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Research Paper

Evaluating crop water stress through satellite-derived crop water stress index (CWSI) in Marathwada region using Google Earth Engine

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ABSTRACT

Accurate information of crop water requirements is essential for optimal crop growth and yield. Assessing this information at the appropriate time, particularly during the vegetative and reproductive stages when water demand is highest, is crucial for successful crop production. Our study centered on the drought-prone Marathwada region, specifically targeting the years 2015 to 2020, encompassing the challenging drought year of 2015 and the favourable year of 2020. The crop water stress was detected using crop water stress (CWSI) index and compared with normalized difference vegetation index (NDVI) and normalized difference wetness index (NDWI) derived from satellite data. Our findings reveal a negative correlation between the CWSI and satellite derived vegetation indices NDVI and NDWI. Notably, the NDWI index exhibits stronger alignment with CWSI compared to NDVI. The correlation demonstrates particular robustness during drought or deficient rainfall years such as 2015, 2017, and 2019, while weaker correlations are observed in 2016, 2018, and 2020. Moreover, these correlations display variations across different areas within distinct rainfall zones.

Keyword: CWSI, NDVI, NDWI, vegetation indices, evapotranspiration, thermal band, SWIR

The availability of irrigation information at the right time is of utmost importance in agriculture, as it not only increases crop production but also ensures food security (Surendran and Madhava Chandran, 2022; Wang *et al.,* 2023; Yang *et al.,* 2022). Therefore, it is vital to assess crop water stress and establish suitable irrigation schedules based on the crop water requirement during different growth stages (Geerts and Raes, 2009; Kumar *et al.,* 2019; Wang *et al.,* 2023). Typically, traditional methods involve measuring soil moisture availability for crop in the soil (i.e., available water for crop transpiration) and determining the actual evapotranspiration requirement (Feng *et al.,* 2023; Katimbo *et al.,* 2023; Kheir *et al.,* 2021; Maguire *et al.,* 2022) of the crop (i.e., crop water demand) to assess irrigation requirement and crop stress (Allen *et al.,* 1998). Additionally, information of crop type and growth stage is also taken into consideration during the assessment (Anila Bahadur *et al.,* 2021; Sanjay Satpute *et al.,* 2021).

The utilization of satellite remote sensing technology for crop monitoring and evaluation has become extensive (Brijesh Yadav *et al.,* 2023; Rahul Nigam *et al.,* 2023), and it has the potential to transform the efficiency of irrigation management. Regular periodic acquisition of satellite data allows for frequent updates on crop health and water requirements, which can be utilized to enhance irrigation scheduling and minimize water waste. Furthermore, various remote sensing indices can be utilized to estimate crop health and water stress, serving as critical indications of water deficiency that can activate irrigation events. By merging this information with weather forecast data and soil moisture, irrigation schedules can be customized to satisfy the unique needs of each crop and field (Rahul Nigam *et al.,* 2023).

The Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Temperature

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Condition Index (TCI), Vegetation Health Index (VHI), and Crop Water Stress Index (CWSI) are widely used to evaluate crop health and water stress (Swoish *et al.,* 2022; Woldesellasse *et al.,* 2019). The CWSI, in particular, is a powerful tool for assessing water stress and recommending irrigation (Jamshidi *et al.,* 2021; Veysi *et al.,* 2017). It measures crop water stress by comparing the amount of water transpired by a stressed crop with that of a well-watered crop. This difference in water transpiration causes a corresponding increase in canopy surface temperature, which can be easily detected using satellite thermal sensors (Veysi *et al.,* 2017).

The objective of this research paper is to investigate the application of satellite-derived crop water stress index (CWSI) in crop water stress assessment. To accomplish this, the first step involves estimating the CWSI over the Marathwada region. Subsequently, the CWSI index is also compared with two other satellite-derived health indices, NDVI and NDWI.

