frontiers | Frontiers in Environmental Science

TYPE Original Research
PUBLISHED 23 February 2026
DOI 10.3389/fenvs.2026.1770300

Check for updates

OPEN ACCESS

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RECEIVED 18 December 2025
REVISED 17 January 2026
ACCEPTED 20 January 2026
PUBLISHED 23 February 2026

CITATION
Aksoy E (2026) Drought vulnerability assessment of a climate sensitive GI crop using earth observation: the Korkuteli Karyağdı pear. *Front. Environ. Sci.* 14:1770300. doi: 10.3389/fenvs.2026.1770300

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Drought vulnerability assessment of a climate sensitive GI crop using earth observation: the Korkuteli Karyağdı pear

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Introduction: This research aims to spatially determine the risk associated with climate change impacting the Geographical Indication (GI) registered Karyagdi Pear variety, which is grown in the Korkuteli district of the Antalya Province in Turkey, where the area in question contributes greatly to the country's tourism and agricultural economy and was previously identified for its high biodiversity and microclimate variations. Besides being home to a valuable biological diversity, this area is where the GI product is grown. The increased drought stress imposed by global warming affects this region, which is threatened both by the biological environment and the economic viability of the production sector, as well as the sustainability of the GI status.

Methods: In the Google Earth Engine (GEE) platform, data sets such as Moderate Resolution Imaging Spectroradiometer (MODIS), ECMWF Reanalysis v5 (ERA5) Land Reanalysis data, and Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) from the years 2001 to 2023 were analyzed to provide estimates for the Normalized Difference Vegetation Index (NDVI), Vegetation Condition Index (VCI), Land Surface Temperature (LST), ambient temperature data, evapotranspiration (ET), soil moisture (SM), and precipitation anomaly. Data sets were then rescaled to a range between 0 and 1. In addition to the aforementioned data sets, other subindices created included the Vegetation Drought Index (VDI), the Hydro Thermal Index (HTI), and the Meteorological Drought Index (MDI). The Composite Drought Risk Index (CDRI) map was created through the assembly of the aforementioned elements.

Results: The results of the study revealed that SM was low, surface temperature was high, and vegetation vitality was low. Bayat, Esenyurt, Kargin, Küçükköy, and Yazir neighborhoods were identified as high drought risk areas, while Asagipazar, Tatköy, and Karsiyaka districts were found to be low drought risk areas. The study's findings indicate that GI crop production areas are at risk from drought. Unlike drought analyses that rely on a single indicator, this study employed a multiindex methodology that considers vegetation vitality, atmospheric changes, and hydrothermal dynamics together. This study is a pioneering work in establishing a drought risk index for GI crops using ground observation technology.

KEYWORDS

climate change impact assessment, composite drought risk, earth observation, geographical indication products, hydro thermal stress index, meteorological drought index, vegetation drought index

1 Introduction

GI products are influenced by both the geographical features of the environment in which they are grown and their socioeconomic characteristics. GI products carry not only the geographical features of the product but also the cultural heritage passed down through generations in the region. In this respect, making GI products resilient to climate change is also important in terms of carrying cultural heritage to future generations. Furthermore, many studies have shown that GI products are an important tool in strengthening local communities in terms of employment and combating poverty, as they are a source of income for the regional economy (Belletti et al., 2017).

GI is considered in two categories. The first category is origin, and the second is geographical indication. Origin means that all stages of the product's production take place within a designated area. Geographical indication, on the other hand, requires that while the product is produced within a designated area, its processing stages may also take place outside that area. Both categories reveal that the identity of a GI product is inherently linked to the region's ecological and cultural fabric. In GI research, the notion of terroir is fundamental terroir is basically referred to as the unique combination between geomorphology, climate, soil characteristics, landscape arrangement, altitude, and human factor that affects product particularity as a whole. Low differences in these elements affect product quality (Van Leeuwen, 2022).

Current literature shows an increasing trend in the study of the impacts of climate change on Agricultural GI products. Studies show that there have been changes in the optimal areas of production defined by an increase in temperature and a decline in precipitation for the European wine, olive, and cheese sectors, as well as for the Chinese citrus, rice, and apple GI sectors (Hannah et al., 2013). The findings demonstrate the high vulnerability of GI products to negative climate change impacts.

Turkey is one of the greatest European countries in terms of agricultural diversity, biodiversity, and agriecological potential. The region around Antalya and Korkuteli is home to many varieties of fruit plants because of the significantly large elevation gradient in that region coupled with the regional flora. The Korkuteli Karyağdı pear is the main focus of this case study because it is one of the representatives of the agrifood products that is an important part of that region's system and retains close socioeconomic links to it. The product under study receives positive support from its own resistance as well as its environmental biodiversity characteristic (Gül and Kart, 2024).

The Mediterranean Basin is one of the regions most affected by climate change. Decreasing rainfall, rising air temperatures, decreasing soil moisture, increased evaporation, and prolonged drought periods put the region and its geographically indicated products at high risk (Lionello et al., 2014; Chmielewski and Rötzer, 2001). The fact that the locations of geographically indicated products are determined and documented eliminates the option of changing the location of the products. This increasing vulnerability rate and positional stability are characteristics that increase the vulnerability of GI products (Henry, 2023).

Geographic Information Systems (GIS), Remote Sensing (RS), and Earth Observation (EO) technologies are widely used in stress studies related to agricultural drought. Vegetation indices (e.g., NDVI, VCI) are used for assessing vegetation health and productivity, LST helps with thermal anomaly detection, ET and SM data sources can define hydrological anomalies, whereas rainfall anomalies can be mapped using CHIRPS precipitation products (Tucker, 1979; Funk et al., 2015). No single variable can represent the dynamics of drought occurrence; hence, the multiple index approach offers an overall performance methodological framework that combines the capabilities of multiple indices for a better evaluation (AghaKouchak et al., 2015; Hao and Singh, 2015). GEE represents an important platform that supports the efficient examination of space time dynamics over large scales and has become widely used for agricultural monitoring and space related modeling researches (Gorelick et al., 2017).

Although the literature on environmental risks impacting agricultural GI products is relatively limited, existing studies predominantly focus on conservation policies, branding strategies and socioeconomic dimensions (Bowen, 2010; Ilbery and Kneafsey, 2000). The use of EO based methodologies in GI vulnerability has not been widely utilized in current studies. The use of EO technology with a spatial approach in this field makes a significant contribution to the subject of this study.

This research contributes to the field by developing a CDRI for the Korkuteli Karyağdı Pear using a multi sensor EO approach. CHIRPS precipitation, ET (water loss), soil moisture (moisture deficit), LST and air temperature (thermal stress), and NDVI, VCI (vegetation vitality) were integrated within the GEE environment using a unified normalization and modeling workflow. The variables were normalized between 0 and 1, and secondary indices MDI, HTI and VDI were derived. These indices were then aggregated to produce the CDRI drought risk maps. The resulting spatial risk patterns provide actionable, evidence based insights for decision makers seeking to strengthen climate resilience strategies for agricultural GI products.

2 Materials and methods

This research uses an integrated methodology framework incorporating satellite imagery, climate data, and ground observations from the GEE platform to estimate the risk of drought in the Korkuteli Karyağdı pear growing region due to climate change. The results cover the period from 2001 to 2023. Open source resources such as CHIRPS, MODIS, and ERA5 Land were considered due to their long term accessibility and public availability.

The data was created in a layered structure. All layers were created to share a common projection. The time interval was created to be a common time interval for all data layers. Normalization was performed to ensure comparability of the data layers. This process scales the data between 0 and 1. After this process, HTI, MDI, VDI, and MDI were obtained. The CDRI was derived using an equally weighted formula of these three findings.

