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Research Article

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Analysis of Drought Severity and Vegetation Condition Prediction Using Satellite Remote Sensing Indices in Kolar and Chikkaballapura Districts, Karnataka State

Harishnaika N[1*], Arpitha M[1], S A Ahmed[1]

Department of Applied Geology, Kuvempu University, Shankaraghatta (577451), India

[*]Corresponding Author
Harishnaika N, Department of Applied Geology, Kuvempu University, Shankaraghatta (577451), India

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Abstract

Drought is a natural hazard with far-reaching effects including economic losses, and soil damages, and threatens the health of residents and livelihood. The present research aimed to observe the vegetation health index across the semi-arid regions of Karnataka state in 2015-2019 using GIS and remote sensing techniques. Landsat-8 dataset images, with a 30 m spatial resolution and from various platforms were used to recognize the Vegetation Condition Index and Temperature Condition Index. The VCI is dependent on the NDVI datasets. The Temperature Condition Index used LST. As an outcome, the VHI was generated and classified into 5 categories of drought: no drought, mild, moderate, severe, and extreme drought. The results indicate that the highest % of the extreme agricultural drought found in Chinthamani taluk is about 740.20 squares Km (20%) area. In the S-W monsoon showed Bagepalli is about 397.70 squares Km (18%), and Sidhlaghatta taluk is about 26 % (338.55 squares Km). In the North-east Monsoon extreme drought severity was affected in Malur at 22% (704.05 squares Km), Mulubhagilu at 26 % (909.99 squares Km), and Bangarapete at 21% (879.64 sq. km) of the area have severely affected the agriculture and vegetation from 2015-2019 respectively. Severe to moderate drought occurred in the north–east part of both areas of Kolar and Chikkaballapura districts. 2016 and 2017 experienced a less level of drought % with compared to the other study years. This study allows the monitoring of decision-makers, resolves drought conditions, and investigates more beneficially.

Keywords: Drought, Vegetation Health Index, Vegetation Condition Index, Temperature Condition Index, Kolar and Chikkaballapura Districts.

Introduction

In semi-arid regions, the production of rain-fed agricultural activity is a majorly risky operation because sensitivity is very high to climate extremes, including drought and other calamities [1, 2]. Several researchers have noticed that drought events cause a serious decline in agricultural productivity and production all over the globe. This can happen with no caution, without identified economic or borders and political differences [3]. For example, during the time of periods 2001–2012, extreme-exceptional (EE) covered about 1–7% of Severe-exceptional (SE) 8–16%, moderate to-exceptional (ME) 18–36%, of the total land area of the globe, respectively. Respectively, For instance, the droughts period in Russia from 2010 and 2011 to 12 in the United States of America produced substantial global and local economic impacts [4, 5]. As an outcome, the balance of food demand and supply was affected significantly due to extreme and severe droughts (SD) at global, regional, and local scales level [6]. In semi-dry regions, where the precipitation pattern is extremely variable, the susceptible collapse is realized [7]. Different regions of the globe, mainly the grain-growing nations like the USA, China, Russia, India, and the European Union are thus encountered an incline in the intensity and frequency of droughts events [8]. In developed nations, drought mitigation, monitoring, and early warning structure are situated on earth observation data products and it is most effective, while in most Asian countries (including India) the location depends highly on the in-situ climatic data format only, Which largely affects the smallholder farmers of the countries. It also scarcity the continuous temporal and spatial range needed to monitor and characterize the detailed temporal pattern and spatial extent of drought events [9]. Karnataka is one of the main revenue states of India; some regions of the state were affected by frequent drought periods and events due to erratic and poor precipitation variability where the problem is extreme and severe in the south-eastern parts of the state. Some researchers reported that the occurrence of El Nino climate event droughts and dry events has also been regularly occurring over the several decades triggering different threats to the agriculture sector. Particularly the semi-arid area has been majorly affected by the recurrent droughts events [10]. The duration, cessation, severity, frequency, and spatial extent of drought in the regions are high. Despite the substantial growth and health in the major crop types maize, wheat, barley, sorghum, and other crops). Were noticed in terms of area and productivity coverage, these yields are low when assess by international standards. Because production is largely susceptible to weather events, particularly dry events and drought. Agricultural cultivation and production, majorly in the poor regions have endured highly dependent on the climate and weather (A. Zhang, Jia, and Wang n.d.). The challenges stand up may also in the future as the natural resources are highly overexploited due to increasing population growth. Agriculture is the sector firstly affected by the hydro-meteorological period droughts because it negatively affects vegetation growth as well as crop production, but behind move on to other water resource-dependent sectors [11, 12]. Agricultural drought is expressed by the depletion of crop productivity and production due to a shortfall of precipitation as well as insufficient soil moisture to the zone of crop root [13]. However, the dependency on weather and climate data alone is not enough to monitor and prediction in the region of drought events, especially when these data are sparse, untimely, and incomplete [14]. The conventional ways of dry events monitoring which highly depend only on weather grid stations lack repeated spatial coverage to monitor and characterize the spatial pattern of dry incidences in-depth. Monitoring the health of vegetation status of the research area is significant to describe the events of agricultural drought, then it requires 5 years of satellite data observation suitable drought indices Furthermore, the monitoring, mitigating, and understanding of drought are become a difficult aspect because of the natural phenomenon [15]. Yet, satellite data observations have some limitations to meteorological observations, giving the possibility for cost-effective, spatially and temporarily dynamic and explicit scale drought monitoring. Satellite product observation like NDVI, eMODIS, and MOD11A2 LST supported with highly advanced remote sensing drought indexes such as VHI (Vegetation Health Index) can help to evaluate the occurrence of agricultural droughts events. Kogan and Liu (1996) express that the seasonal and inter-annual drought events can be represented by using the VCI (Vegetation Condition Index) and TCI-Temperature Condition Index because both indexes can help to calculate and generate VHI [16, 17]. Vegetation Health Index has been the accepted agricultural drought indices. but, it needs both LST and NDVI data [18]. The target of this research was to monitor the agricultural drought for 5 years period of duration, onset, cessation, severity, frequency, and spatial and temporal extent utilizing the Vegetation Health Index (VHI) which combines NDVI, LST, VCI, and TCI in Kolar and Chikkaballapura district area of Karnataka state. The study is conclusive for understanding, monitoring, and managing the events of droughts through meteorological and satellite earth observation data.

Methods

Study Area

This study has been conducted in Kolar and Chikkaballapura districts lying between 12º 45'N - 13º 57'N latitude and 77º 24'E - 78º 35'E longitude as shown in figure 1. These areas are stationed in the south-eastern region, which is the semi-arid agro-climatic zone of Karnataka state, As per the Köppen Geiger climate classification system, 30 sub-types and 5 main classes are defined to classify the world climate pattern [19]. The climate classification for the research area is defined by Equatorial Winter Dry (Aw) covering the major portion and along the northern part of the districts, we find Arid Steppe Hot (BSh) Figure1. It covers a total area that is extended up to 8241.02 km2 (Chikkaballapura - 4249 km2 and Kolar-3992.02 km2) with the topographic elevation extending from 507m to 1389 m from the MSL. The slope is gentle across the plains and very steep across the hilly ranges. The average rainfall of the Kolar is 748 mm per year and Chikkaballapura is 756 mm per year. The average mean temperature ranges between 14.5º C and 35.7º C overall the statistics of the area shown in Table 1 and Figure 1.