MATERIAL AND METHODS

Study area

The present study focuses on the Marathwada region of the Maharashtra state which comprises of eight districts: Aurangabad, Jalna, Beed, Latur, Osmanabad, Nanded, Parbhani, and Hingoli. This region is situated in the rain shadow belt of the Sahyadri mountain range at the western ghats of Maharashtra, with a latitude extent ranging from 17°37’ North to 20°39’ North and a longitudinal extent ranging from 74°33’ East to 78°22’ East. The average annual rainfall in the region is approximately 750mm, which is relatively low compared to other regions of Maharashtra. As a result, the region is highly susceptible to droughts (Khetwani and Singh, 2020) and water scarcity, which have a significant impact on the agriculture and economy of the region. Agriculture is primary source of livelihood in this region with major of people are engaged in farming. The region is known for producing a variety of crops, including cotton, soybean, sugarcane, and pulses. However, water scarcity is a major challenge for farmers in Marathwada, and many rely on rainfed agriculture due to a lack of irrigation facilities and groundwater resources, exacerbating the water problem and leading to crop failure and economic losses.

Data

Land surface temperature (LST): Satellite-based LST is the Earth’s surface temperature which is a critical parameter in many applications, including drought monitoring, climate studies, hydrology, agriculture, forest fire detection and urban planning. In this study, MOD11A2.061 product of the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor on board the Terra satellite is utilized. It provides data on land surface temperature (LST) at a global scale with a spatial resolution of 1 km and a temporal resolution of 8 days. MOD11A2.061 uses a split-window algorithm to retrieve LST from MODIS observations in two thermal bands centred at 11 and 12 µm (Wan *et al.,* 2021). MODIS LST data was obtained from https://earthexplorer.usgs.gov/.

Normalized difference vegetation index (NDVI) and Normalized difference water index (NDWI): NDVI and NDWI are most popular and well recognized vegetation index from satellite observation (Kshetri, 2018). NDVI is a measure of greenness of vegetation while NDWI is measure of water content in the plants. In this study MOD13Q1.061 product of MODIS sensor on board Terra/Aqua satellite (Didan *et al.,* 2021) is utilized. It provides data at a global scale with a spatial scale of 250 m and temporal resolution of 16 days. The product includes multiple layers of information, such as NDVI, EVI and other surface reflectance information of red surface reflectance (645 nm), near infrared (NIR) surface reflectance (858 nm), Blue surface reflectance (469 nm), mid infrared (MIR) surface reflectance (2130 nm/ 2105-2155 nm). MODIS vegetation index data was obtained from https://earthexplorer.usgs.gov/. NDVI product is directly available in this product while we computed NDWI from surface reflectance band. NDVI and NDWI values show variations throughout different crop stages, with minimum values observed during sowing and maturity stages, and maximum values during the vegetative stage. To assess crop stress, anomalies in these indices are compared to historical values.

Rainfall gridded data: In this study, we have used daily rainfall gridded data from National Climate Centre (NCC) of India Meteorological Department (IMD) (https://www.imdpune.gov.in/lrfindex.php) which is available at daily frequency with 25km X 25km spatial scale. This gridded rainfall data is prepared from the 6955-rain gauge station using inverse distance weighted (IDW) interpolation method (Pai *et al.,* 2014).

Crop water stress index (CWSI) computation

Canopy temperature is an indicator for detecting water stress in crops (Clawson *et al.,* 1989; Fuchs, 1990; Jackson *et al.,* 1981). Idso *et al.,* (1981) and Jackson *et al.,* (1981) introduced a normalized index CWSI (crop water stress index) which is estimated based on the canopy temperature and air temperature difference using thermometer. CWSI ranges between 0-1 in which 0 or lower baselines represents *no water stress* and plant transpires at the potential rate while 1 or upper baselines for *high water stressed* conditions (Jamshidi *et al.,* 2021).

$$\boldsymbol{CWSI = \frac{(T_c - T_a) - (T_c - T_a)_L}{(T_c - T_a)_U - (T_c - T_a)_L}}$$

Where T_c is a crop temperature and T_a is air temperature and subscriptions U and L represents the upper and lower limit of difference of canopy and air temperature.

