The detailed assessment of agricultural drought conditions using the VCI, a satellite-derived metric that evaluates vegetation health by comparing current vegetation vigor to long-term historical norms, thereby isolating the impact of weather-related stress from other factors like soil type or land management (Farooq et al., 2009). The study focuses on the Kharif (monsoon) seasons of 2000, 2015, and 2020, revealing stark contrasts in vegetation health across these years. In 2000, a large area suffered severe drought, with VCI values between 1 and 25, showing that the vegetation was extremely stressed by the lack of rainfall or a long dry spell, which probably caused severe crop failure and the decrease in agricultural yield. In 2015 however, the pains of drought in the region was far lessened as evidenced by the VCI, it was having normal vegetation health with large areas of the taluk being impacted suggesting better monsoon or a proper prevention or withdrawal from drought by means of irrigation or changes in crops. 2020 displayed more variability with average VCI values varying between 71.28 and 143.43, signifying overall healthy vegetation with areas of moderate stress that could be attributed to localized rainfall deficits or soil moisture conditions. The geospatial representation of these trends, which is presented in the figure 5, reveals the spatially explicit nature of vegetation stress and allows for the identification of hotspots and resilient zones, which is essential to the calibration of targeted agricultural interventions. For example, areas with consistently low VCI values, such as what was recorded in 2000, could benefit from improved irrigation facilities or introduction of drought-tolerant varieties of crops, whereas those with high VCI values, such as what was experienced in 2015, could also act as a model for good farming practices.

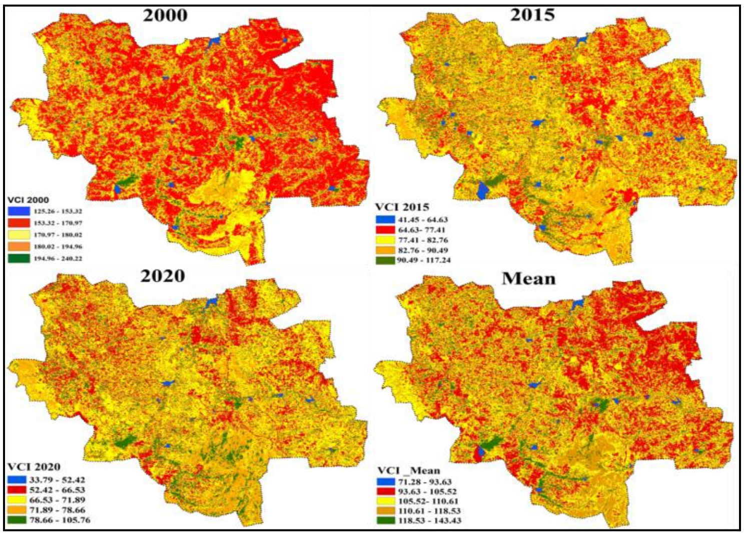

Fig. 5. VCI trends in 2000, 2015, 2020 and mean

5. Normalized Difference Water Index (NDWI)

The comprehensive study of hydrological drought assessment using the NDWI, a satellite-derived metric that evaluates water availability by analyzing the reflectance of green