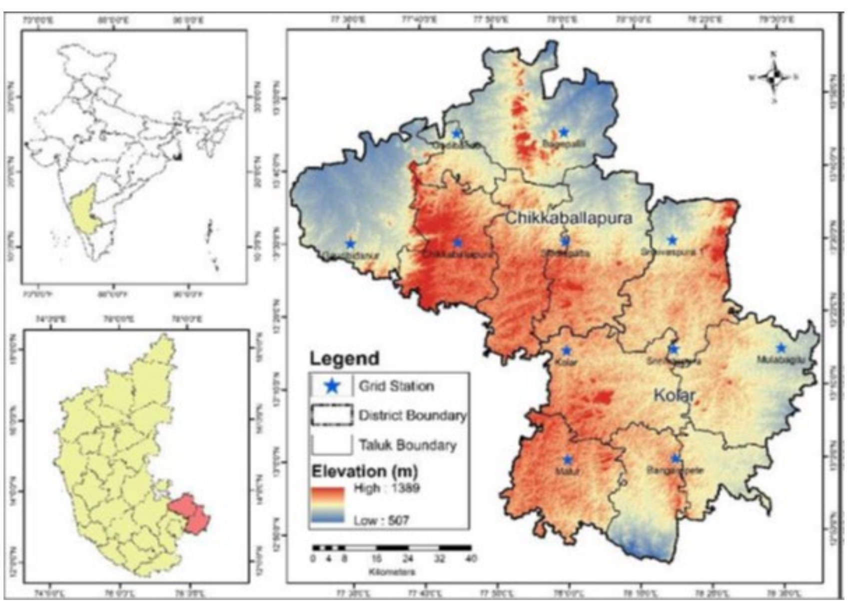

Figure.1: Geographic location and elevation of Kolar and Chikkaballapura District

Data Acquisition

Expedited MODIS (eMODIS) TERRA NDVI

Tsiros et al. (2004) describe that remote sensing data should effectively be used to monitor drought events, vegetation response, and cessation of the drought period. In this research, the agricultural drought of the research region was inspecting the historical EROS Moderate Resolution Imaging Spectroradiometer and real-time Earth observation data products. A multi spatial-temporal monthly and weekly, Terra eMODIS-NDVI, (advance Moderate Resolution Imaging Spectora diameter Normalized Difference Vegetation Index) data from the period of 2015 to 2019, at 250 m spatial resolution. The data (Terra eMODIS-NDVI) are finer for agricultural drought understanding and monitoring than Aqua.

Land Surface Temperature (LST)

In this research, the MOD11A2 Emissivity and LST Terra 16 days temporal resolution (later aggregated into Monthly days bases) data were acquired from the NASA (National Aeronautics and Space Administration) —USGS (United States Geological Survey) Lands and Processes allocate LP DAAC (Active Archive Centre). The intention to use the LST daytime (Terra) data exists in its temporal extension. describe that the temporal-spatial evolution of Land Surface Temperature gets during the daytime is finer to get in details than the Aqua because a change in LST can be observed during the night-time [20]. Yet, in the nighttime, LST remains stable as an outcome, and the limitation on time differences could be mitigated. The MODIS Land Surface Temperature introduces a quality of LST than the AVHRR satellite sensor due to its spatial and temporal differences and updated algorithms such as satellite view zenith, azimuth angle, and time of acquisition quality for interpretation of the products are easy. This satellite data was utilized to compute the Temperature condition index (TCI) and VHI, which is an integrated and latest drought monitoring model in agriculture.

Rainfall

Rainfall data are highly useful meteorological components in drought-related research. In this study, the long-term daily rainfall data were obtained from the India Meteorological Department (IMD) 2015–2019. The rainfall data were primarily used to examine the response of drought to precipitation.

Data Analysis and Processing

Expedited MODIS (eMODIS) TERRA NDVI

E MODIS is a procedure for creating a specific suite-community of vegetation examination products based on the NASA (National Aeronautics and Space Administration's), EOS (Earth Observing System) MODIS (Moderate Resolution Imaging Spectroradiometer) and produced in the USGS (U.S. Geological Survey's), EROS (Earth Resources Observation and Science) Center. Described that the eMODIS (NDVI) data are a match for vegetation-related research because the remote sensing data were captured with a repeated frequent cycle.

Table.1. Statistical information of the research area

Station name	Long	Lat	Elevation	Max Rainfall (mm)	Min Rainfall (mm)	Mean Rainfall (mm)	Standard deviation
Bagepalli	78	13.75	674	1026.41	220.15	531	174.5
Bangara ete	78.25	13	754	1443.68	237.49	684	245.9
Chikkaballapura	77.75	13.5	863	1155.40	178.00	611	217.1
Gauribidanur	77.5	13.5	663	1168.58	337.48	740	204.1
Gudibande	77.75	13.75	662	1068.61	68.92	532	209.5
Kolar	78	13.25	762	1198.47	401.74	701	201.7
Malur	78	13	783	1398.46	348.61	755	223.7
Mulabhagilu	78.5	13.25	659	1447.01	270.00	790	207.9
Shidlaghatta	78	13.5	769	1213.14	316.00	619	205.5
Srinivaspura	78.25	13.25	717	1297.26	331.87	696	212.1
Chinthamani	78.25	13.5	673	1296.03	347.54	731	210.5

Rhee et al. (2010) suggested that the NDVI has been used for drought detection and monitoring. But, Normalized Difference Vegetation Index data cannot show the severity and magnitude of the drought. Hence, the multi-temporal investigation of eMODIS (NDVI) supported by TCI and VCI can notably correct the early warning systems and drought monitoring. suggested that the NDVI can be calculated based on the band red, which has NIR high reflectance and reflectance is low value for portions of the wavelength. mainly, in non-drought times, vigorous and green vegetation reflects very little light in the visible spectrum due to large absorption by chlorophyll in the light and more reflection in the NIR (near-infrared) part due to the precision of scattering light by water content and internal leaf [21]. In this study, the healthy vegetation (VI) is greatly absorbed the red (visible incident solar) and it reflects less amount of solar radiation in the VS (visible spectrum). Hence, the unhealthy vegetation highly reflects the NIR (near-infrared light). Consequently, dense and healthy vegetation has a high normalized difference vegetation index value generally > 0.5 than the unhealthy. The eMODIS NDVI data is better to calculate the chlorophyll density confined in vegetative cover (Frey, Kuenzer, and Dech 2012). (Kogan and Guo 2016) suggests that normalized difference vegetation index data helps to calculate the Vegetation health index (VCI) development reflects both precipitation and temperature conditions. The NDVI was statistically computed as follows equation (1):

$$NDVI=(NIR\text{-}RED)/\ (NIR+RED) \qquad 1)$$

Where RED=visible red reflectance and NIR=near-infrared reflectance. In this research, the row eMODIS NDVI data were rescaled, processed, and analyzed in ArcGIS 10.8 and 10.4.1 package to find the real normalized difference vegetation index value of the research area as following equation (Eq. 2):