In-situ data upscaling over a large spatial region is challenging (Jamshidi *et al.,* 2021). To address this, remote sensing approach is suggested for estimation of CWSI (Idso, 1982 and Jackson *et al.,* 1981). Hot and cold pixel approach is utilized in direct estimation of CWSI (Veysi *et al.,* 2017) and the same method also utilized in many studies for evapotranspiration estimation using energy balance approach (Bastiaanssen *et al.,* 1998).

$$\boldsymbol{CWSI_{Remote\ sensing} = \frac{(CT) - (CT)_{Cold}}{(CT)_{Hot} - (CT)_{Cold}}}$$

Where CT is canopy temperature extracted from remote sensing LST data, canopy temperature represents the average temperature

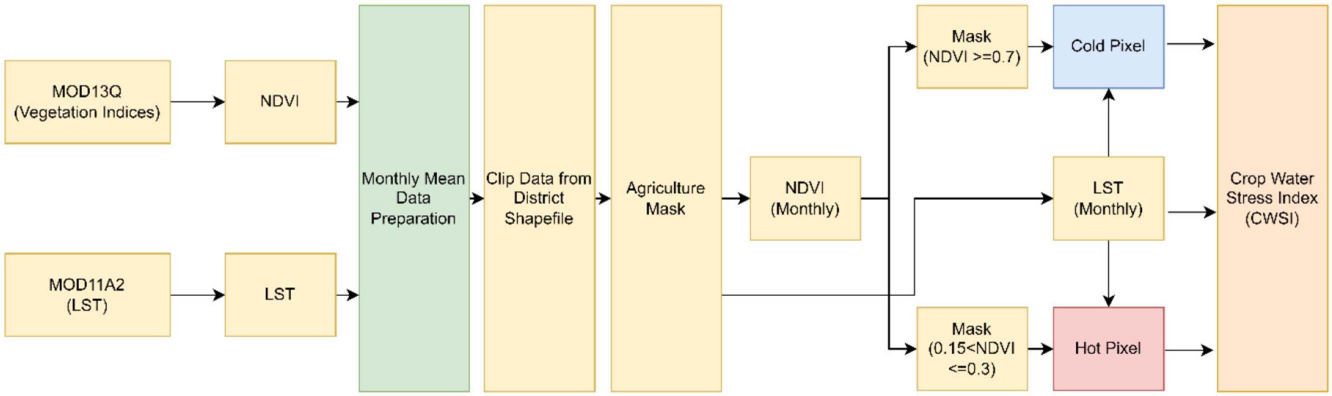

Fig.1: Flow chart for crop water stress index (CWSI) computation

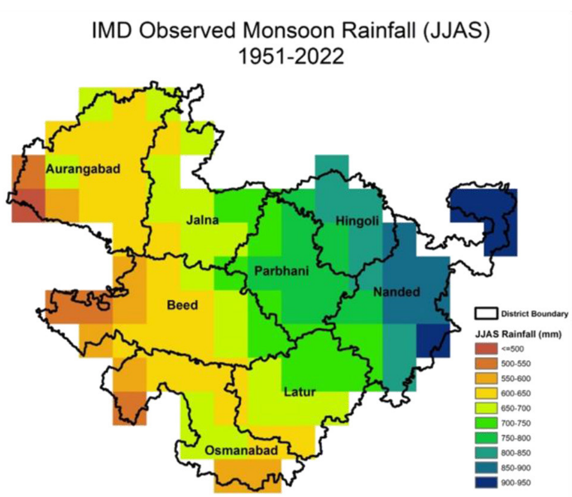

Fig. 2: Observed IMD gridded rainfall climatology (June to September) 1951-2022

of the entire plant canopy while crop temperature focuses on the temperature of individual plants. According to Allen *et al.,* 2007; Bastiaanssen *et al.,* 1998, the criteria of cold pixel selection should be minimum LST of the vegetation whose NDVI values is ≥ 0.7 and similarly the criteria of hot pixel selection should be maximum LST of the vegetation whose NDVI values lies between 0.1≤ NDVI ≤ 0.28 (Fig. 1).