This study proposes a methodology suggesting that a methodology based solely on meteorological data is insufficient for determining the drought risk of agricultural GI crops;

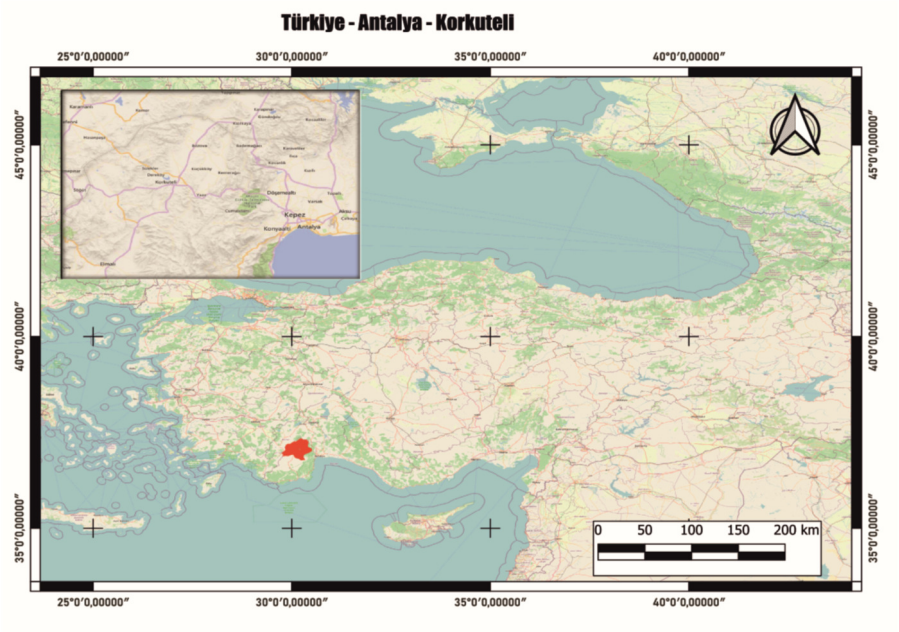


FIGURE 1
Study region map.

therefore, other parameters related to GI crops, such as vegetation characteristics and thermo hydrological criteria, should also be considered.

2.1 Study region description

Due to its geodetic plateau shape, the study area exhibits a diverse range of microclimates. The area has the characteristics of a transition zone between steppe and forest ecosystems and shows a high degree of endemism (Gül and Kart, 2024). The Karyağdı Pear is a geographically indicated product specific to the region with a limited cultivation area. Water stress, temperature anomalies, and precipitation scarcity have direct negative impacts on product quality and plant physiology (Vicente-Serrano et al., 2015; Henry, 2023).

In the study, GAUL Level 2 district boundary data were used. The datasets were converted into layers and spatial accuracy checks were performed using the open source geographic information system software QGIS (Figure 1).

2.2 Dataset overview and processing

All datasets used in the study were downloaded for the 2001–2023 period using a program developed on the GEE platform. The data were designed to be grouped under three main categories: vegetation indicators (*NDVI, VCI; source: MODIS MOD13Q1*), thermal and hydrological indicators (*LST, AT, ET, SM; source: MODIS and ERA5 Land*), and meteorological precipitation data with the derived drought index (*MDI; source: CHIRPS*).

Since the input datasets used in the study have different native spatial resolutions (*MODIS: 500–1000 m, ERA5 Land: 9 km, CHIRPS: 5 km*), a spatial harmonization procedure was applied before index calculations. All raster datasets were resampled to a common working grid of 250 m resolution, which served as a standardized analytical surface for the CDRI model.

MODIS based layers (*NDVI, VCI, LST*) were downscaled using bilinear interpolation, appropriate for continuous EO variables. ERA5 Land variables (*AT, SM, ET*), originally at coarse resolution, were resampled via cubic convolution to minimize blocky artifacts while acknowledging that this step does not increase inherent spatial detail but provides geometrical compatibility across layers. In this study, CHIRPS precipitation data was obtained as a numerical dataset through spatial sampling using the nearest neighbor assignment method.

In this study, data layers were created to have a common scale due to their different locations. This workflow is generally the preferred workflow model when using remote sensing techniques in spatial risk assessment. This process was also followed in this study.

Since these data types reveal different aspects of drought components, they are widely used in a similar manner in the literature (Kogan, 1995). The technical specifications of the datasets used in the study are presented in Table 1.

Due to the requirement that all datasets used in the study be in a common projection system, all data were transformed into the World Geodetic System 1984 (WGS84) projection. As the contributing datasets differ substantially in their native spatial resolutions, all layers were spatially harmonized to a unified 250 m grid prior to index computation. MODIS datasets (500–1000 m) were downscaled to 250 m using bilinear interpolation, while the coarser ERA5 Land (9 km) and CHIRPS

TABLE 1 Remote sensing and climate datasets used in the study.

Data name	Data type	Spatial resolution	Data description/purpose	Data source
NDVI	Vegetation index	500 m	Vegetation vitality and stress detection; input for VCI and VDI.	NASA MODIS
VCI	Vegetation stress index	500 m	Long-term NDVI anomaly; indicator of vegetation drought	MODIS
LST	Land surface temperature	1000 m	Thermal stress assessment; HTI component	NASA MODIS
Air temperature	Climate parameter	9 km	Air temperature anomaly; HTI component	ECMWF ERA5-Land
ET	Evapotranspiration	9 km	Water loss estimation; hydrological stress component	ERA5-land
Soil moisture	Soil moisture	9 km	Detection of moisture deficit; VDI and HTI component	ERA5-land
CHIRPS precipitation	Precipitation data	5 km	MDI calculation; precipitation deficit analysis	CHIRPS
MDI	Meteorological drought index	5 km	Normalized precipitation deficit; CDRI component	CHIRPS
VDI	Vegetation drought component	500 m	Combination of NDVI' + VCI'; vegetation stress assessment	MODIS
HTI	Hydro thermal stress index	9 km 250 m	Multi stress model integrating ET + SM' + LST + TEMP.	ERA5 + MODIS
CDRI	Composite drought risk index	250 m	Integration of VDI + HTI + MDI; final risk model	This study

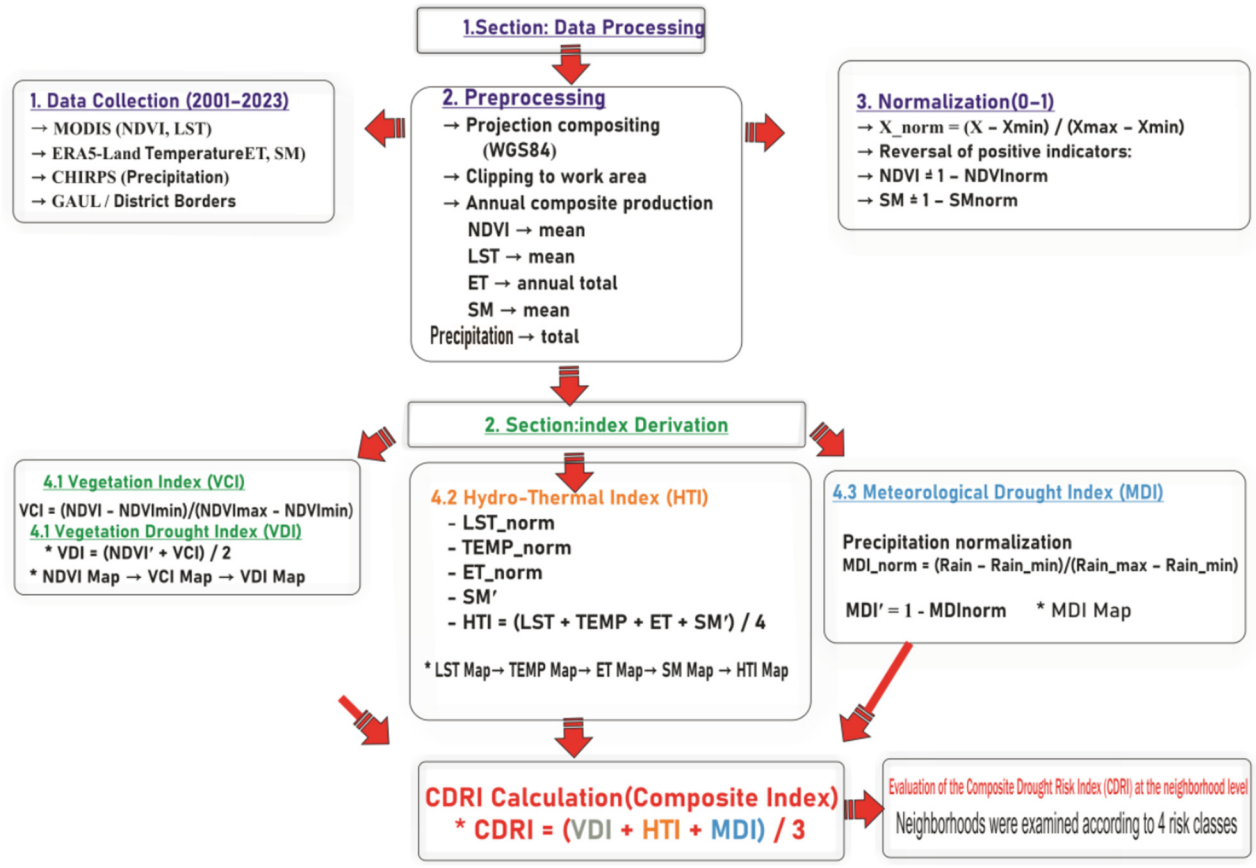


FIGURE 2
Workflow diagram.