E -MODIS NDVI = Float (Smoothed e-MODIS NDVI – 100) / 100

2)

The value of NDVI (e-MODIS) ranges from −1.0 to + 1.0. The unit of NDVI is the NDVI ratio. The NDVI negative ratio indicates less unhealthy or vigorous vegetation cover majorly appeared in a rock outcrop (barren rock), and sand, and positive NDVI values indicate the healthy vegetation. NDVI values are high indicating dense and healthy vegetation than Water, bare soil, and rocks (Kogan 1995). Comparable, grasslands, and shrubs/bushes are sparse vegetation cover may result in NDVI values moderate between 0.2 to 0.5. Higher NDVI values between 0.6–0.9 indicated dense health vegetation in the tropical and temperate crops or forests at their peak high growth stage. The NDVI data were utilized as a component to calculate the VCI (vegetation condition index) only

Vegetation Condition Index (VCI)

Different drought indexes have been advanced for monitoring the drought event's characteristics such as duration, intensity, spatial extent, and severity [22, 23]. The vegetation condition index which is calculated from remote sensing satellite data has been used with vegetation cover and state. The indices are applicable for monitoring the response of vegetation and vegetation stress. The VCI allows not only the explanation of vegetation but also and calculation of temporal and spatial weather impacts on vegetation and vegetation changes (Kogan 1990). In this research, the smoothed 16 days NDVI data was used as a parameter, to compute the vegetation condition index model. The VCI was applied to calculate the agricultural drought events status of the research area as following Equation 3:

$$VCI = 100 \times (NDVI_i\text{-}NDVI_{min})\ /\ (NDVI_{max}\text{-}NDVI_{min}) \qquad 3)$$

Where NDVI=the smoothed value of I ^{the} month, NDVI max and NDVI min are from (2015– 2019) absolute maximum and minimum value (NDVI) for different pixels at a specific period. The VCI value is measured in % between 0 - 100. A big value of VCI indicates unstressed vegetation and healthy condition, this region is free from agricultural drought events. The value of VCI 50–100 shows above wet or normal conditions. This indicates that there are no events of drought, then between 35 - 50 % indicates the area under the moderate drought (MD) condition and VCI between 20 - 35 % indicates severe drought (SD) events. Moreover, the annual and seasonal VCI values of 0 to 20 % are showing very severe drought events (SD). Hence, the combination of both TCI and VCI calculate from MOD11A2 (LST and NDVI) Terra data are to calculate agricultural droughts.

Temperature Condition Index (TCI)

Land Surface Temperature (LST)

Land Surface Temperature expresses the radiative temperature of the land obtained from solar radiation. The MOD11A2 LST and emissivity measure the temperature of the earth's surface. These assess soil moisture, vegetation health status, and the impact of thermal. In this research, the MOD11A2 Terra 16 days LST data was acquired at a 1-kilometer spatial resolution get in HDF–EOS Format (Hierarchical Data–Earth Observing System). Hence, the MODIS Tool Re-projection (MRT) v 4.1 evolves in 2011 March to resample the 1 km resolution LST MOD11A2 data in 250 m resolution jointly with the NDVI data. The MRT (Re-projection) is also used to turn the HDF (Hierarchical Data Format) into a GeoTIFF format to conduct interpretations and better analysis of the MOD11A2 (LST) and NDVI (eMODIS). In this research, the land surface temperature data were rescaled and then converted into °C degree Celsius units as following equation

$$LST=(\varpi\times 0.02)\text{-}273.15 \qquad 4)$$

Where LST-Land Surface Temperature (Degree Celsius), ϖ= SDS (Row Scientific data). The temperature condition index accepts that higher temperature has a movement to cause failure or drought during the growth period of vegetation; while temperatures are low it is The TCI was evaluated using the following expression:

$$TCI=100\times(LST_{max}\text{-}LST_i)/(LST_{max}\text{-}LST_{min}) \qquad 5)$$

Where LST_i=LST value of i^{th}-month, LST min, and LST max are the smoothed several-year minimum and maximum LST

Vegetation Health Index (VHI)

Rhee et al. (2010) noticed that the newly developed drought indices like NDWI, NMDI, and NDDI did not execute better than the normalized difference vegetation index (NDVI) with a 1-kilometer resolution in the semi-arid area. The Research indicates NDVI only is not able to depict non-drought or drought conditions. The Vegetation Health Index model has existed in robust agricultural monitoring drought indices and it has the efficiency to inspect the temporal and spatial scale of agricultural extreme and severity drought period. In the semi-arid area, VHI was exceptionally correlated to the situ variables (Mishra and Singh 2011) ,suggest that the Vegetation Health Index (VHI) combination of VCI and TCI is main to specify the spatial-temporal extent, the severity, and the magnitude of agricultural droughts in a fine agreement with rainfall patterns. The vegetation stress caused due to wetness and the dry situation was assessed to investigate the agricultural drought severity in the research area. Both the TCI and VCI index specified an equal weight due to the temperature and moisture contribution during the period of vegetative growth (Kogan 2001). The lack of more correct information on the effect of TCI and VCI on the VHI in the Kolar and Chikkaballapura districts, the coefficient of the vegetation health index was fixed at 0.5. The vegetation health index was mathematically calculated as the following equation:

$$VHI = a \times VCI + (1-a) \times TCI \quad 6)$$

Where VHI (Vegetation Health Index), a = 0.5 (TCI and VCI), VCI (Vegetation Condition Index), TCI (Temperature Condition Index).

Drought Period Assessment Using Satellite-Based Vegetation Health Index (VHI).

The satellite data-based VHI data product can be used to monitor thermal conditions, moisture stress conditions, vegetation health conditions, and regional drought. The time, duration, affected region, and drought intensity can be computed based on various ranges of VHI values. The ranges of VHI including TCI, VCI, and VHI started from extreme stress (0) to the most favourable condition (100), with normal drought conditions ranging from 25–40 corresponding to the mean cumulative moisture content, vegetation health conditions, and temperature. Higher ranges of values showed better moisture area, vegetation condition, or thermal. For Example, VCI < TCI 50 indicates moisture conditions favourable for the crop. A decrease in VHI value from 35 to 0 indicates sufficient vegetation stress and for VHI from 50 to 100 and vice versa, the value of the drought conditions in VHI was shown in Table 2.

Table 2. The severity of Agricultural drought by VHI (Source: Kogan 2001)

Severity level	VHI values
Extreme drought	**<10**
Severe drought	<20
Moderate drought	<30
Mild drought	<40
No drought	>50

Results and Discussion

Agricultural Drought Assessment

Figure 3 indicates the multi-temporal sequence of NDVI- LST, TCI-VCI, and rainfall— VHI for the period 2015 to 2019. The low-land region of districts reveals that the average NDVI was between 0.27 and 0.31 and this scattered value of NDVI is extremely low when it is calculated by mathematically accepted threshold values, while the Land Surface Temperature was very high and it is between 37.4 and 42.91 °C. Therefore, the value of low NDVI is reached at very high LST ranges because the thick vegetation is under very high water stress assets.

