EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology, 2025, 26(9), 211–219
https://doi.org/10.12912/27197050/209596
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Received: 2025.07.30
Accepted: 2025.08.15
Published: 2025.09.01

A MODIS-based long-term spatiotemporal assessment of agricultural drought in Haveli Tehsil (2008–2024)

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ABSTRACT

Drought is a hazardous event occurring in every climatic division of the world and has killed millions. It severely impacts societies, agriculture, and the environment, which are responsible for lowering national growth. It develops slowly due to the deficient rainfall in the region. The deficient rainfall and high temperature are the primary causes for triggering the water stress in the crop. However, the regional responses vary due to the soil's water-holding capacity. Therefore, we have used long-term records of the MODIS satellite for drought analysis in this research study. The drought indices, such as the vegetation condition index (VCI), temperature condition index (TCI), and vegetation health index (VHI), were used on long-term satellite image datasets from January 2008 to December 2024. The Haveli Tehsil's vegetation conditions have been investigated for 2024 with government-declared drought years such as 2008, 2012, 2015, etc. The results show that only 15% of the region has faced drought conditions in 2024, as 84% of the area has good vegetation due to sufficient rainfall in 2024. The results of this study are helpful in early detection of droughts and their monitoring accordingly.

Keywords: vegetation monitoring, agricultural drought assessment, land surface temperature, vegetation health index, vegetation condition index, temperature condition index.

INTRODUCTION

Drought causes famine, affecting the nation's food security and increasing migration from affected villages to cities in search of livelihood (Etzold et al., 2014; Asefawu, 2022). Therefore, it increases the pressure on the city's urban resources. It has also been observed that the crime rate increases in drought regions due to a lack of employment. A total of 1.5 billion people on the planet have been affected by the drought disaster in the past two decades (Liu et al., 2018). According to the World Meteorological Organisation (WMO), drought will affect 75% of the world's regions in the year 2050 (Degefie, 2019). During the drought episodes from 1964 to 2007, the global average harvested area was reduced by 4.1% (Sheffield and Wood, 2012). Agriculture is the most vulnerable sector due to food security and its contribution to the national GDP. Several businesses are based in the agriculture sector, such as grain production, fodder for cattle, milk production, and food processing. Agriculture is one of the backbones of several countries' economies, including India (Pawlak and Kołodziejczak, 2020; Gaikwad et al., 2021-a).

Traditionally, drought monitoring has been done via ground surveys, manual mapping, and manual calculations. However, traditional manual methods are tedious and time-consuming. Therefore, satellite-based drought monitoring is used to monitor droughts due to its cost-effectiveness and near-real-time observation of the region. Several countries use satellite datasets, weather stations, and ground surveys to monitor drought conditions with the help of a drought monitoring system to solve the issues of drought episodes. These systems issue automatic early warning alerts to civilians and the associated agencies of the government. In addition, such measures support the government in taking necessary actions and preparing a mitigation strategy (Devereux, 2008; Gaikwad et al., 2019-a; Mishra et al., 2021). Moreover, satellite observations are crucial for soil, water, crop monitoring, crop yield estimation, irrigation, fertilizer, pesticide and insecticide management (Kubitza et al., 2020; Nakalembe et al., 2021; Khasanov et al., 2023), etc.

The drought is classified into three categories based on its characteristics: meteorological, agricultural, and hydrological drought. Where deficient precipitation causes meteorological drought. Furthermore, deficient precipitation leads to crop failure due to reduced soil moisture. Such a phenomenon is known as agricultural drought. Similarly, the unavailability of surface and groundwater leads to hydrological drought. It is responsible for the water scarcity problem in the domestic, industrial and agricultural sectors, etc (Gaikwad et al., 2019-b; Vibhute et al., 2020; Mishra et al., 2021; Jahura et al., 2024).