(5 km) variables were resampled using cubic convolution to preserve continuous spatial gradients. In this study, district boundaries are at a resolution of km. The process of creating all layers at a single scale, where both plant indices generated from 250-m high resolution MODIS data and low resolution data including administrative boundaries are considered holistically, does not create a spatial risk in the study. Since the study ultimately focuses on neighborhood based risk assessment, the commonly determined resolution is sufficient. This is a generally accepted practice in neighborhood based studies of spatial agricultural research.

It is reiterated that the resampled layers at 250 m resolution do not add to the inherent information present in the coarse resolution data sets; they help in offering a standardized spatial reference system which is required for the formation of the composite indices and zonal statistics.

The study area was clipped using the district boundary vector data so that only the areas falling within the district boundaries were included. NDVI, LST, ET, SM, and precipitation (CHIRPS) datasets were generated as annual data products. The methodological workflow followed in the study is presented in Figure 2 below.

2.2.1 Data normalization (0–1 scaling)

Normalization was performed to ensure that the datasets used in the study were on a common scale. This is a widely applied method in EO studies (Shastri and Mujumdar, 2025). To ensure comparability across datasets with different units and numerical ranges, all continuous variables were normalized to a common 0–1 scale using min and max normalization. This procedure enables each variable to contribute proportionally to the composite drought index without being dominated by variables with larger numeric ranges.

$$X_{norm} = (X - X_{min}) / (X_{max} - X_{min}) \quad (1)$$

(X = original pixel value; X_{min}, X_{max} = minimum and maximum values within the study area; X_{norm} = normalized value ranging from 0 to 1).

2.2.2 Inversion of positive variables

Some variables have inherently positive interpretations (*e.g., high NDVI or high soil moisture indicates healthy conditions rather than drought*). To ensure that all indicators increase with increasing drought severity, these variables were inverted after normalization.

$$X' = 1 - X_{norm} \quad (2)$$

Since the zero value of some datasets used in the study represents a positive *("good condition")* indicator unlike others, inverted values were employed. The fact that lower LST values (closer to 0) are favorable for vegetation health, whereas higher precipitation values (*closer to 1*) indicate favorable conditions constitutes the rationale for this operation.

$$NDVI' = 1 - NDVI_{norm} \quad (3)$$

$$SM' = 1 - SM_{norm} \quad (4)$$

Below are examples of inverted NDVI (*plant vitality → vegetation stress*) and inverted soil moisture (*moist soil → wetness stress*).

This inversion ensures that higher values consistently represent higher stress across all indicators, producing a unified orientation when constructing VDI, HTI, and CDRI. Such transformations are standard practice in multi index drought assessment models.

Normalization and inversion were applied to bring heterogeneous datasets (*vegetation, thermal, hydrological, meteorological*) onto a unified, dimensionless scale where higher values consistently correspond to higher drought stress. This ensures mathematical compatibility among indices and prevents scale related bias when computing VDI, HTI, and CDRI. These procedures are widely adopted in satellite based drought modeling frameworks.

Following these operations, all raster layers were made compatible with the CDRI model. Similar inversion approaches are frequently employed in vegetation stress models (Achille et al., 2021). The formulas required for the operations in the section titled Data normalization and Inversion of positive variables are given in Formulas 1–4 below.

2.3 Vegetation indices (NDVI, VCI) and derived vegetation stress index (VDI)

$$VCI = (NDVI - NDVI_{min}) / (NDVI_{max} - NDVI_{min}) \quad (5)$$

NDVI in the MODIS satellite acted as an indicator of vegetation health, assessing the strength of the cover that exists. In an attempt to provide an indication of the general health, the VCI was calculated, utilizing the long term NDVI values, namely the historical maximum and minimum values. NDVI basically represents the photosynthesis processes and green mass of plants, an idea that was first conceptualized by Tucker and colleagues in 1979. We derive an indication of the state of the vegetation, based on NDVI changes, that is, the VCI. The equations for VCI and VDI are explained below.

VDI was derived from the integration of NDVI' and VCI components to enable a highly sensitive assessment of vegetation drought. Similar composite vegetation stress indices are preferred in the literature, as they provide a more accurate representation of agricultural drought conditions (Zhang et al., 2017; Rhee et al., 2010). VDI integrates two fundamental indicators of vegetation drought. NDVI' (*normalized and inverted NDVI*) and VCI (*long term NDVI anomaly*). VDI was derived using NDVI and VCI with equal weights. The formula used in the derivation is given below.

$$VDI = (NDVI' + VCI) / 2 \quad (6)$$

The VDI methodology, derived from two equally weighted indicators, is frequently used in the literature. Of these indicators, NDVI reveals plant health, while VCI reveals anomalies over a long period of time.

2.4 Thermal indicators (LST, TEMP, SM, ET) and HTI

The Hydro thermal Stress Index (HTI) was derived using ERA5 Land air temperature (AT), SM, MODIS LST, and

Evaporation (ET). This formula, using the derived HTI, shows that drought is not solely due to low rainfall. It highlights the need to consider thermal stress as a significant parameter in soil moisture balance, alongside low rainfall, in order to address the issue further (Otkin et al., 2014; Anderson and Kustas, 2008). The HTI formula is given below.

$$HTI = \left(ET_{norm} + SM' + LST_{norm} + TEMP_{norm}\right) \Big/ 4 \quad (7)$$

The derived HTI was created by considering many parameters in the occurrence of stress (Otkin et al., 2014; Senay et al., 2020).

2.5 Meteorological drought index (MDI)

CHIRPS derived the MDI using annual data. The MDI formula is given below).

$$MDI_{norm} = \left(Rain - Rain_{min}\right) / \left(Rain_{max} - Rain_{min}\right) \quad (8)$$

The dataset was inverted because there is an inverse relationship between high stress and low rainfall.

$$MDI' = 1 - MDI_{norm} \quad (9)$$

Since low rainfall causes high stress on vegetation and corresponds to meteorological drought, this approach is widely used in such studies. The rainfall regime is compatible with drought conditions.

2.6 Composite drought risk index (CDRI)

In this study, a multi data type and multi index method was developed for creating a drought index. The study considered three main components: MDI, VDI, and HTI.

$$CDRI = \left(VDI + HTI + \mathrm{MDI}'\right) \Big/ 3 \quad (10)$$

MDI, HTI, and VDI indices were derived as raster maps with numerical values ranging from 0 to 1. These index types are preferred in in depth research on stress processes. In the literature, it has been found that the multiple index methodology applied in this study, in addition to considering only LST, NDVI, and precipitation regime together, yields values closer to the truth (Zargar et al., 2011; Abdelrahim and Jin, 2025).

In this study, a CDRI model was developed by taking a holistic approach to meteorological anomalies, hydro thermal stress, and agricultural drought using numerical data. This study provides a significant contribution to decision makers in preventing risks that may arise for GI crops.

3 Results

This study utilized ground observation data covering the period 2001–2023. The findings indicate that the three main components of drought decreased vegetation vitality, increased thermal stress, and rainfall deficit are spatially concentrated within the Korkuteli Karyağdı Pear production area. Although the drought components appeared at different intensity levels, the risks were generally found to converge on the southern and southeastern slopes. This result supports the applicability of a multicomponent drought model. The study utilized ground observation data from 2001 to 2023. Spatial distribution risks were obtained for the production areas of the GI crop, which is the subject of this study, as decreased vegetation health, increased thermal stress levels, and decreased rainfall yield. Drought was presented at different levels. It was determined that the southern and southeastern slopes of the study area have high risk regions. The applicability of a multicomponent drought model is demonstrated by the results obtained in this study.