The west and south areas of the study areas showed relatively better NDVI ranges between 0.39 and 0.58 was indicated, although the Land Surface Temperature (LST) was between 31.3 and 35. 79 °C. In this region, the LST ranges were comparatively less than the low-land region express but it is quite an unfavourable situation for the thick vegetation and very high moisture water stress. In the high region, well coverage NDVI ranges between 0.52 and 0.59 were indicated. Other than that, very low LST between 21.3 and 23.9 °C was shown in the same region. Very High LST directs the vegetation growing time may happen vegetation stress. Thus, the gradual increase in surface temperature (ST) may influence vegetation evaluation. Singh et al. (2003) describe that NDVI is the most important tool for monitoring vegetation cover and growth of vegetation analysis. Especially, this research indicated that NDVI presented during the major rainy season declined by 5–9 % in all regions of both districts. Yet the LST has increased by 0.49–1.16 °C. Overall agro regions as well as both districts in the last 6 years. The increase in land surface temperature and the decrease in NDVI provides extensive moisture stress that can cause the occurrence of agricultural drought. The results indicate that the vegetation stress was caused due to rising surface temperature (ST). In the low area, the ranges of Vegetation Condition Index were between 39.12 and 43.13, So the TCI was high between 36.18 and 38.12. In the middle area of the district, the value ranges of VCI were 49.76 and 63.18, although TCI was 48.59–62.3. In the high area, the VCI ranged values between 58.91 and 65.13, and then TCI was 63.113–65.85. Furthermore, VHI and precipitation value was diminished in the main rainy season. This showed that the occurrence of agricultural drought enhances more severe and frequent because of the sensitivity to soil moisture, especially in the low region, and several parts of the high and midland area were affected seriously. For example, the VHI of the low area was between 34.39 and 41.53, although the precipitation was about 345.41–467.89. The Stations wise seasonal drought mean value and total area of square Kilometre in Pre -monsoon season from 2015-2019 showed in Table 3, 4, and 5.

Table 3: Stations wise drought mean value and total area of square Kilometre in Pre -monsoon season from 2015-2019

Grid Stations		Drought Category in Area of square Km in Pre-Monsoon			Mean rainfall in mm	
Extreme	Severe		Moderate	Mild	No drought	
Bagepalli	633.21	605.41	664.49	639.05	2003.57	79.7
Bangarapete	106.83	477.97	818.26	717.27	2164.07	119.5
Chikkaballapura	331.23	535.08	568.39	530.94	1194.58	106.0
Gauribidanur	369.44	564.07	631.91	621.59	2155.49	109.0
Gudibande	123.97	150.90	146.12	141.80	565.06	80.0
Kolar	225.12	553.53	777.73	720.57	1661.06	117.3
Malur	129.30	416.68	732.76	634.30	1199.70	151.9
Mulabhagilu	314.08	581.11	740.94	703.11	1693.17	130.9
Shidlaghatta	305.67	526.49	606.26	531.83	1332.63	97.8
Srinivaspura	606.69	863.13	705.80	581.34	1497.69	118.4
Chinthamani	740.20	985.54	696.35	450.76	1555.57	115.5

Table 4: Stations wise drought mean value and total area of square Kilometre in S-W monsoon season from 2015-2019

Grid Stations		Drought Category in Area of square Km in S-W Monsoon			Mean rainfall in mm	
Extreme	**Severe**		**Moderate**	**Mild**	**No drought**	
Bagepalli	397.70	375.53	270.11	189.91	587.17	546.3
Bangarapete	73.61	108.54	272.55	370.80	859.08	694.9
Chikkaballapura	273.63	247.31	210.25	190.81	341.48	650.1
Gauribidanur	209.27	388.38	463.10	339.74	338.92	840.1
Gudibande	99.77	134.19	97.91	56.75	58.01	564.6
Kolar	83.62	128.93	233.08	227.00	903.35	735.5
Malur	278.22	100.21	124.95	158.32	587.36	756.5
Mulabhagilu	127.87	222.55	309.82	242.52	710.03	785.2
Shidlaghatta	338.55	205.54	167.27	129.72	480.12	649.2
Srinivaspura	89.16	211.38	226.86	206.99	964.68	712.4
Chinthamani	330.55	361.08	176.07	89.67	812.47	744.2

Table 5: Stations wise drought mean value and total area of square Kilometre in N-E monsoon season from 2015-2019

Grid Stations		Drought Category in Area of square Km in N-E Monsoon			Mean rainfall in mm	
Extreme	**Severe**		**Moderate**	**Mild**	**No drought**	
Bagepalli	460.14	172.88	292.46	342.84	3275.63	173.79
Bangarapete	879.64	361.94	505.70	531.76	1899.63	212.3
Chikkaballapura	451.57	171.28	227.55	285.32	2196.78	175.25
Gauribidanur	267.65	133.45	238.98	334.07	3369.76	205.05
Gudibande	31.94	19.39	34.88	260.85	555.65	165.1
Kolar	704.60	296.54	387.46	534.53	2020.10	210.9
Malur	704.05	227.74	245.18	293.00	1645.96	219.10
Mulabhagilu	909.99	332.48	421.82	459.57	1907.58	261.1
Shidlaghatta	367.58	177.40	261.61	348.69	2147.78	191.6
Srinivaspura	562.10	315.73	478.60	650.25	2240.44	215.9
Chinthamani	374.79	241.99	356.82	530.89	2921.74	238.2

Temporal and Spatial Variation of Vegetation Growth, Based on VHI.

To reveal the temporal and spatial difference in the vegetation growth process in past decades, the Geographical area's average values of the TCI, VCI, and VHI throughout the growing season were researched for each grid station between 2015 and 2019 in Kolar and Chikkaballapura districts. As represented in **Figures 2, 3, and 4.** the average values of VCI throughout the growing period for each grid station were between 33 and 59 in the pre-monsoon season (**Figure 2**), in contrast with the Temperature condition Index within the ranges of 26–79 and Vegetation health index from 45 to 84 (**Figure 3**), respectively. The different VHIs and different stations with the maximum (83) and minimum (3) values in VCI were found (**Figure 3**), and the Vegetation health index (VHI) had a relatively small variation in value in pre-monsoon (**Figure 4**).

Spatially, the study results showed that 65% of the Kolar and Chikkaballapura regions had a positive value for VCI, and the remaining 35% was negative based on the TCI and 63 % for VHI. Indicating that the vegetation had increased in the majority of the study area for both VHI and VCI. Hence the regions with increasing vegetation stress based on the VHI were wider than that of VCI. This was evident in big semi-arid districts such as Kolar and Chikkaballapura districts. Comparable with that of VCI showed that the area might sustain more water moisture stress for seasonal vegetation growth. In the case of the Temperature Condition Index, the decreasing value detected in the northeastern part of both districts suffered from moisture conditions for vegetation growth, especially in semi-arid regions. Most of the northern part of the study region showed increasing temperature based on TCI and VCI in Pre monsoonal season, showing that the southwest part of the area province might happen to less thermal stress.