Several researchers have been working on agricultural drought analysis and monitoring using satellite data and vegetation indices. For instance, Kulkarni et al. (2020) have used combined drought indices such as normalised difference vegetation index (NDVI), land surface temperature (LST), and standardised precipitation index (SPI) and developed a new index for analysing the drought conditions in the Marathwada region. The principal component analysis (PCA) method was used to reduce the dimensionality of the time series dataset. Their finding shows that the LST and NDVI provided sufficient information on droughts to analyze their conditions in the studied region. Similar case studies were conducted by (Swain et al., 2022) for the agricultural drought analysis using SPI and NDVI indices of the Marathwada region of 2019-2023. Their experimental analysis shows that the region is highly vulnerable to drought because it is in the rain shadow region of Maharashtra. The study (Gaikwad et al, 2021-b) analysed seasonal changes of the *Kharif* and *Rabi* seasons in Vaijapur Tehsil of Maharashra, India using NDVI to analyze the vegetation cover. Similarly, Singh et al. (2022) studied the Marathwada region using satellite-based vegetation status indicators like VCI and the advanced drought response index (ADRI). Their (Singh et al., 2022) study claimed that 5% of the area has faced severe drought conditions, and over 70% has been vulnerable to drought conditions for a decade. Nandargi and Kamble 2017) investigate the temporal and spatial analysis of the precipitation and NDVI over the Pune district of Maharashtra. It was observed that the region had faced many of the worst drought episodes for decades, from 1972 to 2009. It is also observed that the region receives less rainfall than average rainfall every 3–4 years. In addition, Paul et al. (2024) investigated the applications of optimized soil adjusted vegetation index (OSAVI) for vegetation condition analysis of the Pune district of Maharashtra, India. The Author has used the MODIS product MOD13Q1 over the 23 years (2000–2022) of spatial resolution 250M to accurately assess the vegetation condition mapping using Google Earth Engine.

Several researchers have used NDVI for vegetation monitoring. However, there were several limitations, such as soil reflectance influencing the NDVI values, limited sensitivity of the chlorophyll, and saturation in dense and moderate vegetation. Similarly, the LST has specific challenges like cloud cover blocking the thermal radiation of the spatial objects.

Therefore, the present study analyses the agricultural drought using the vegetation indices. The primary objective of this study is to analyze the vegetation conditions of the Haveli Tehsil in the year 2024, with previous drought years 2008, 2012, and 2015 using VCI, TCI, and VHI indices.

STUDY AREA

This study selects Haveli Tehsil (Figure 1), a subdivision of the Pune district in Maharashtra, India. The altitude of the area ranges from 550 to 1051 meters. The Haveli Tehsil is located between 18°42’51.97” N and 18°43’30.24” N. The Haveli Tehsil in Pune, Maharashtra, has a total area of 1164 sq KM as per the census report 2001. Figure 1 demonstrates the study area for the present study.

DATASETS USED

This research study used the MODIS (MOD11A2 V6.1) dataset, which provides an average 8-day land surface temperature (LST) with 1 km resolution. The MOD13A2 V6.1-based NDVI and Enhanced Vegetation Index (EVI) products were also used in this study for vegetation analysis. It provides a 16-day composite of the NDVI data with long-term records. The dataset is available in the 1200 × 1200 spatial grid. The product MOD11A2 is a composite of the 8-day average