Below, the spatial outputs of NDVI, VCI, LST, AT, ET, SM, MDI, and the composite CDRI generated by integrating these numerical outputs are presented. The results reveal that the study area is exposed to multicomponent drought pressure.

3.1 Vegetation indices (NDVI, VCI) and derived vegetation stress index (VDI)

Further analysis of the NDVI map makes it clear that on average, the region sustains a moderate condition of vegetation vitality. A low condition of NDVI values, particularly one that expands throughout the summer, indicates lower vitality of the vegetation in the western and southern parts of the region. These locations are identified as vulnerable zones with respect to water stress.

VCI was calculated based on the long term minimum and maximum NDVI range, and the results identified pronounced stress zones close to the central parts of the study area. Yazır and Tatköy neighborhoods were found to have low VCI values. This index indicates the plant health of these neighborhoods. The results obtained are consistent with NDVI. The numerical spatial patterns produced by the study reveal that the stress levels of the plants are increasing regularly.

The obtained NDVI values are generally moderate in the study area. NDVI values were found to be significantly lower in the south-facing regions. This is shown in Figure 3. Stress levels are high and vegetation density is low in these regions. For NDVI, VCI, and SMI, the value of 0 is shown in yellow, unlike the others.

The VCI anomaly is shown in Figure 4. The VCI value calculated between the minimum and maximum values over a long period reveals the formation of persistent stress areas during the summer months.

The VDI map given in Figure 5 shows the spatial distribution of vegetation stress. High VDI values were found in areas where VCI was lower than the long term average and NDVI was low. This finding is consistent with drought induced vegetation stress models presented in the literature (Funk et al., 2015; Ilbery and Kneafsey, 2000).

3.2 Hydro thermal indicators (LST, TEMP, SM, ET) and HTI

Figure 6 shows the spatial distribution of LST obtained from MODIS. Surface temperatures peak in the southern and southeastern parts of the district, while the southwestern area remains comparatively cooler.

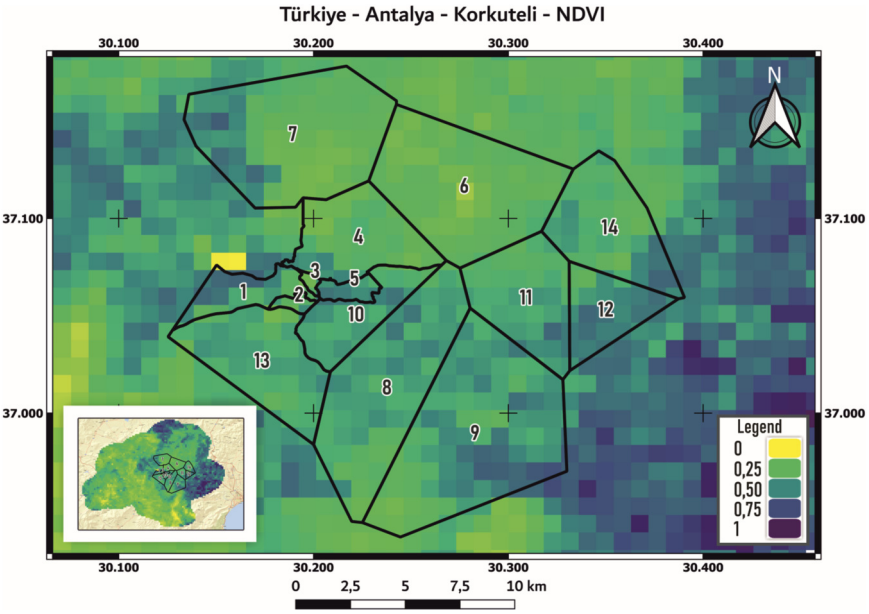


FIGURE 3
NDVI spatial distribution.

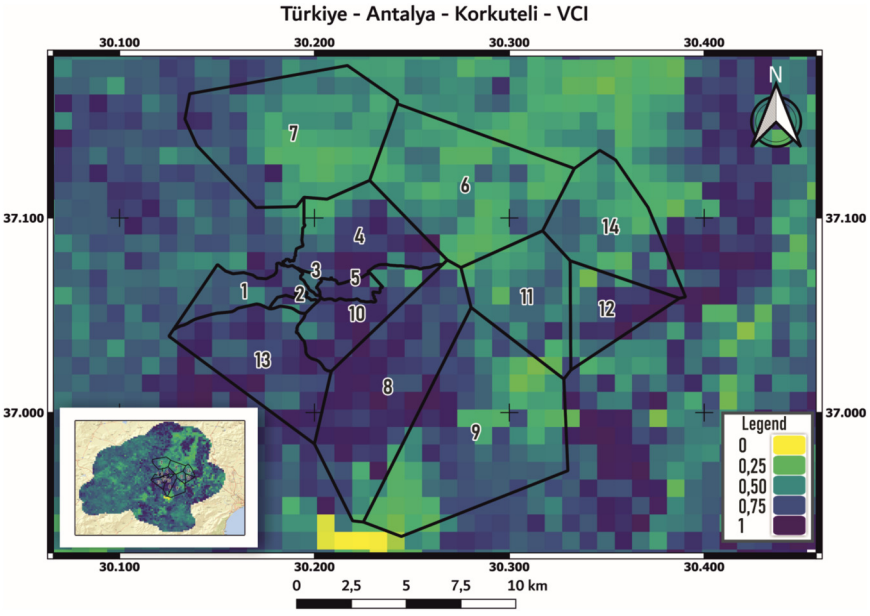


FIGURE 4
VCI spatial anomaly map.

The spatial distribution map of AT created from the ERA5 data source is shown in Figure 7 below. The LST map exhibits similar spatial characteristics to the AT map in many areas.

Figure 8 illustrates the spatial distribution of evapotranspiration (ET), showing noticeably higher water loss in the western and southwestern parts of the district, indicating increased hydro-climatic stress in these areas.

SM is shown in Figure 9. High SM values were obtained in the eastern part of the study area. The findings clearly reveal the inverse relationship between SM and ET and the hydrological stress load. Due to the visualization required, the generated was arranged differently from the others, with a 1–0 ratio.

HTI reveals the relationship between soil moisture, temperature, and evaporation. HTI is made from the ET, the SM, as well as the

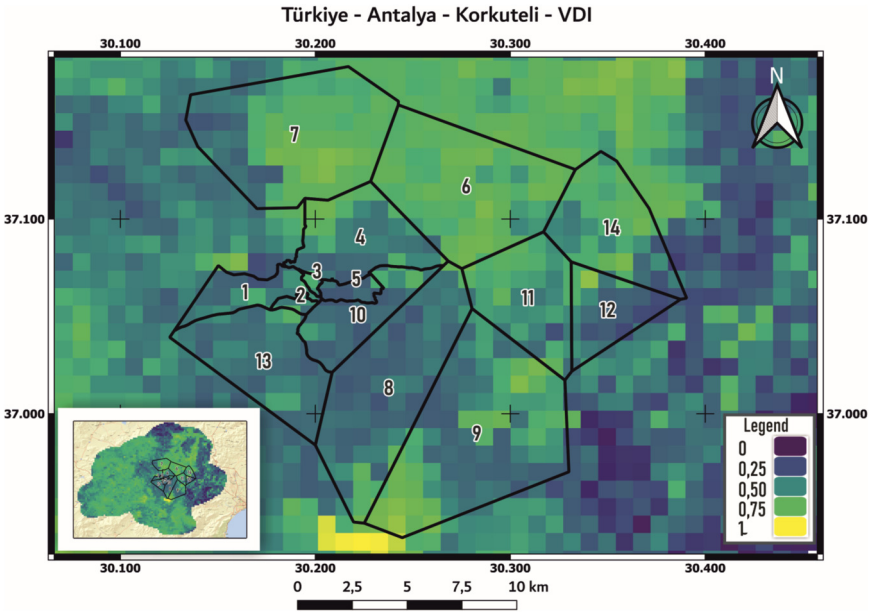


FIGURE 5
VDI map of vegetation drought stress.

temperature. It acts as a measure of how vegetation responds to water supply constraints as well as heat stress. An increase in HTI leads to increased hydro thermal stress in vegetation. This is due to drier soils, increased ET rates, as well as rising ground temperature and AT. SM in the study area is shown in Figure 10.