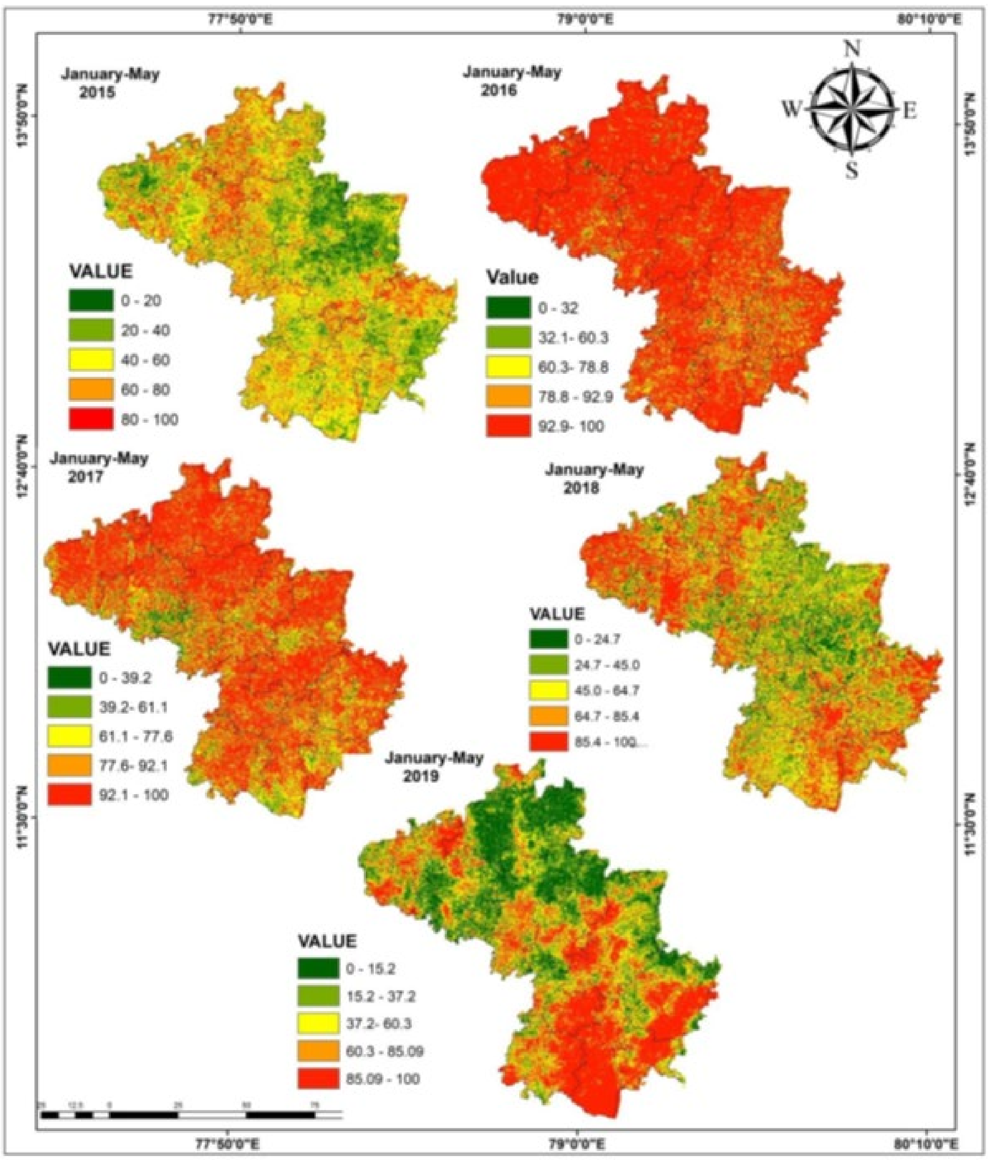

Figure 2: VCI spatial pattern of five-year values during the growing season in Pre monsoonal period of 2015–2019