RESULTS AND DISCUSSIONS

Spatial-temporal variability of observed rainfall climatology

The distribution of rainfall during the south-west summer monsoon (June to September) in the Marathwada region is divided into three distinct zones based on climatological rainfall patterns. These zones are characterized by high, medium, and low rainfall. The high rainfall zone (750-900mm) includes Hingoli and Nanded, while the medium rainfall zone (650-750mm) comprises of certain eastern areas of Jalna, Latur, and Parbhani. On the other hand, the low rainfall zone (<650 mm) includes Aurangabad, Beed, and Osmanabad. The regions with low and medium rainfall are particularly vulnerable to drought and this rainfall distribution is illustrated in Fig. 2.

Crop water stress (CWSI) and relation with vegetation indices

The year 2015 was a severe drought year that severely impacted the major agricultural area (Rajeevan and Nayak, 2017; Soni *et al.,* 2023) while 2020 was a normal year. As per the IMD subdivision rainfall data, the Marathwada region received -40% less rainfall compared to the long period average (LPA) rainfall (Kulkarni *et al.,* 2016). In this study, the Crop Water Stress Index (CWSI) was estimated for the period 2015 to 2020 and compared with the satellite-derived vegetation greenness index NDVI, as well as the crop water index NDWI. The findings of the study indicated that there exists a stronger negative correlation between CWSI and NDWI in comparison to the alignment observed between CWSI and NDVI. The CWSI index demonstrated a notable agreement, particularly during drought or instances of deficit rainfall years (Fig. 3). The degree of alignment between CWSI and vegetation indices exhibited variations across different years and precipitation patterns. Notably, a strong agreement was observed in regions with low rainfall, specifically in districts such as Osmanabad, Aurangabad, and Beed. In the context of the Osmanabad district, the agreement range between CWSI and NDWI varied from -0.34 to 0.67. Intriguingly, a strong correlation was established during the years 2015, 2017, 2019, and 2020 (Fig.4a). Similarly, the compatibility between CWSI and NDVI showed positive results for the years 2015 and 2019 (Fig.4b). Moving to Aurangabad district, the agreement range between CWSI and NDWI was noted to between the range of -0.21 and -0.81. Notably, a high correlation was observed during the years 2015, 2017, and 2019, following a similar trend for the NDVI index (Fig. 4b). In the Beed district, certain western and central areas fall within the low rainfall zone, whereas the eastern part falls within the mid rainfall zone. The correlation between the CWSI and the NDWI index displays a range of variation from -0.04 to -0.71. Strong concurrence was evident in the years 2015, 2017, 2018, and 2019, while a weaker correlation was observed for the normal year 2020 (Fig. 4a).

The mid-rainfall districts of Jalna, Latur, and Parbhani exhibited a consistent pattern, displaying a significant correlation in the years 2015, 2017, and 2019, while indicating a less pronounced correlation in the years 2016, 2018, and 2020. For these specific districts, the correlation range between CWSI and NDWI ranged from -0.14 to -0.58 for Jalna, -0.08 to -0.69 for Latur (Fig 3e), and