3.3 Meteorological drought: MDI

Figure 11 illustrates the numerical MDI map derived using precipitation data from CHIRPS. The areas where rainfall is low and arid regions are represented by low MDI index values and are found to be concentrated in the western and southwestern regions. The MDI index values are high in the eastern regions. This indicates the spatial extent of meteorological drought.

3.4 Composite drought risk index (CDRI)

The distribution of drought risk in Korkuteli is clearly shown in Figure 12 CDRI map below. Low CDRI values in the western and central parts represent a calm drought situation, while high CDRI values in the eastern and southeastern parts indicate a stressful drought situation. Therefore, green coded agriculture is under more stress due to the drought situation in the eastern parts, while the western regions are experiencing favorable conditions.

3.5 Trend analysis (2001–2023)

The values for the EO variables paint a specific picture of a deteriorating drought situation. NDVI has been trending lower in various Southern and Western suburbs, indicating that vegetation is steadily decreasing with limited water availability. Indeed, land surface and AT are constantly increasing. This corroborates information that vegetation is under increasing water stress. Soil moisture values drop, and evapotranspiration amounts keep increasing. All indicators currently point towards a switch to a hot and dry climate.

These same factors are what are causing the scores in the CDRI for the areas of Kargın, Bayat, Esenyurt, and Küçükköy. The Mann Kendall tests would probably indicate that NDVI and soil moisture have negative slopes similar to Sen's in both cases, although the other variables are expected to have positive slopes. In conclusion, it seems that drought has been aggravating in the region of GI production for the past 23 years.

3.6 Neighborhood scale assessment of the composite drought risk index (CDRI)

The CDRI map was classified into four classes at the neighborhood scale.

The neighborhood level conditions of these classes were quantified by calculating mean values using the Zonal Statistics method in QGIS software. Neighborhoods shown in brown were identified as high risk areas. Neighborhoods represented by other symbols were classified as risky, low risk, and lowest risk areas, as illustrated in Figure 13.

The CDRI map was divided into four groups at the neighborhood scale. All these groups were quantified for every neighborhood by calculating the mean values using Zonal Statistics in QGIS. brown colored neighborhoods were considered high risk. The rest of the symbols are risky, low risk, and lowest risk, as shown in Figure 13.

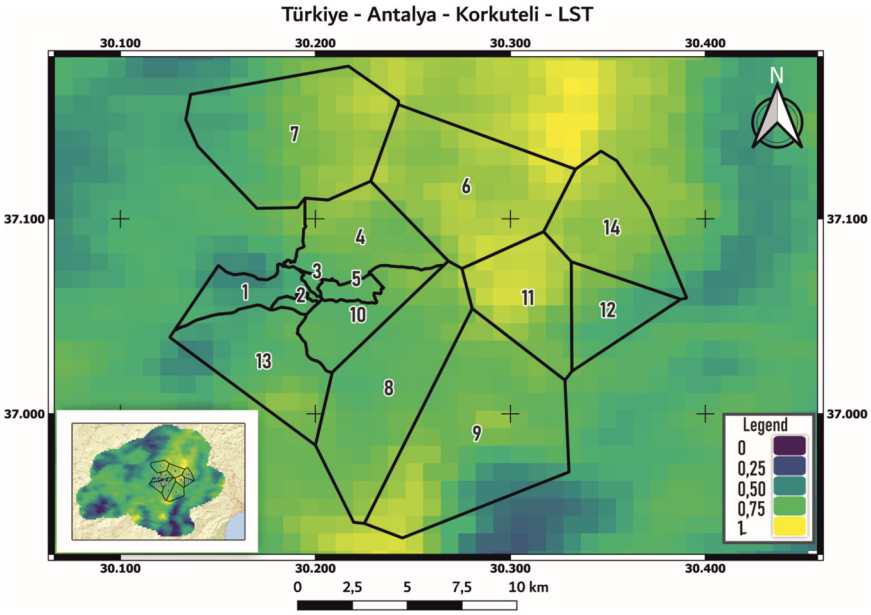


FIGURE 6
LST distribution map.

3.7 Comparison of the palmer drought severity index (PDSI)

The PDSI is a traditional drought indicator derived from meteorological water balance variables but lacks sufficient resolution to be applicable at the neighborhood level. The new CDRI combines SM, ET, LST, vegetation indices (VCI and NDVI), and precipitation anomalies to address agricultural stress, hydro thermal stress, and meteorological stress under a unified framework. Based on the advantages of the new framework, the new tool, the CDRI, has higher sensitivity compared to the traditional tool, the PDSI; the new tool has flexibility with varying spatial resolutions; and the new tool has the potential to be updated frequently. Table 2 presents the comparison between the new and traditional tools at the neighborhood level.

4 Discussion

In examining drought stress factors, this research attempts to identify how these factors are distributed across the Korkuteli Karyağdı Pear Protected GI and determine the quantitative sensitivity of the GI crop to climate change. Results indicate that vegetation stress and hydro thermal and meteorological stresses cooccur in the same areas, making direct contributions to environmental conditions. Negative values of NDVI and VCI indicate reduced vegetation health, while elevated land surface temperatures and AT suggest an increased thermal load. High evapotranspiration rates and reduced ground storey moisture suggest an increase in hydro stress. The irregular rainfall distribution in the MDI dataset reflects more severe dry spells.

The CDRI, constructed based on these multi sensor indicators, reveals a spatially well dispersed pattern of medium and high risk areas, especially along the southern and western slopes. The fact that stress factors lineup in places underlines how sensitive the Karyağdı Pear is to changes in conditions due to very narrow tolerance to environmental changes. Increased water and heat stress are indeed detrimental to fruit development, the structure of tissues, flavor, and the proper setting of fruits by flowers, ultimately lowering the quality of the final product. Such findings are consistent with the patterns of vulnerability to climate change in other GI certified crops around the world, hence indicating similar risks of a climatic origin facing the Korkuteli GI variety.

The use of the GEE allowed the integration of EO data over the years in order to analyze the processes of drought without having dependence on a single index. The multi index approach allowed seeing that the meteorological aspect does not fully represent the process of agricultural drought; it is necessary to introduce the vegetation and hydro thermal aspect in order to have a more defined picture. The territorial organization of the CDRI allows decision makers access to an easy map of the areas that concentrate high risks in order to plan the irrigation of the areas, the reviving of the orchards, the adaptation of the cultivars.

Despite its contributions, the study also has limitations. Satellite based datasets, while consistent over broad regions, may not fully represent microclimatic variability within small orchard parcels. The spatial resolution of MODIS and ERA5 restricts the detailed detection of fine scale heterogeneity. The use of annual composites may mask short term extreme events and phenologically critical stress periods. Fixed threshold values employed in CDRI classification may limit the ability to detect alternative risk distributions. Furthermore, assigning equal weights to all components may not fully capture the true physiological

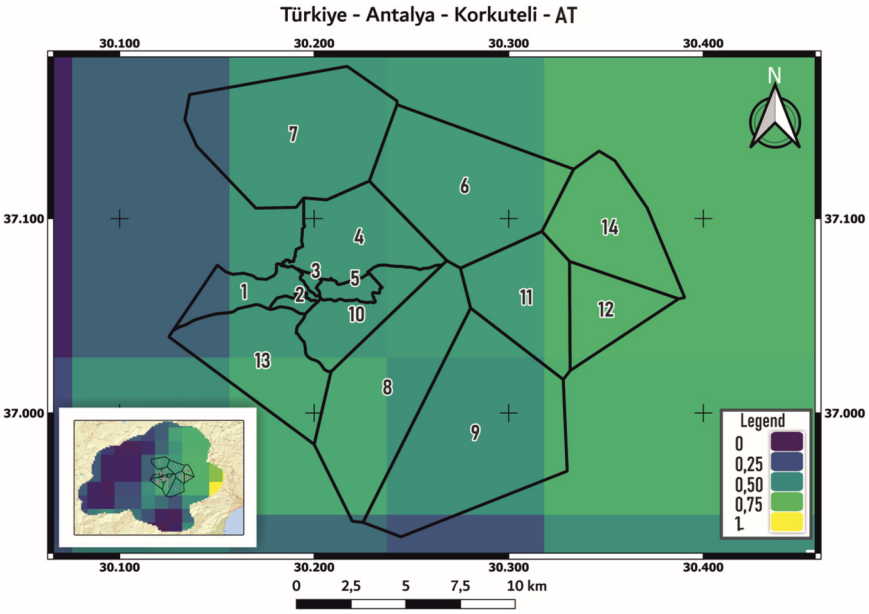


FIGURE 7
Air temperature map.