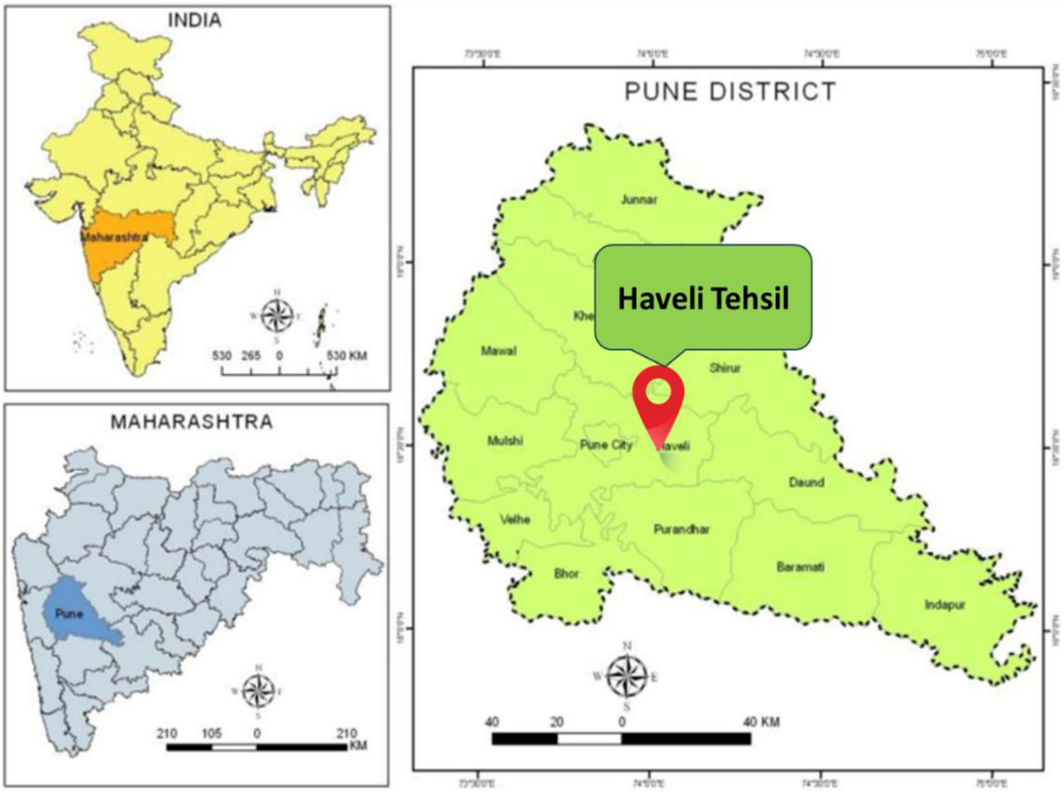

Figure 1. The study area is Haveli Tehsil of Pune district, Maharashtra, India

of the pixels. The Terra and Aqua platform revisits the exact location twice in the 8 days. In the study area, the Monsoon season starts from June to October, and the Rabi season from October to March. Hence, we have selected NDVI composite images of these months for vegetation condition analysis. We have acquired a dataset for April to June 2008, 2012, 2015, and 2024, respectively.

METHODS

In this research study, we used Google Earth Engine (GEE) and QGIS software for the experimental analysis and map preparation, respectively. The GEE provides the preprocessed dataset of MODIS satellites to the end users. Additionally, it offers high computation power and functions for complex geoprocessing and statistical operations in the code editor.

Temperature condition index (TCI)

In this study, we used the TCI index (Kogan, 1995) to analyse the temperature profile of the region and vegetation stress due to high temperature or high wetness conditions. Table 1 shows the TCI index based on brightness temperature and represents the current month's recorded maximum value deviation. The TCI index is calculated using Equation 1.

$$TCI = \frac{(BTmax - BT)}{(BTmax - BTmin)} \times 100 \tag{1}$$

where: BT, $BTmax$, and $BTmin$ are smoothed weekly brightness temperatures with absolute maximum and minimum values. The values near zero show extreme drought, whereas values > 50 show normal vegetation conditions and values near 100 show healthy vegetation conditions (Bento et al., 2018).

Table 1. TCI drought severity range

Sr. No.	TCI Range	0% to 100%
1	Normal condition	>50%
2	Severe condition	>0%
3	Healthy condition	100%

Vegetation condition index (VCI)

VCI is computed using the long-term records of NDVI images, which are used to find the greenness in the vegetation. Higher values indicate healthier conditions, and lower values indicate stressed or damaged vegetation. It uses the red and near-infrared bands of the satellite imagery for NDVI computation. Equation 2 was used to compute the NDVI index.

$$NDVI = \frac{(NIR-RED)}{(NIR+RED)} \quad (2)$$

where: *NIR* is the near infrared band (MODIS Band 1), RED band (MODIS Band 2).

The VCI is based on average NDVI values. It compares the current NDVI values with the historical trends. It is used to monitor and assess the crop growing conditions and identify the water stress in the region. The VCI index was computed using Equation 3.

$$VCI = \frac{(NDVI-NDVImin)}{(NDVImax + NDVImin)} \times 100 \quad (3)$$

The *NDVI* represents the actual value from the *NDVI* image, with the *NDVI* max and *NDVI* min derived from long-term records. Table 2 illustrates the severity of drought calculated using the range of VCI. Drought severity and vegetation stress become noticeable when the VCI falls below 35%, moderate drought is observed between 35–50%, and healthy vegetation values are greater than 50% (Moussa, 2021).

Vegetation health index (VHI)

The VHI is used to assess the health of vegetation using the VCI and TCI indices. It is significantly helpful for drought monitoring, yield analysis, crop growth and disease monitoring (Kogan and Kogan, 2019). The VHI values range from 0 to 1, where 0 denotes severe vegetation stress, and 1 represents healthy vegetation conditions. Equation 4 was used to calculate the VHI index.

$$VHI = \alpha VCI + (1-\alpha)TCI \quad (4)$$

where: *TCI* and *VCI* are computed from long-term records of the satellite imagery as discussed in sections 4.1 and 4.2, α is a parameter that quantifies the contribution of each component to the overall vegetation health. Table 3 illustrates the VHI severity range.