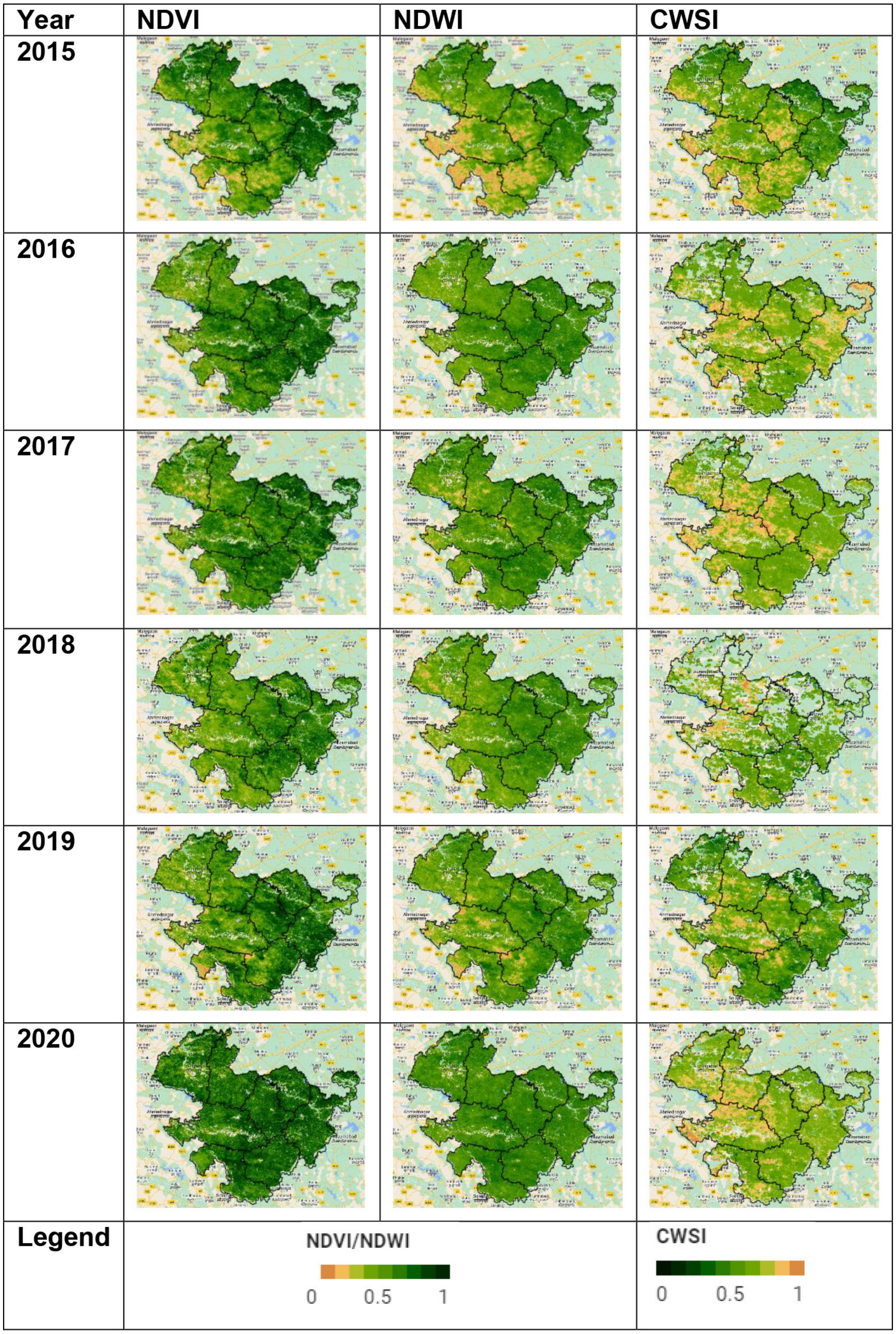

Fig. 3: Spatial maps of indices NDVI, NDWI, and CWSI for Marathwada region

-0.09 to -0.79 for Parbhani (Fig.4a).

The districts with higher rainfall, namely Hingoli and Nanded, demonstrated a distinct pattern. They presented a substantial correlation only during the years 2015 and 2016, whereas in the remaining years, a feeble correlation was observed between the indicators. In the case of the Hingoli district, the NDWI correlation range varied from -0.03 to -0.66, while for Nanded, it ranged between -0.09 and -0.52 (Fig.4a).

Thermal sensors are highly advantageous due to their ability to detect temperature variations in plants, which provides valuable insights into their health and water stress levels. This information can be utilized to optimize irrigation and focus on areas