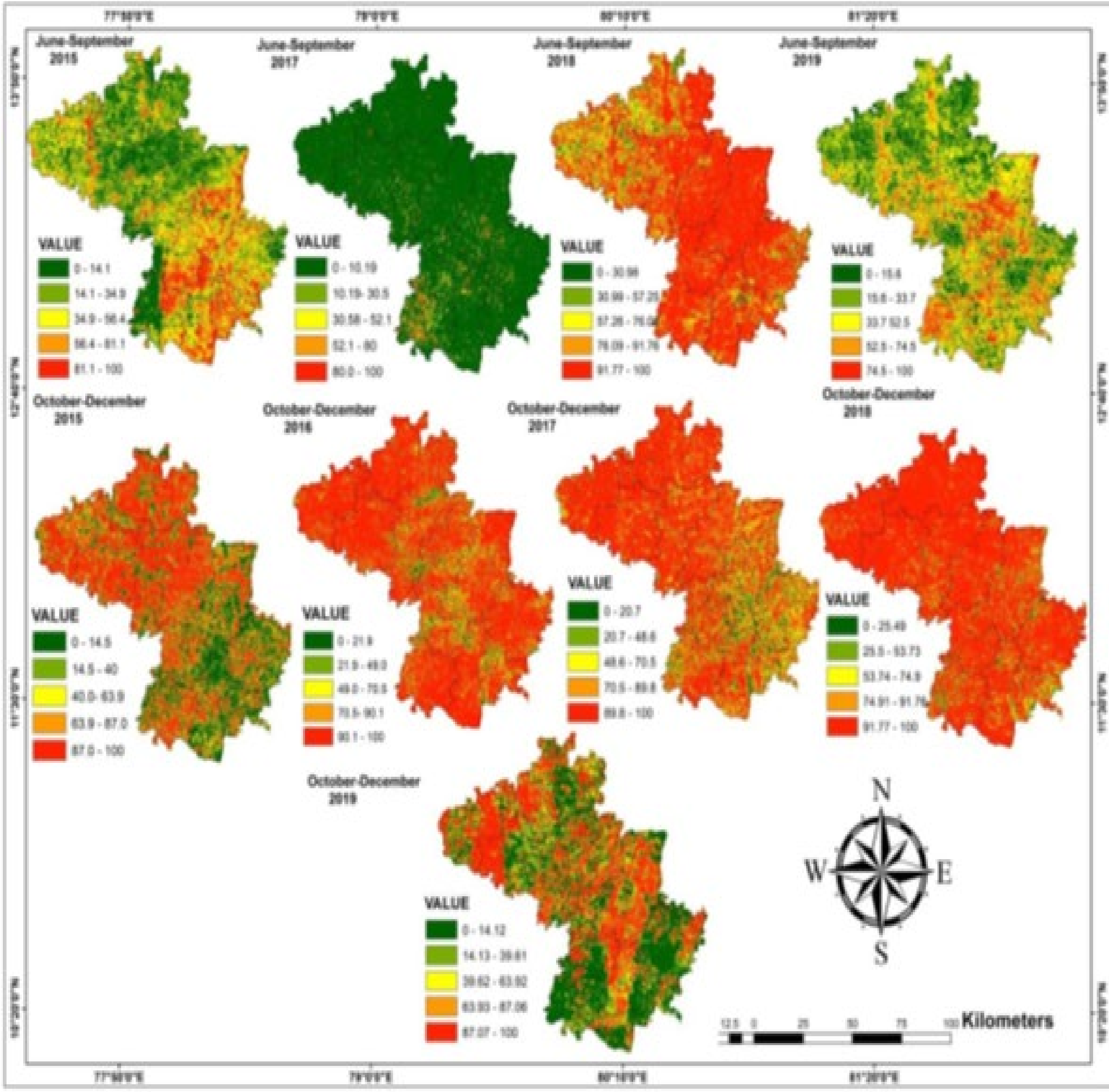

Figure 3: VCI spatial pattern of five-year values during the growing season in the South-west and North-east monsoonal period of 2015–2019

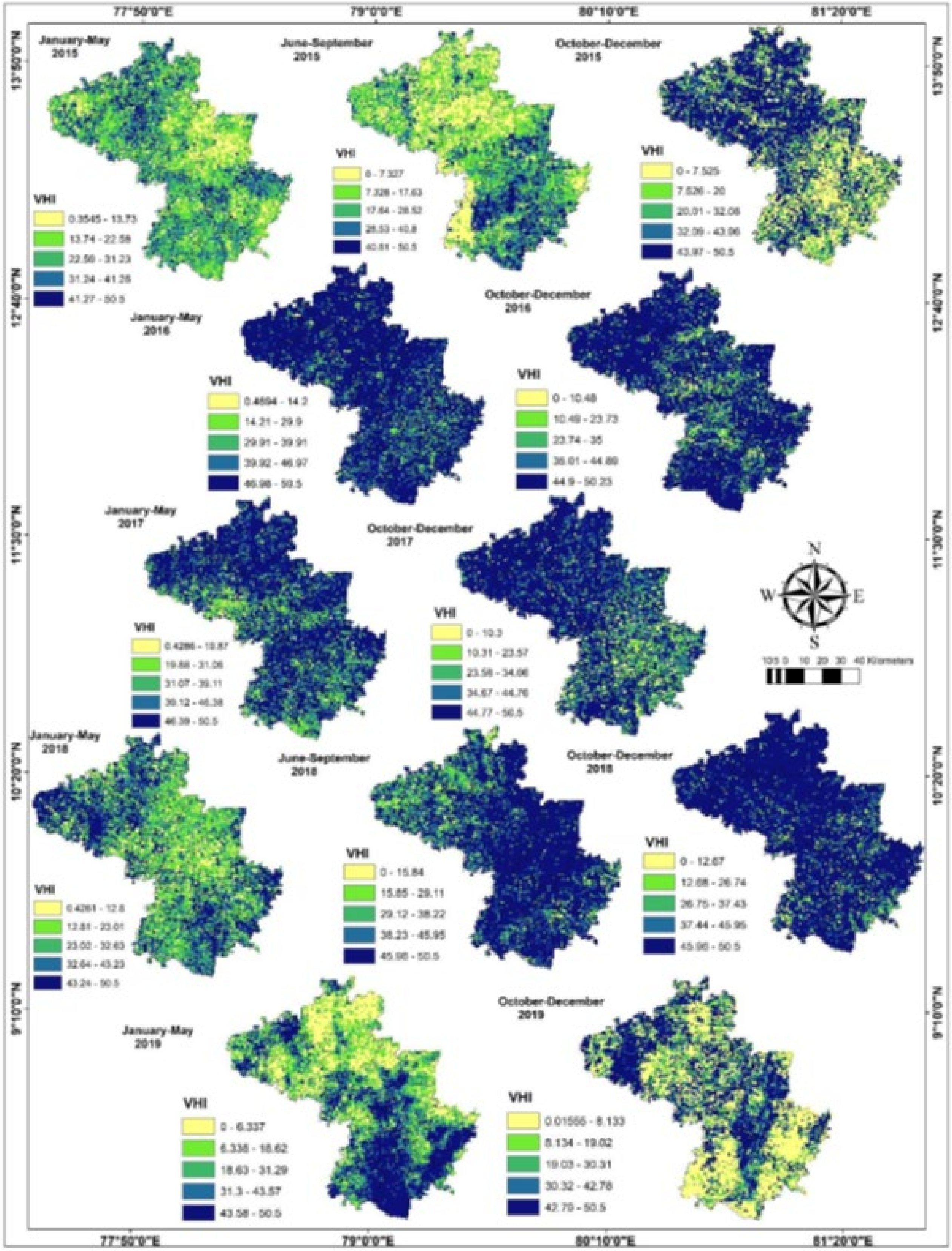

Figure 4: VHI spatial pattern of five-year values during the growing season in Pre, South-west, and North-east monsoonal period of 2015–2019

The percentage of area changes showed vegetation stress is VHI < 40, normal vegetation health condition 40 < VHI< 60, and favourable vegetation condition > 60 were further researched, as shown in Figure 4. Again, the % of the area with vegetation stress VHI < 40 decreased from 2015 to 2019, and at the same time, the % of the area with normal vegetation conditions and favourable vegetation conditions increased from 2015 to 2019. Overall the study indicated that the Average values of % of the area affected by extreme drought in Bagepalli grid station were 14 % affected area as flowed by Chintamani station was affected with the highest percentage in the Pre-monsoon season about 17 % of the area Srinivasapura also affected 15 % Gudibande effected 10 % so the overall station was affected extreme condition of the drought showed in **Figure 3.** For the S-w monsoon season, the Shidlaghatta area suffered 26% of the Extreme drought Condition; Malur station recorded 22 % of the ED, and Gudibande, Bagepalli, and Chikkaballapura top in terms of drought % duration lasting 22.14%, 22.85%, and 22.64% respectively. Srinivasapura and Kolar hold 5 % and 6% of the agricultural drought respectively in the least position; all the stations show a drought % in **Figure 4**

The occurrence of VHI drought in the northeast monsoon is relatively lowered than in the southwest monsoon season. Mulubhagilu dealt with 5 years amounting to 23.17% of VHI Extreme drought duration whereas 2015 to 2019. The lowest ED was happening in Gudibande station with 3 %. Gauribidanur and Malur stations have 25 % of values and a drought duration of 50.72% Overall the stations in the study area witnessed drought in the whole study period shown in **Figure 5.**