RESULTS AND DISCUSSIONS

The preprocessed MODIS dataset for the selected drought years (2008, 2012, 2015) was compared with the current year 2024. The vegetation indices are implemented using the GEE tool to compute drought indices. We have also computed the TCI index using LST. The TCI is used to analyse the stress caused by temperature variations. The lower value (Table 1) indicates high vegetation stress, whereas the higher values show healthy vegetation. Similarly, higher temperature values indicate drought conditions. Figure 2 shows the TCI index map of the Haveli Tehsil computed for 2008, 2012, 2015, and 2024 for monitoring the droughts. Several regions in the studied area faced moderate drought (red highlighted area) in 2008, 2012, and 2015 (Figures A, B, and C). However, there was a minor severe drought (dark red highlighted area) in 2024 (Figure 2-D) due to insufficient rainfall. In 2024, most of the areas had no drought (yellow highlighted area) (Figure 2D). The temperature increased due to less canopy cover in the studied region. The canopy cover is reduced due to the unavailability of water, which results in soil moisture loss in the study area. The canopy absorbs heat and lowers the temperature of the landscape. The temperature analysis is complex due to many parameters like cloud cover, humidity, solar angle, distance from the equator, altitude, distance from the sea, ocean currents, crop and forest cover, etc.

On the other hand, the drought conditions were moderate (Figures 3 and 4A, B, and C) in several regions for 2008, 2012, and 2015 using the VCI index. In addition, there was no drought in several regions in 2024 as per the VCI index (Figures 3 and 4D). Thus, it is confirmed that the VCI index has also been calculated accurately and

Table 2. VCI drought severity range

Sr. No.	VCI range	0–100%
1	Severe condition	<35%
2	Moderate condition	35-50%
3	Health condition	>50%

Table 3. VHI drought severity range

Sr. No.	VHI range	0% to 100%
2	Severe condition	>1% to <30%
3	Moderate condition	>30% to <40%
4	Health condition	>40%

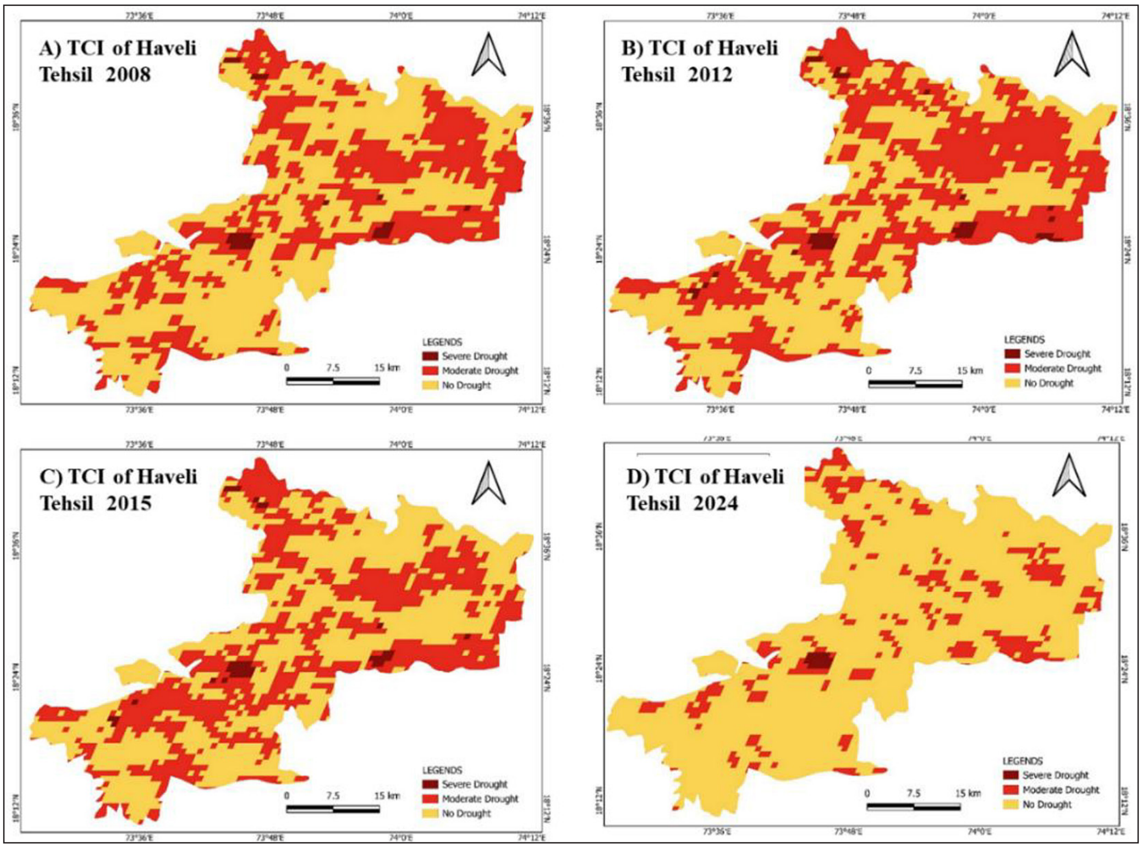

Figure 2. Temperature condition index (TCI) map of Haveli Tehsil, Maharashtra, India