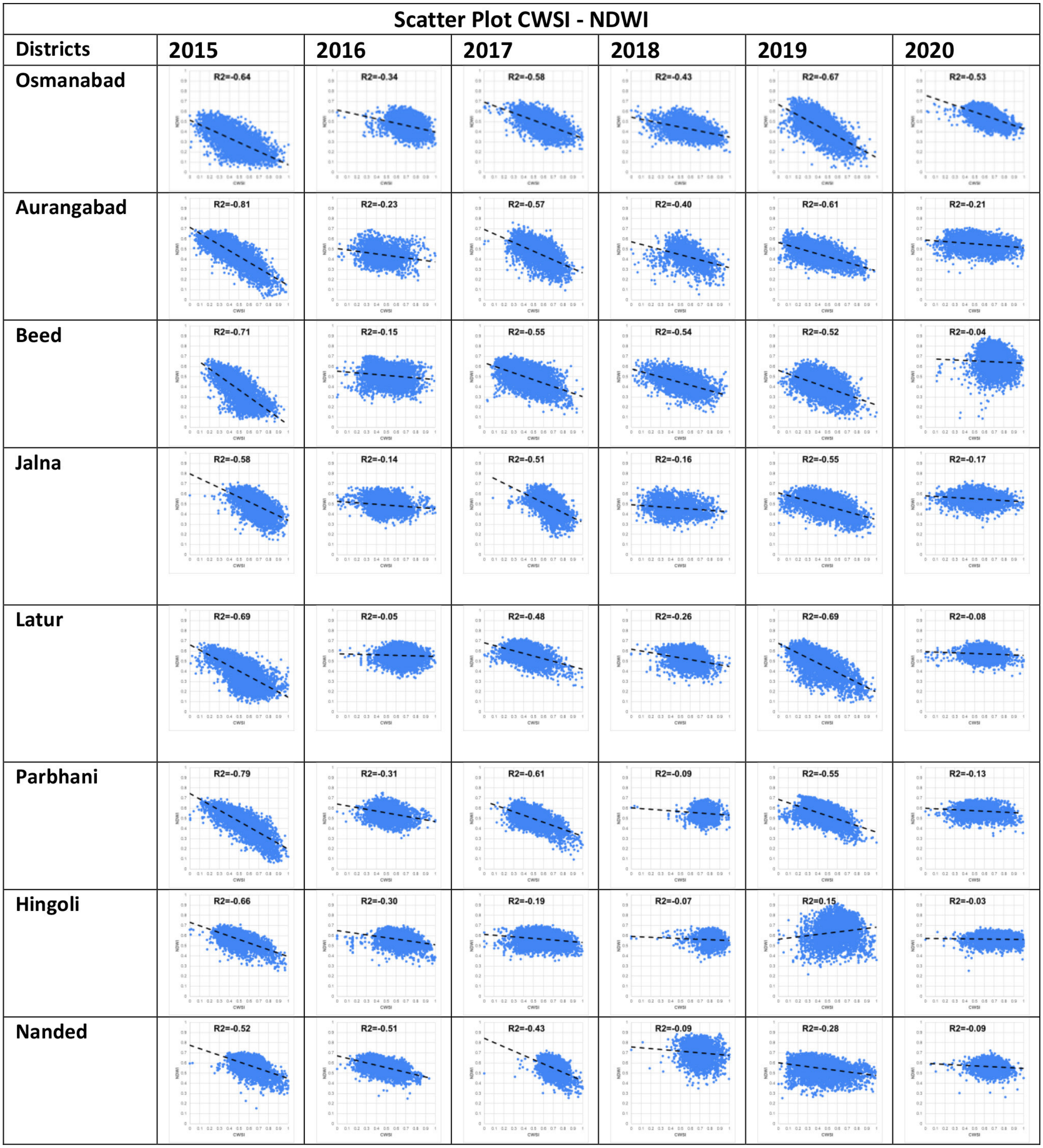

Fig.4 (a): Scatter plot of indices CWSI and NDWI

that may require additional attention. In contrast, shortwave infrared sensors (SWIR) are limited to identifying plant stress caused by water deficit or heat stress. Consequently, thermal sensors are regarded as more beneficial than SWIR for agriculture, particularly in arid or semi-arid regions where water stress is a major concern.

CONCLUSIONS

The Marathwada region experiences distinct rainfall distribution during the southwest summer monsoon, divided into three zones based on rainfall levels: high, medium, and low. The study analyzes the Crop Water Stress Index (CWSI) from 2015 to