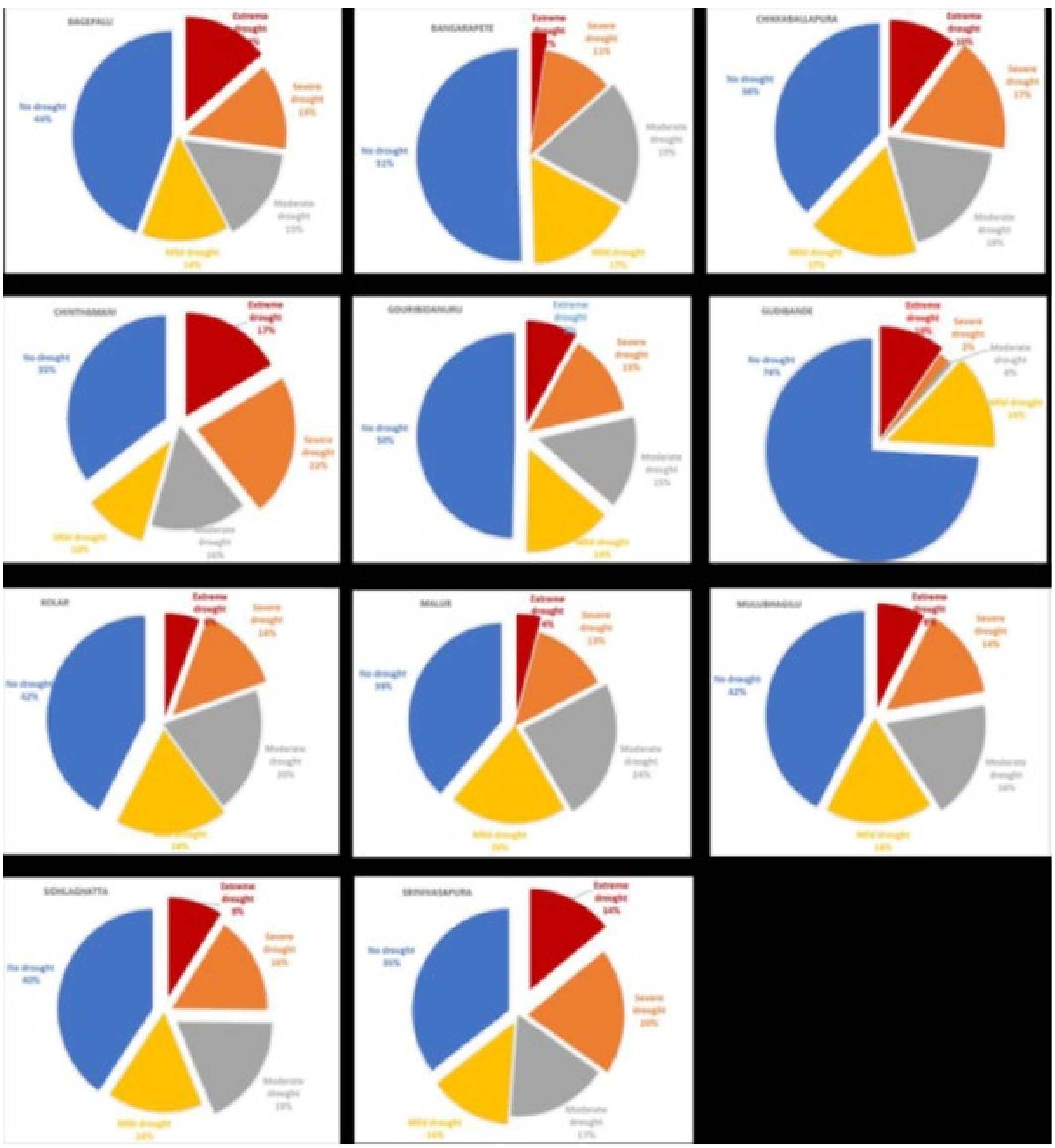

Figure 5: Agricultural Drought areas in percentage according to km2 to the severity of drought in the Pre-monsoon period from 2015 to 2019

Figure 6: Agricultural Drought areas in percentage according to km2 to the severity of drought in the Southwest monsoon period from 2015 to 2019

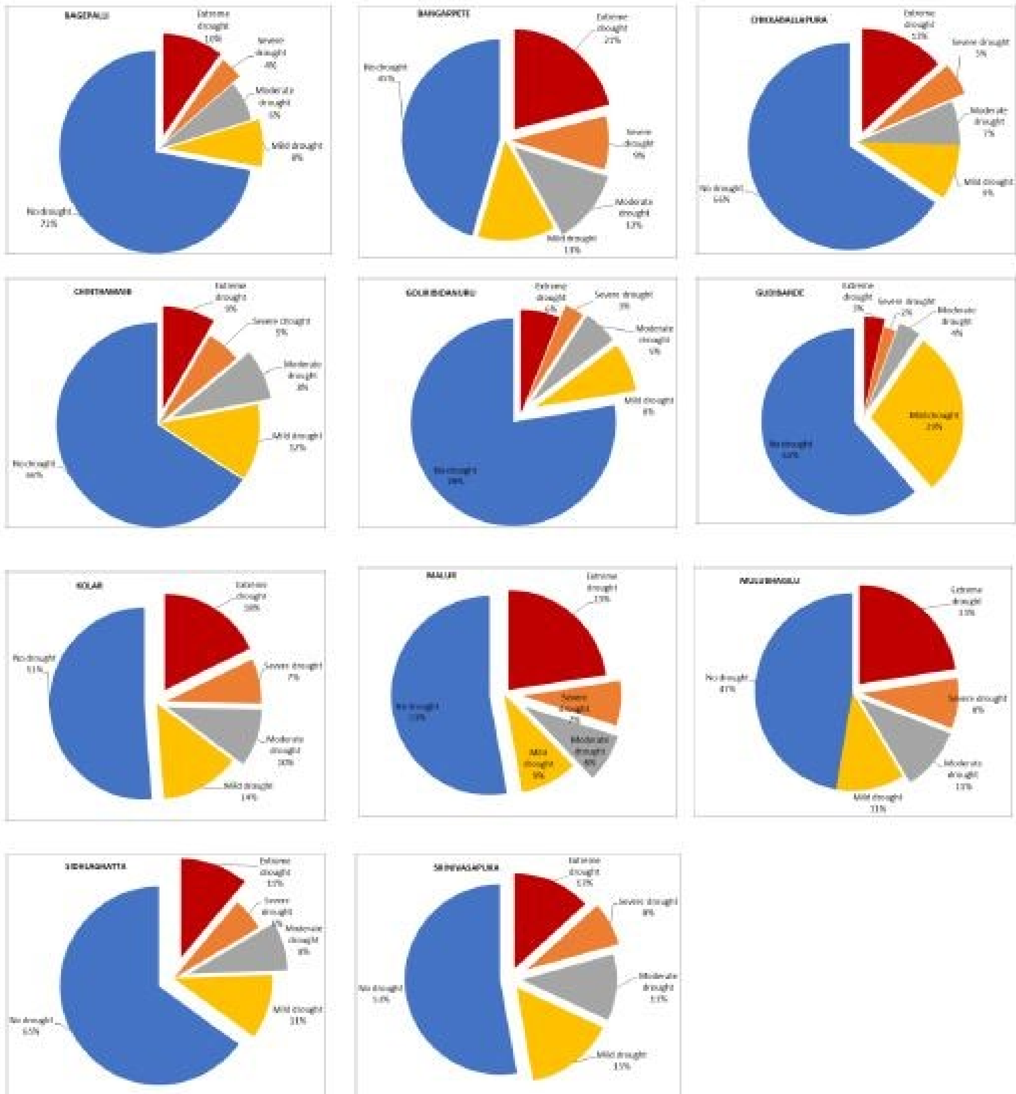

Figure 7: Agricultural Drought areas in percentage according to km2 to the severity of drought in the North-East Monsoon period from 2015 to 2019