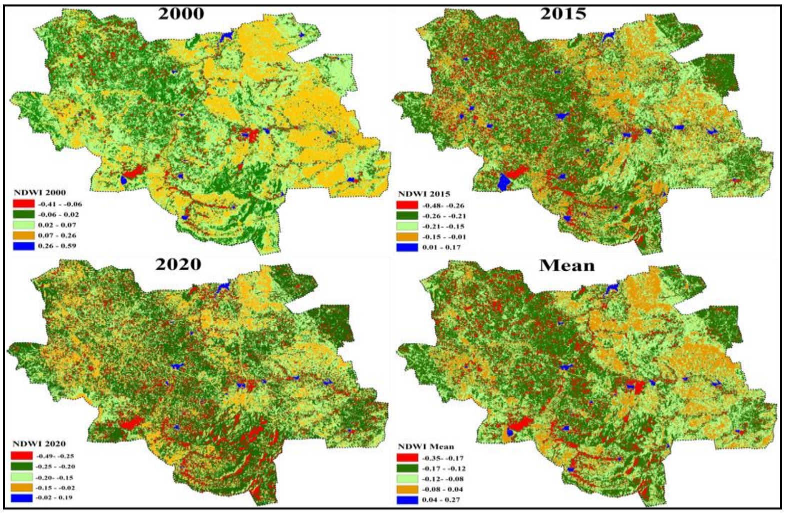

Fig.6. NDWI trends in 2000, 2015, 2020 and mean

and near-infrared light to distinguish water bodies from dry land. The study examines NDWI values across three key years—2000, 2015, and 2020—revealing significant fluctuations in water availability, with 2015 recording the highest NDWI value of 0.39, indicating optimal water conditions, while 2000 exhibited severe drought with a value of -0.41, reflecting acute water scarcity. These values, which range from -0.35 (indicating drought) to 0.3 (signifying no drought), highlight the hydrological variability in the region, with 2000 marked as the driest year and 2015 as the wettest, while 2020 showed intermediate conditions, suggesting a decline in water availability compared to 2015. Looking at the NDWI maps (figure 6), one can easily see the spatially explicit information on water stress. Especially for droughts, where you have potential in identifying areas that are drought-prone and those that have stable water (Aadhar and Mishra, 2023; Shah and Mishra, 2021). Visualization of these trends in geospatial domain also helps in identifying the hotspots like areas with continuous NDWI values in the negative that can be targeted with interventions such as storing the water through groundwater recharge or by improving the irrigation infrastructure. The present study also demonstrates the applicability of remote sensing for large-scale hydrological monitoring, as NDWI is a cost-effective and time-saving substitute for ground-based surveys, particularly in data-poor regions. Thus, this NDWI analysis is found to be a powerful base to have a scientific backing to drought risk assessment in Chitradurga Taluk which shows the potential of the geospatial technologies as tools in solving the water scarcity issues. The study means of integrating NDWI and geomatics provides a replicable template for other drought-prone areas, and gives us a timely reminder of the imperative for integrated, data-driven interventions to the accelerating dangers of climate and water stress.

6. Land Surface Temperature (LST)

This study employs integrated geospatial techniques to assess drought risk in Chitradurga Taluk, Karnataka, India, using Landsat derived LST data (2000–2020) alongside drought indices (VCI, NDVI, NDWI, SPI).

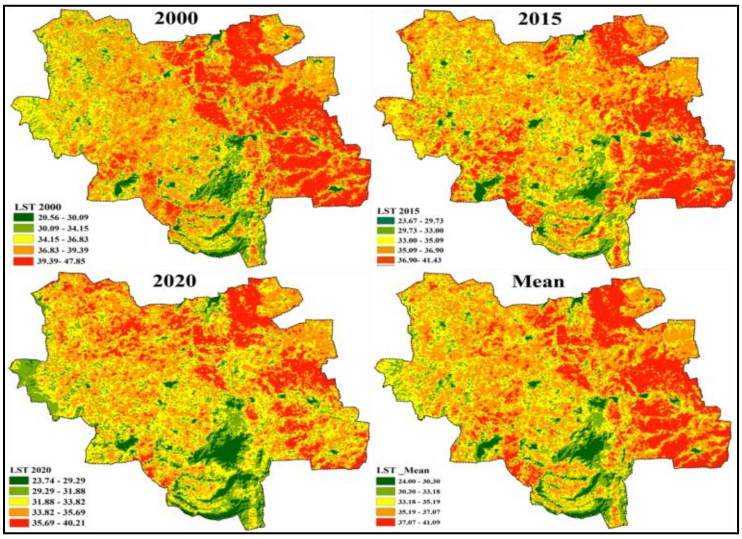

Fig.7. LST trends in 2000, 2015, 2020 and mean

Results reveal significant LST variability (table 4), with 2000 exhibiting extreme temperatures (max: 47°C, min: 20°C), indicating severe moisture stress, while 2015 and 2020 showed moderated thermal conditions (max: 40–41°C, min: 23°C), suggesting reduced drought intensity. High LST is related to lower vegetation health (NDVI) and water stress (NDWI), also intensifying the agricultural drought. Spatiotemporal analysis locates hotspots of thermal anomalies, where elevated LSTs coincide with ecological stress. Localized features (such as vegetation recovering or monsoon variability) might explain LST decreases despite GW. The research highlights the potential of LST data for drought monitoring, supporting its incorporation in early warning application. Constraints, e.g. sensor resolution, require more sophisticated methods. Results highlight the multi-sectoral drought management, use of both heat and hydrological based indices for climate adaptation in semi-arid areas. The model is transferable to similar climatic zones.