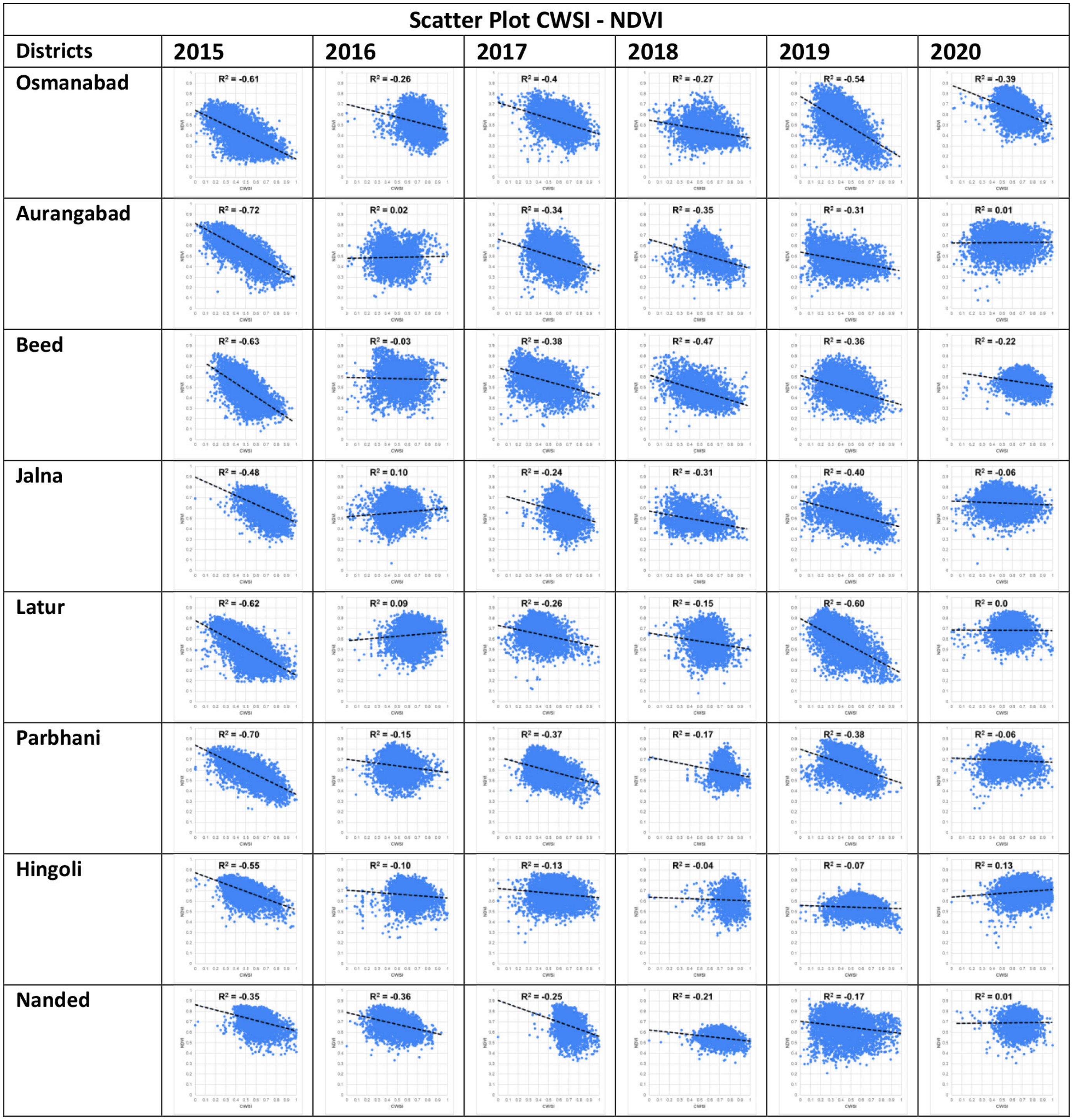

Fig.4 (b): Scatter plot of indices CWSI and NDVI

2020, comparing it with NDVI and NDWI. Results reveal a stronger negative correlation between CWSI and NDWI than with NDVI. Notably, agreement between CWSI and indices is pronounced during droughts, varying across years and precipitation patterns. Strong concurrence was observed in low rainfall regions, like Osmanabad, Aurangabad, and Beed. Similarly, mid-rainfall districts exhibited consistent correlations (Jalna, Latur, Parbhani), while high rainfall districts (Hingoli, Nanded) showed correlations mainly in 2015 and 2016. The study's findings suggest that the CWSI index offers valuable insights during periods of drought or inadequate rainfall, but its applicability might be misleading in years with ample rainfall.

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