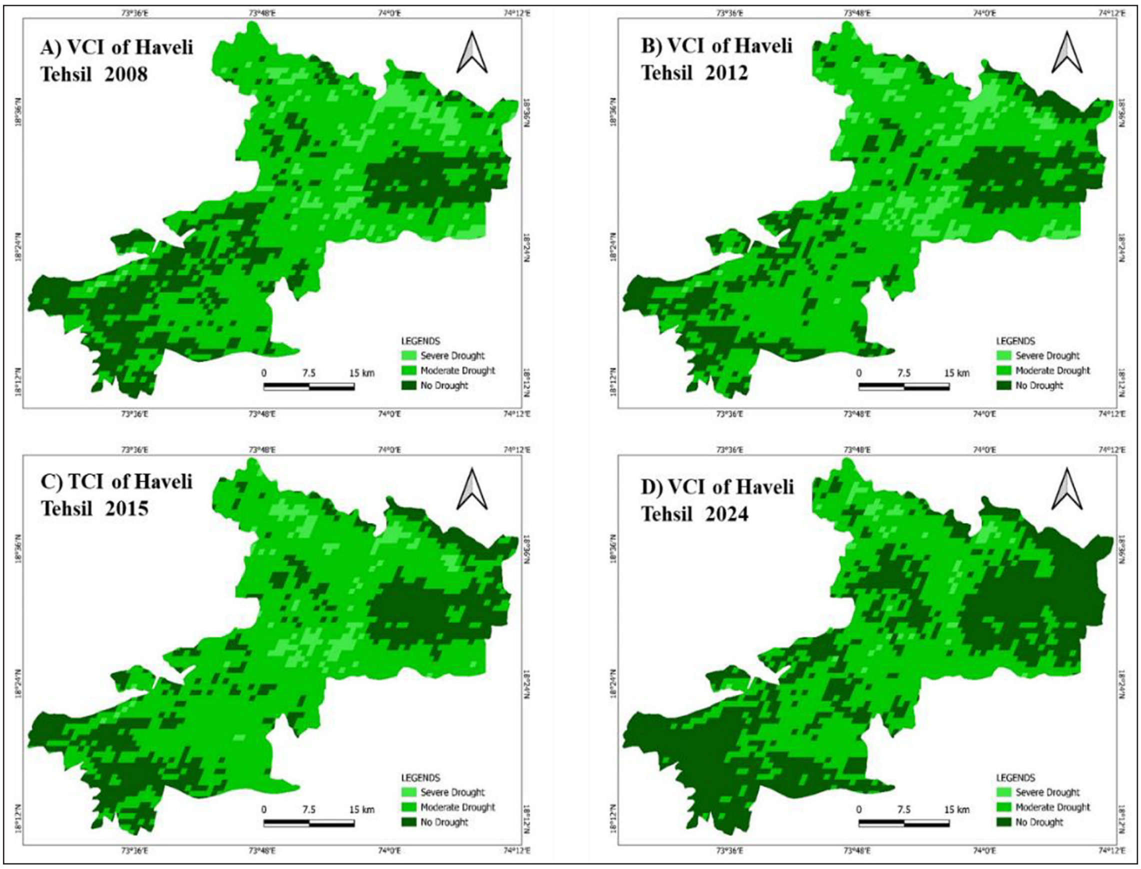

Figure 3. Vegetation condition index (VCI) map of Havel Tehsil, Pune, Maharashtra, India

that the studied region has been mapped accordingly to show its effectiveness in drought analysis. Figures 3 and 4 show the vegetation cover map using the VCI and VHI indices, respectively.