Table 4. Land surface temperature trends in the study area

LST (years)	Mini temp (℃)	Maxi temp (℃)
2000	20	47
2015	23	41
2020	23	40

Indices Comparative Analysis

The comprehensive analysis of drought risk in Chitradurga Taluk, Karnataka, India, integrating Rainfall, SPI, NDVI, NDWI, VCI and LST data through geospatial techniques, reveals a multifaceted understanding of drought dynamics across temporal and spatial scales. The rainfall analysis (2000–2020) highlights significant variability (figure 2), with some stations like Bahadhurghatta recording extreme fluctuations (e.g., 270.96 mm in 2010 to zero in subsequent years), while others like Holalkere and Horakedevapura HD maintained relatively stable averages (778.44 mm and 824.16 mm, respectively), emphasizing the region's erratic precipitation patterns (Sadiq et al., 2020) . The SPI analysis (figure 3) quantifies these rainfall anomalies, identifying severe droughts in 2019 (SPI: -2.16 in Chitradurga RLY) and extreme wet conditions in 2011 (SPI: 2.00 in Sirigere), demonstrating the utility of SPI in classifying drought intensity and linking meteorological deficits to agricultural and hydrological impacts. Complementing this, the NDVI (figure 4) analysis (2000, 2015, 2020) captures vegetation health, with 2000 showing stressed conditions (NDVI: -0.3 to 0.41) due to low rainfall and high LST, while 2015 and 2020 exhibited recovery (NDVI up to 0.41), aligning with improved SPI and rainfall trends. The NDWI maps (figure 5) further contextualize hydrological drought, with 2000 marked by severe water scarcity (NDWI: -0.41) and 2015 by optimal water availability (NDWI: 0.39), directly influencing NDVI and VCI outcomes. These results are supported by VCI (figure 6) data where, during 2000 (severe drought; VCI: 1–25), vegetation's health was at its worst because of a combined effect of drying (SPI) and extremely high heat (47°C), whereas during 2015 (normal VCI: 71.28–143.43), the vegetation recovered, potentially because of better water retention (NDWI) and relatively moderate heat (LST: 41°C). The LST analysis (figure 7) demonstrates that drought was largely conditioned by thermal stress, 2000 maximum LST peak (47°C) tendency toward intensification of moisture loss and vegetation stress, while 2015 and 2020's lower 40–41°C maxima favor improved ecological conditions.

Geospatial composite of these indices combined with LST demonstrates the relationship between meteorological (SPI), eco-ecological (NDVI/VCI) and hydrological (NDWI) anomalies, with LST playing a role as a thermal stress inducer. For example, the 2000 drought under the high LST and low NDWI was accumulated suffering (low NDVI/VCI), while the moderate LST and the high NDWI in 2015 enabled recovery. This synergy is observed in the maps (e.g., NDVI, NDWI, LST spatial distributions in Figure 8) and allow for joint activities (e.g., focus irrigation in low NDWI/NDVI areas or reforestation in the area with high LST). Through the combination of these indices, the study offers a universally applicable framework for comprehensive drought management, highlighting that an effective way of alleviating drought is attending precipitation, temperature, vegetation, water supply together. Such integrations are critical for the agrarian economy of Chitradurga Taluk, where droughts jeopardize livelihoods, food security, and environmental sustainability, and provide a template for other semi-arid regions around the world under threat from climate change. Overlay of Rainfall, SPI, NDVI, NDWI, VCI, and LST through geospatial approach not only provide high-resolution mapping of drought risk, but also uncover the intricate processes behind such patterns, and raise deliberate responses grounded in science to protect people and ecosystems at risk at Chitradurga Taluk and beyond.

Summary and Conclusions

A comprehensive mapping of drought risk has been obtained through the integrated assessment of multi-variants such as Rainfall, SPI, NDVI, NDWI, VCI, and LST at (Chitradurga Taluk) in Karnataka, India has been achieved, using GIS, for better perception of drought processes all over time and space. We notice the rainfall variation over the period 2000–2020 is quite varied; at some of the stations such as Bahadhurghatta, (270.96 mm in 2010, nil in the next year), and elsewhere the variation is not much; for example, at Holalkere station the average rainfall was 778.44 mm and is relatively static, which gives us an insight to the uncertainty of the climate in this region. The SPI analysis measure meteorological droughts competing occurrences of severe drought in 2019 (SPI: − 2.16) and wet extreme in 2011 (SPI: 2.00), droughts with acute precipitation deficit that in turn have directly translated in irrigation requirements. Figure 6 shows the NDVI and VCI trends in vegetation condition, with year 2000 characterized by severe stress (NDVI: −0.3; VCI: 1–25) and low rainfall and high temperature (LST in 47°C), whereas recovery (2005–2010), from better rainfall and moderated temperature (LST in 40–41°C) to the good condition (NDVI in 0.41; VCI in 71–143) for years 2015–2020 can be indicated. NDWI maps provide more context on hydrological drought: water stress (NDWI -0.41) in 2000 versus surplus in 2015 (NDWI 0.39) driving vegetation resilience.

The synergy of these indices reflects how meteorological (SPI), agricultural (NDVI/VCI), hydrological (NDWI) and thermal (LST) variables influence the evolution of drought events positively or negatively. For example, combined high 2000 LST, low NDWI and rainfall deficits induced ecological stress, whereas favorable conditions in 2015 were conducive to recovery. Geospatial visualization identifies risk areas, to which targeted responses like irrigation in low-NDWI spots or heat-resistant varieties could be implemented. The research highlights the importance of multi- index drought monitoring to consider these complexities; because the use of single indicators (such as SPI) fails to account for important factors such as temperature or vegetation response. This holistic approach built on data can not only contribute to making Chitradurga Taluk more resilient to drought, but also be replicated in other semi-arid regions around the world as an example of a model that provides solutions for mitigating climate risks and securing livelihoods in face of growng climatic variability.

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Conflicts of interest
The authors declare that there are no conflicts of interest regarding the Publication of this paper.

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