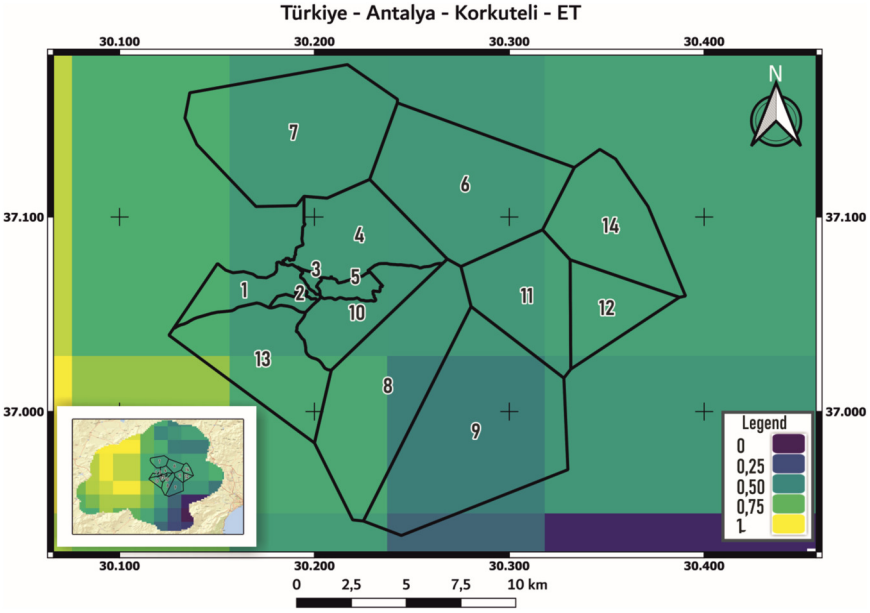


FIGURE 8
ET distribution map.

sensitivity of the crop. The lack of terrestrial measurement data in this study creates limitations in verifying satellite images, which are a remote sensing data source. These limitations were addressed by developing a solution using multiple data and multiple index approaches. The findings of this study reveal that meteorological parameters alone are insufficient in agricultural drought studies. It was determined that the multicriteria approach models presented by AghaKouchak et al. (2015), Rhee et al. (2010), and Zhang et al. (2017) are the closest to accurate models in determining drought risk levels. They highlighted the importance of multiple data and multiple index approaches in drought modeling in areas with heterogeneous microclimates. The intense stress findings obtained on the southern slopes of the district are consistent with drought trends revealed in similar regional studies (Lionello et al., 2014).

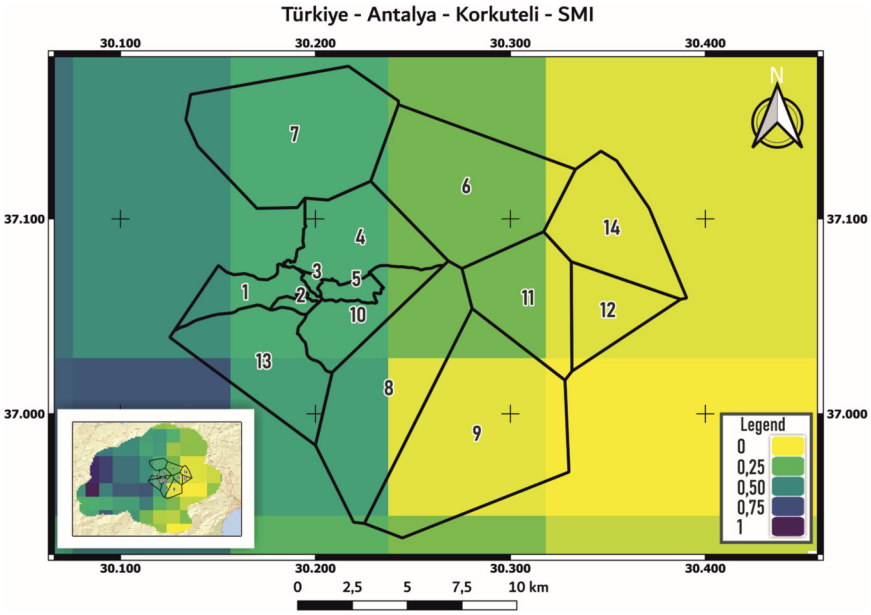


FIGURE 9
Soil moisture map.

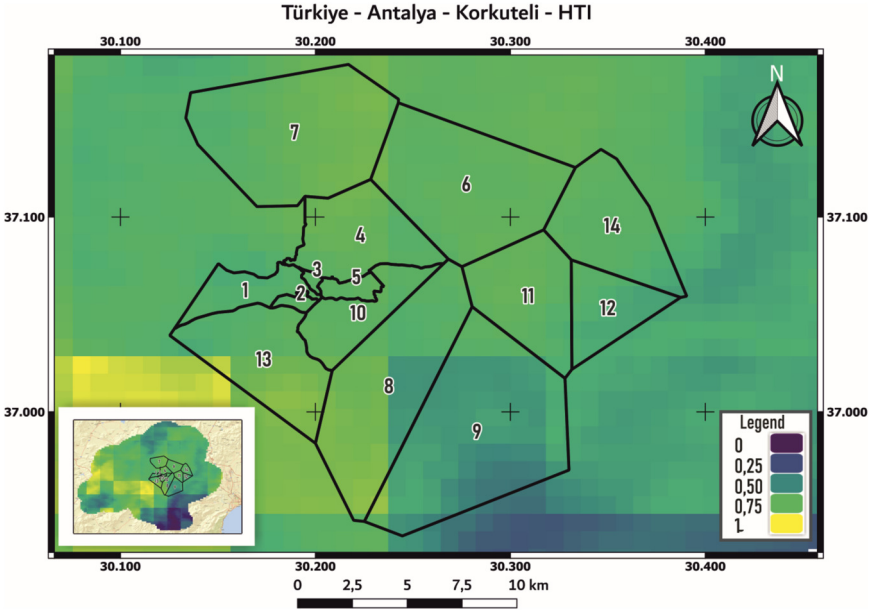


FIGURE 10
HTI distribution map.

Studies on the relationship between climate change and terroir sensitivity of agricultural GI products such as olive varieties, fruits, and wine grapes reveal common findings in this study (Hannah et al., 2013; Bowen, 2010; Henry, 2023). An increase in negative impacts due to climate change in GI product regions is a common finding.

The results obtained from this study confirm the biophysical mechanisms revealed by previous remote sensing techniques. The findings indicate accelerated evaporation due to increasing surface temperature (Otkin et al., 2014). Furthermore, increasing temperature negatively impacts soil moisture and leads to a decrease in NDVI values (Kogan, 1995). Additionally, VCI anomalies demonstrate the persistence of long term negative impacts on plant health (Zhang et al., 2017). These findings demonstrate that CDRI is an important metric in stress detection.