Figure 5 shows the temperature pattern in 2008, 2012, and 2015, but changed in 2024 due to sufficient yearly rainfall. Therefore, the region recorded a normal temperature in 2024 compared

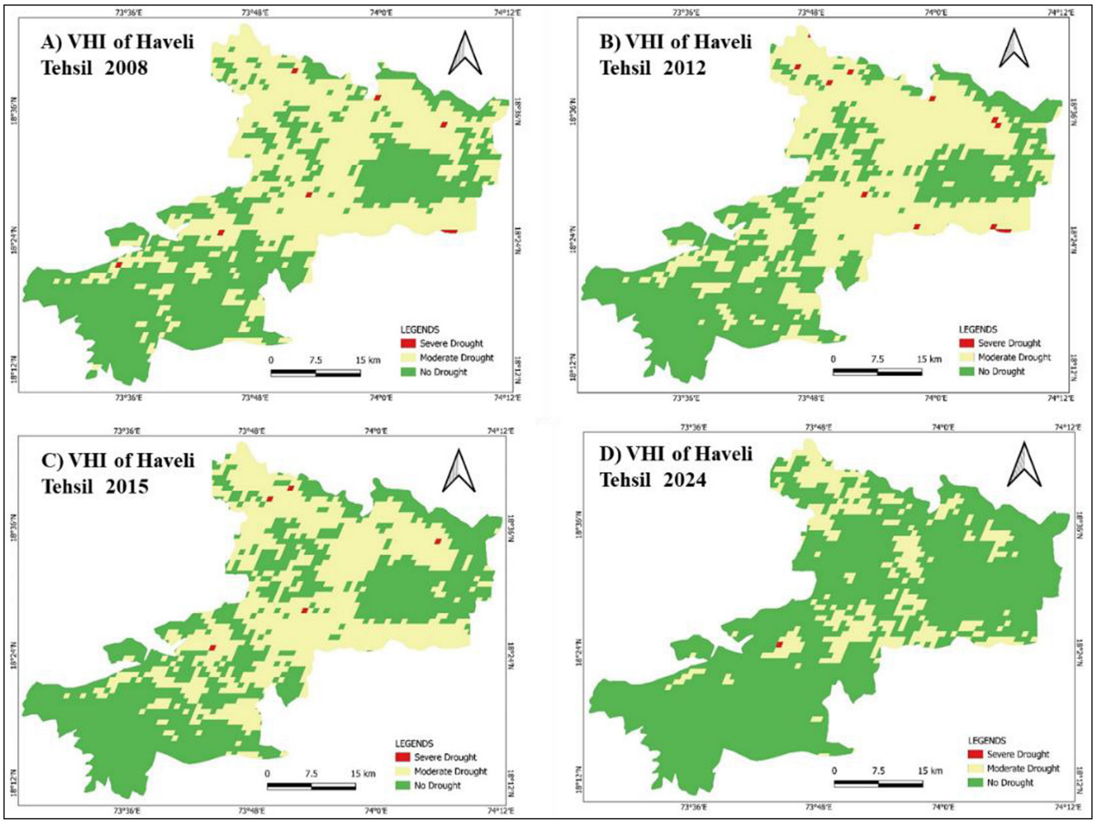

Figure 4. Vegetation health index (VHI) map of Havel Tehsil, Pune, Maharashtra, India

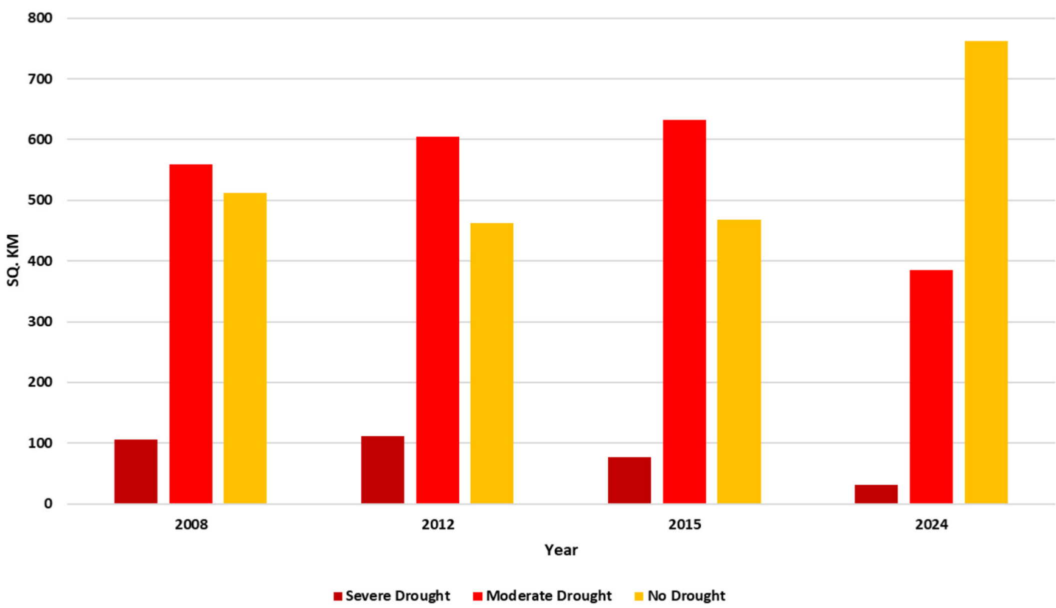

Figure 5. Temperature condition index (TCI) results (Haveli Tehsil, Pune)