We see that the vegetative drought Index assessment in terms of TCI and VCI shows different results over some stations of Kolar and Chikkaballapura. hence, useful to apply such an index for drought which takes into cause both the TCI and VCI i.e. surface moisture as well as thermal stress of vegetation. This is completed utilizing the VHI for drought monitoring. In Figure 8 we show the Vegetation health index for the total area affected in different grid station in square kilometres in the pre-monsoon season the Srinivasapura and Chintamani taluks was affected by more than 300 squares Kilometre in the Extreme drought Category. Severe drought in the Bangarapete and Gauribidanur suffered 200 square Kilometres affected in the severe drought category and different stations indicate the affected area in square Kilometre in seasons Figure 8.

In the same area, mild to moderate severity of the drought was also indicated in the rest of the areas. Moreover, the outcome of the VHI as a drought severity detection index depends on the acceptance that LST and NDVI at a given pixel value in satellite images will differ inversely over the period, with variations in TCI and VCI operating by local surface moisture conditions. This research also exhibited that the occurrence of the agricultural drought was due to a deficit of Precipitation leading to a peak level of surface moisture stress caused by the drought conditions.

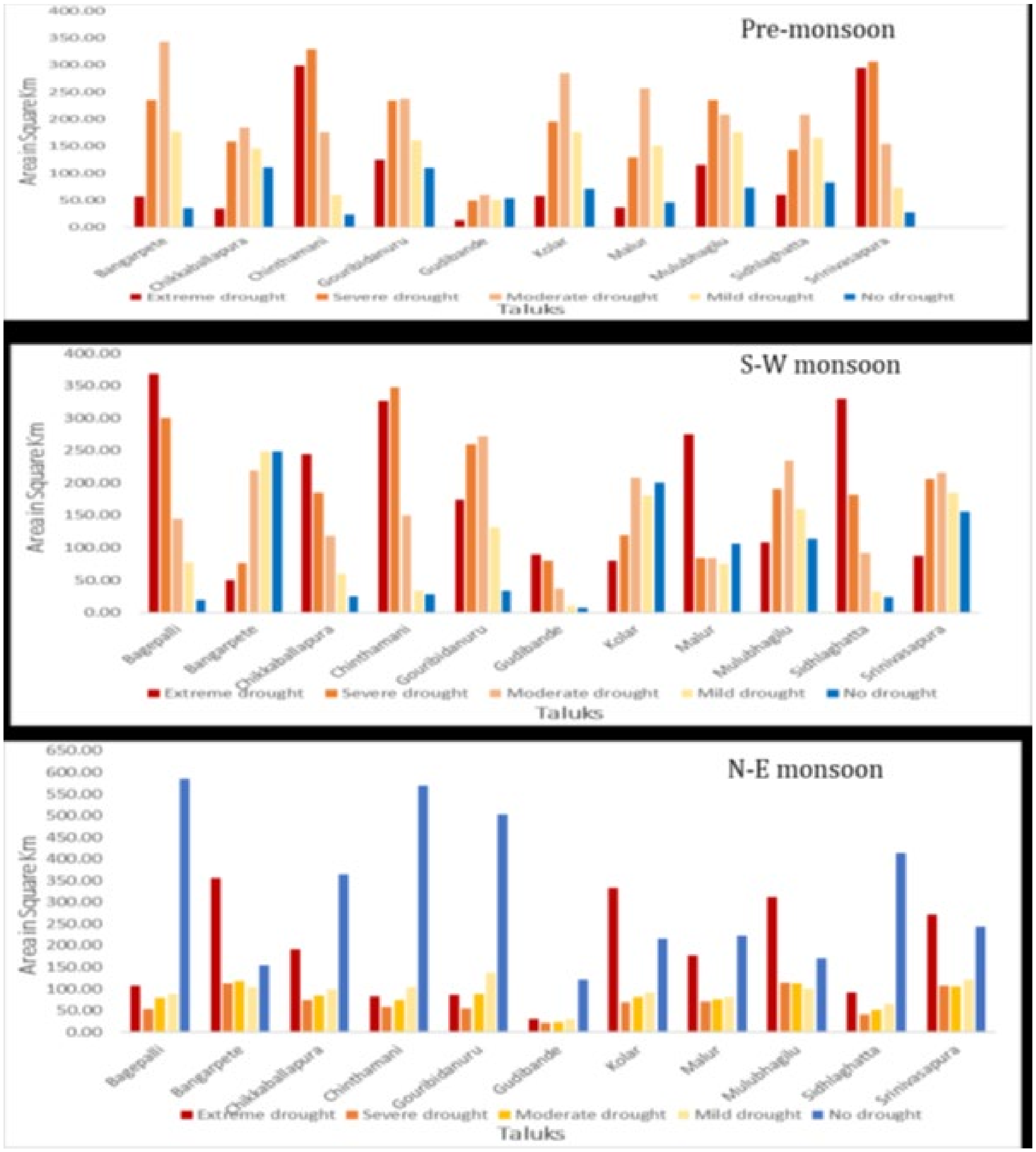

Figure 8: Agricultural Drought areas in Square Kilometres according to the severity of drought in Seasonal period from 2015-to 2019

Conclusion

GIS and remote sensing-based agricultural drought can be improved and monitored by the Vegetation Health Index composed of TCI and VCI agricultural drought indices. This Research showed the duration, severity, and spatial extent of agricultural drought areas using TCI, NDVI, VCI, and VHI at different grid stations in both districts during the Pre, Southwest, and Northeast monsoon season. The Vegetation Health Index model indicate that the year 2019 and 2015 was extremely drought (ED) period whole the study area where the average VHI value range was less than 10. Our outcome in this research provides the evaluation of regional growth of vegetation activity and drought time and area estimation, which shall be useful for the vegetation growth productivity management, Drought prevention, and detection help agriculture assessment for decision-makers and farmers. Especially, the yearly drought model income showed the drought severity status at the different spatial resolutions, which is considered by drought management decision-makers and former at regional levels. If all spatial maps can be evaluated by the local communities, these maps also help estimate land conditions. Drought severity like extreme stress, moderate stress, severe stress, near normal, poor vegetation, good vegetation, fair healthy vegetation, very good healthy vegetation, and excellent healthy vegetation was appraised in terms of % area coverage.

This study reveals that the effect of agricultural drought could be lessened by requiring smallholder farmers to a range of on-farm practices. The research may also contribute implementation and formulation of drought mitigation and coping programs in the Kolar and Chikkaballapura Districts.

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Data Sharing Statement
The datasets used and/or analysed during the current study available from the corresponding author on reasonable request

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