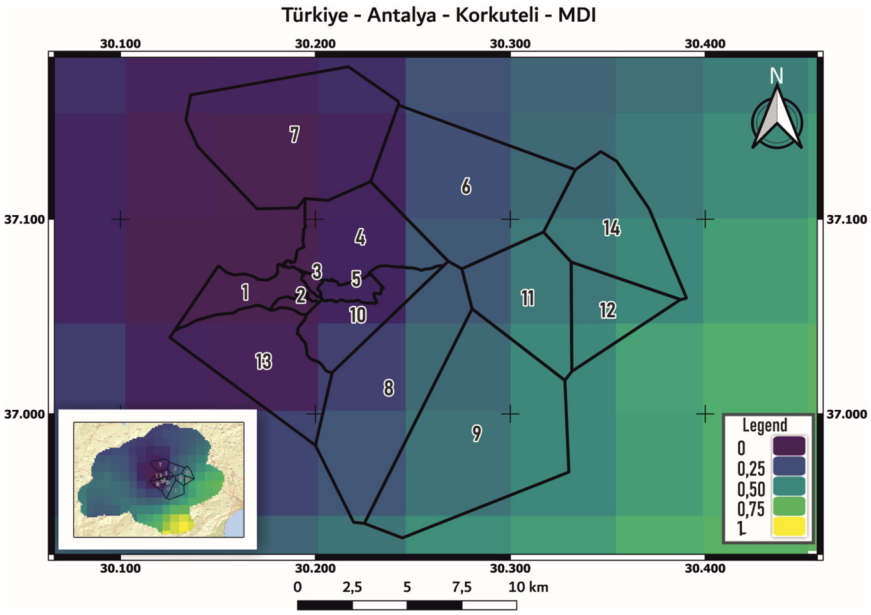


FIGURE 11
Meteorological Drought map (MDI).

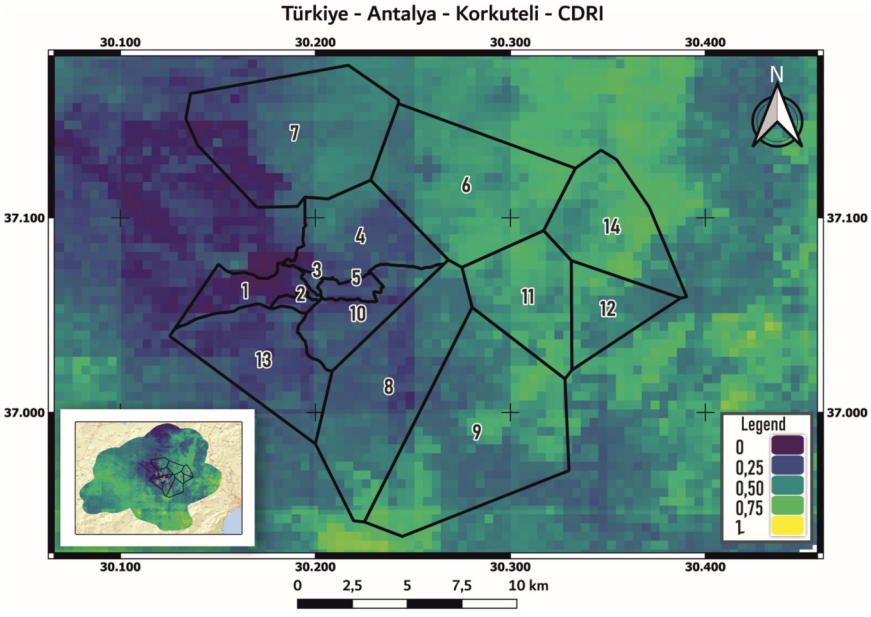
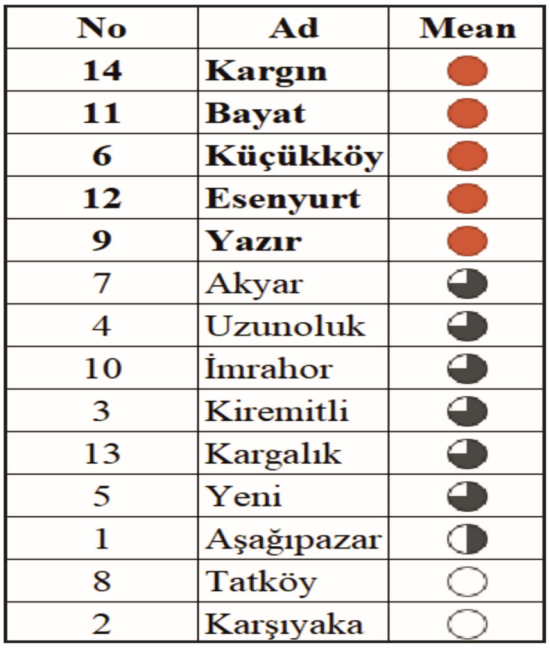


FIGURE 12
Composite Drought Risk Index map (CDRI).

Although globally validated satellite datasets (MODIS, CHIRPS, ERA5 Land) were used, the absence of ground based measurements remains a limitation for independent verification of the index components. To mitigate this constraint, internal cross validation among EO variables (NDVI, VCI consistency, LST, TEMP coherence, ET, SM hydrological complementarity, and CHIRPS precipitation anomalies) was employed, a widely accepted approach in drought monitoring when field data are unavailable. Nevertheless, the study acknowledges that future work should integrate UAV thermography, *in situ* soil moisture sensors, and phenological field observations to externally validate and further refine the CDRI model at orchard scale.

PDSI is a widely used tool to monitor large scale drought events but is rather focused on precipitation and evapotranspiration only. The proposed CDRI incorporates VDI, HTI, and rainfall deficit into



No	Ad	Mean
14	Kargın	
11	Bayat	
6	Küçükköy	
12	Esenyurt	
9	Yazır	
7	Akyar	
4	Uzunoluk	
10	İmrahor	
3	Kiremitli	
13	Kargalık	
5	Yeni	
1	Aşağıpazar	
8	Tatköy	
2	Karşıyaka	

FIGURE 13
Neighborhood-based KRI.

TABLE 2 Comparison of PDSI.

Feature	If PDSI were used	Obtained with CDRI
Vegetation vitality	Cannot be represented	Can be directly measured using NDVI/VCI
Microclimate effects	Cannot be represented	Can be monitored in detail using LST and temperature
Water stress	Estimated through modeling	Can be measured using ET and soil moisture (SM)
Neighborhood scale risk	Not possible	High risk areas such as Kargın, Küçükköy, and Esenyurt can be identified
Consistency with crop physiology	Weak	Very strong

a multidimensional system. This provides it with an advantage to assess risks which affect agricultural systems only. The ability to map drought sensitivity at the neighborhood scale and provide no meteorological variables to be included in the model enhances its capability to analyze risks too.

Despite these acknowledged limits, the study indicates the production zone is edging toward greater vulnerability as droughts intensify. The overlapping pressure from vegetation stress, heat, and weather conditions suggests that both yield and quality are likely to suffer more as climate pressures persist. Better water management, testing of heat tolerant varieties, boosting of soil organic matter, and adopting microclimate focused orchard practices are some of the key highlights in terms of urgent calls for adaptation. In the near future, the model will be improved by the integration of higher resolution satellite data, Unmanned Aerial Vehicle (UAV) observations, on the ground measurements, and tracking of phenology. The addition of climate projections will also give further support to the development of long term risk scenarios.

5 Conclusion

In the research, the drought related stress areas are identified and matched in the Korkuteli Karyağdı Pear cultivation region, and the vulnerability level of the area against the impact of climate change is determined. From the observations, the areas of stress due to vegetation, hydro thermal stress, and meteorological stress have overlapped, and the region is facing drought stress. The reduced values of NDVI and VCI indicate reduced vegetation health, while the increase in LST and AT values shows an increase in the surface load and air load, respectively. Additionally, the increase in evapotranspiration and the reduced value of SM indicate stronger water stress, while the irregular values of MDI indicate drought stress is increasing in the region due to irregular rainfalls.

While the PDSI relies primarily on long term precipitation and evapotranspiration balance to characterize meteorological drought, the CDRI proposed in this study integrates vegetation stress indicators (NDVI, VCI), hydro thermal stress components (LST, AT, ET, SM), and precipitation anomalies within a multidimensional EO framework. Therefore, whereas PDSI is

limited to a broad scale, atmosphere focused perspective, CDRI incorporates ground surface ecological responses detectable at finer spatial scales, enabling a more sensitive and plant specific assessment based on openly accessible EO datasets.

It is noticed in the CDRI surface that medium to high risk areas are widening, and the harshest drought bears upon the southern part of the district. Overlapping stressors in these zones make the Karyağdı Pear which lives in a pretty narrow ecological window particularly sensitive to shifting environmental conditions. Water scarcity and increased heat stress negatively affect tissue development, fruit growth, flavor, and flowering processes, leading to a decrease in quality. The study reveals these negative effects, and the similar situations observed in other regions of the world demonstrate the study's consistency with other regions. This study highlights a global, not just regional, impact.