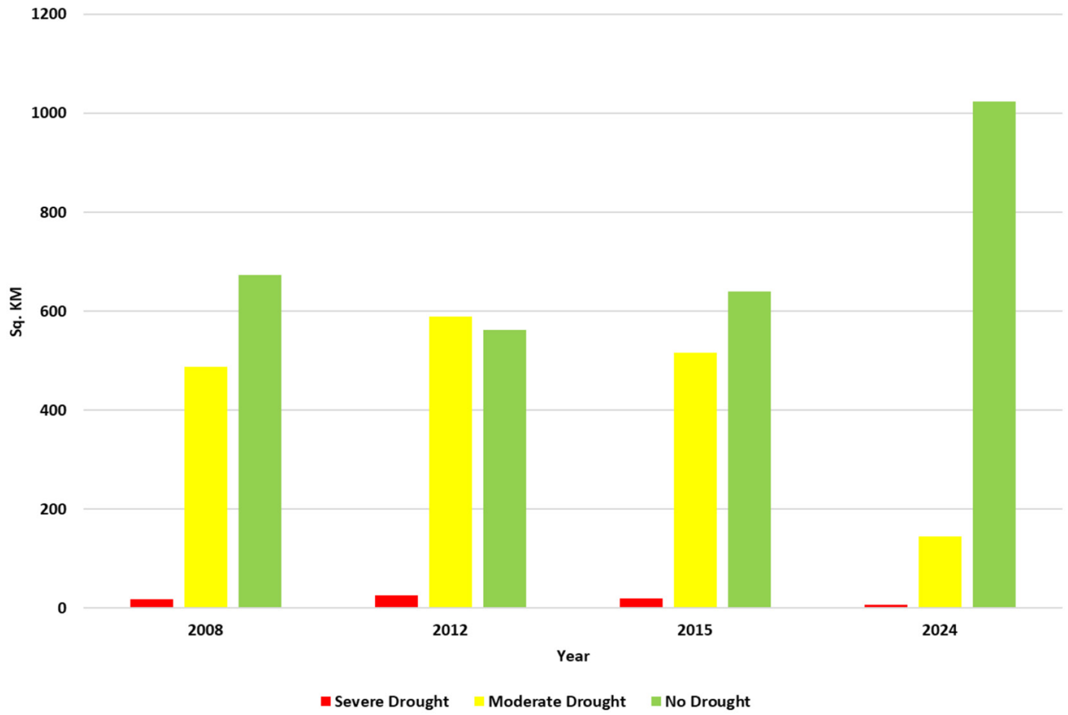

Figure 6. Vegetation condition index (VCI) results (Haveli Tehsil, Pune)

to the other years. The vegetation cover plays an important role in the temperature fluctuations.

Figure 6 shows VCI results for analysing 2008, 2012, 2015, and 2024 vegetation conditions. During this period, Haveli Tehsil experienced moderate rainfall in 2008, 2012, and 2015, while the state faced extreme drought conditions. The primary reason is that the Haveli Tehsil is surrounded by the Shayadri mountains, resulting in a typical good amount of annual rainfall. However, during the study periods, the region received less rainfall than the average, leading to moderate and extreme drought conditions in some villages of Haveli Tehsil. Table 4 demonstrates the results of vegetation indices, indicating the total area computed per the classification of vegetation conditions for 2008, 2012, 2015 and 2024. Between 2008 and 2024, less than 25 km^2 of the region was affected by extreme drought. On the other hand, 486.86 km^2 in 2008, 588.94 km^2 in 2012, 516.51 km^2 in 2015 and 144.81 sq.km area were affected by the moderate drought, where 512.28 km^2 in 2008, 461.89 km^2 in 2012, 467.9 km^2 in 2015 and 761.65 km^2 in 2024 indicate the healthy vegetation conditions. Nevertheless, half of the region did not face drought conditions due to adequate water availability in nearby dams and reservoirs. The Haveli Tehsil received above-sufficient rainfall, resulting in no drought conditions in 2024.

Table 4. Total area calculated as per the criteria of vegetation indices

Sr	Index	Classes	2008	2012	2015	2024
			Area in km^2			
1	TCI	Severe drought	17.8179	25.9779	20.316	7.5337
2	TCI	Moderate drought	486.86	588.94	516.51	144.81
3	TCI	No drought	672.65	562.41	640.5	1022.99
4	VCI	Severe drought	105.302	110.841	76.795	31.1887
5	VCI	Moderate drought	559.75	604.6	632.64	384.49
6	VCI	No drought	512.28	461.89	467.9	761.65
7	VHI	Severe drought	24.3835	16.2619	12.9	5.5762
8	VHI	Moderate drought	600.89	625.67	524.8	179.75
9	VHI	No drought	552.06	535.4	639.63	991.99

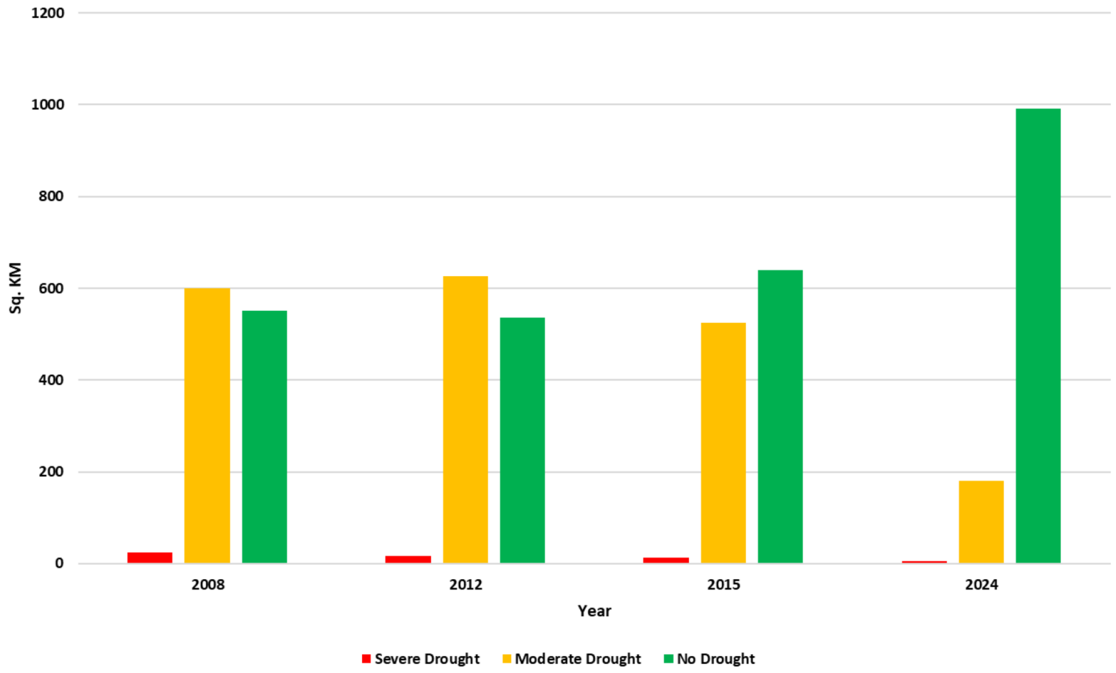

Figure 7. Vegetation health index (VHI) results (Haveli Tehsil, Pune)

Figure 7 shows that, in 2008, 2012, and 2015, a total of 600.89 sq km, 625.67 sq km, and 524.8 sq km were affected by the moderate drought, whereas in 2024, a total of 179 sq km was affected by the moderate drought, which is the lowest in overall years. The total 992 sq km region of the Haveli Tehsil shows healthy vegetation conditions due to sufficient rainfall. Thus, it is concluded that the study region faces moderate drought episodes.

CONCLUSIONS

In the present study, we have used long-term records of the MODIS satellite dataset for vegetation condition analysis for the monitoring of drought conditions of Haveli Tehsil of Pune district, Maharashtra, India, for the years 2008, 2012, 2015, and 2024. In this regard, the VCI using the time-series NDVI index, TCI from LST and VHI using the VCI and TCI indexes have been computed to analyse the drought conditions. The results show moderate drought conditions in 2008, 2012 and 2015, whereas 2024 faced no drought conditions in the region. The outcome of this study is validated with government and rainfall records, and it is confirmed that the studied region faced moderate droughts due to less rainfall in 2028, 2012, and 2015. In addition, other districts of Maharashtra have faced extreme droughts in recent years. Therefore, the state government declared this year's drought in Maharashtra, India. It is concluded that the VHI index is crucial for long-term vegetation condition analysis.

Acknowlegements

We gratefully acknowledge using Google Earth Engine to provide the datasets and tools used in this research.

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