Obtaining CDRI at the neighborhood level revealed that Bayat, Kargın, Küçükköy, Kargın, Esenyurt, and Yazır have the highest risk. This risk is influenced by low NDVI, high surface temperatures, and dry soil areas. Kargalık, Akyar, Uzunoluk, İmrahor, Kiremitli, and Yeni neighborhoods emerged as medium risk areas. Tatköy, Aşağıpazar, and Karşıyaka neighborhoods were found to be in the low risk group. Establishing neighborhood level CDRI significantly contributes to the preparation of drought mitigation action plans. It provides valuable assistance to implementers in carrying out drought mitigation activities such as regional shading, soil moisture conservation activities, and smart irrigation system designs in high risk areas.

The GEE platform used in this study enables the use of open source data and also allows for the creation of a coding structure that is easily adaptable for common use. By employing an m indexing strategy, it effectively integrates drought due to weather, water, and heat, as well as plant stress. It proves that through the combination of EO data for hydrometeorology, and plant level information, better drought estimates can be obtained than through conventional meteorology inputs for drought estimation. The spatial data of CDRI maps help for better decision making regarding drought mitigation, tracing, and agricultural planning for agricultural growth. This data is of immense use for orchard management and plant variety selection, agricultural economic planning, and irrigation network design.

There are some mentioned constraints, which are largely centered on image resolution and techniques. There are several future suggestions regarding how more advanced image resolution and techniques for decision support may improve this proposed approach for agricultural systems centered on GI. The process and data involved are open source, so updates for this approach can be submitted for revision as new information becomes available, supporting overall sustainability.

Although recent studies have progressed from mere meteorological factors, they have increasingly focused on crop suitability modeling, changes in plant phenology, and bioclimatic analysis. The originality of this study lies in its holistic approach, considering the plant, meteorological, and hydro thermal characteristics of agricultural GI products together. This feature allows it to obtain results that are as close to accurate as possible. Furthermore, the fact that the datasets consist of open source data, making them economical and easily accessible, strengthens the study's sustainability aspect. The updating and open source nature of the dataset used in the study are significant original features.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: The datasets used in this study (MODIS, ERA5-Land, CHIRPS and the derived indices) are open-access and publicly available. There are no legal, ethical, or commercial restrictions beyond complying with the standard terms of use and citation requirements of the original data providers. For this study, the datasets were only spatially constrained to the Korkuteli district and temporally to the 2001–2023 period. Requests to access these datasets should be directed to Ercument Aksoy, ercumentaksoy@akdeniz.edu.tr.

Author contributions

EA: Formal Analysis, Writing – original draft, Investigation, Software, Conceptualization, Resources, Data curation, Visualization, Writing – review and editing, Supervision, Project administration, Funding acquisition, Validation, Methodology.

Funding

The author(s) declared that financial support was not received for this work and/or its publication.

Acknowledgements

I would like to thank the Antalya Governorship European Union and Foreign Relations Directorate, the Turkish Local Products and Geographical Indications Research Network, and the Akdeniz University Geographical Indications Application and Research Center for their informative contributions that inspired me in this study.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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References

Abdelrahim, N. A., and Jin, S. (2025). A novel agricultural remote sensing drought index (ARSDI) for high-resolution drought assessment in Africa using sentinel and landsat data. *Environ. Monit. Assess.* 197 (3), 242. doi:10.1007/s10661-025-13686-3

Achille, L. S., Zhang, K., and Anoma, C. J. K. (2021). Analysis of climate variability and relation to vegetation in garamba national park from 1990-2020. *Open J. Ecol.* 11 (10), 700–723. doi:10.4236/oje.2021.1110044

AghaKouchak, A., Farahmand, A., Melton, F. S., Teixeira, J., Anderson, M. C., Wardlow, B. D., et al. (2015). Remote sensing of drought: progress, challenges and opportunities. *Rev. Geophys.* 53 (2), 452–480. doi:10.1002/2014RG000456

Anderson, M., and Kustas, W. (2008). Thermal remote sensing of drought and evapotranspiration. Eos. *Trans. Am. Geophys. Union* 89 (26), 233–234. doi:10.1029/2008EO260001

Belletti, G., Marescotti, A., and Touzard, J. M. (2017). Geographical indications, public goods, and sustainable development: the roles of actors' strategies and public policies. *World Development* 98, 45–57. doi:10.1016/j.worlddev.2015.05.004

Bowen, S. (2010). Embedding local places in global spaces: geographical indications as a territorial development strategy. *Rural. Sociol.* 75 (2), 209–243. doi:10.1111/j.1549-0831.2009.00007.x

Chmielewski, F. M., and Rötzer, T. (2001). Response of tree phenology to climate change across Europe. *Agric. For. Meteorology* 108 (2), 101–112. doi:10.1016/S0168-1923(01)00233-7

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., et al. (2015). The climate hazards infrared precipitation with stations a new environmental record for monitoring extremes. *Sci. Data* 2 (1), 1–21. doi:10.1038/sdata.2015.66

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R. (2017). Google Earth engine: planetary-scale geospatial analysis for everyone. *Remote Sensing Environ.* 202, 18–27. doi:10.1016/j.rse.2017.06.031

Gül, M., and Kart, F. M. (2024). Cost and profitability of pear farms in Türkiye: the case of korkuteli district of Antalya province. *Appl. Fruit Sci.* 66 (6), 2169–2177. doi:10.1007/s10341-024-01186-6

Hannah, L., Roehrdanz, P. R., Ikegami, M., Shepard, A. V., Shaw, M. R., Tabor, G., et al. (2013). Climate change, wine, and conservation. *Proc. National Academy Sciences* 110 (17), 6907–6912. doi:10.1073/pnas.1210127110

Hao, Z., and Singh, V. P. (2015). Drought characterization from a multivariate perspective: a review. *J. Hydrology* 527, 668–678. doi:10.1016/j.jhydrol.2015.05.031

Henry, L. (2023). Adapting the designated area of geographical indications to climate change. *Am. J. Agric. Econ.* 105 (4), 1088–1115. doi:10.1111/ajae.12358

Ilbery, B., and Kneafsey, M. (2000). Producer constructions of quality in regional specialty food production: a case study from south west England. *J. Rural Studies* 16 (2), 217–230. doi:10.1016/S0743-0167(99)00041-8

Kogan, F. N. (1995). Application of vegetation index and brightness temperature for drought detection. *Adv. Space Research* 15 (11), 91–100. doi:10.1016/0273-1177(95)00079-T

Lionello, P., Abrantes, F., Gacic, M., Planton, S., Trigo, R., and Ulbrich, U. (2014). The climate of the mediterranean region: research progress and climate change impacts. *Reg. Environ. Change* 14 (5), 1679–1684. doi:10.1007/s10113-014-0666-0

Otkin, J. A., Anderson, M. C., Hain, C., and Svoboda, M. (2014). Examining the relationship between drought development and rapid changes in the evaporative stress index. *J. Hydrometeorol.* 15 (3), 938–956. doi:10.1175/JHM-D-13-0110.1

Rhee, J., Im, J., and Carbone, G. J. (2010). Monitoring agricultural drought for arid and humid regions using multi-sensor remote sensing data. *Remote Sens. Environment* 114 (12), 2875–2887. doi:10.1016/j.rse.2010.07.005

Senay, G. B., Kagone, S., and Velpuri, N. M. (2020). Operational global actual evapotranspiration: development, evaluation, and dissemination. *Sensors* 20 (7), 1915. doi:10.3390/s20071915

Shastri, J. N., and Mujumdar, S. S. (2025). Use of satellite-based remote sensing indices for agricultural drought monitoring in Saurashtra, Gujarat. *Meteorol. Appl.* 32 (6), e70132. doi:10.1002/met.70132

Tucker, C. J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing Environ.* 8 (2), 127–150. doi:10.1016/0034-4257(79)90013-0

Van Leeuwen, C. (2022). "Terroir: the effect of the physical environment on vine growth, grape ripening, and wine sensory attributes," in *Managing wine quality* (Woodhead Publishing), 341–393. doi:10.1533/9781845699284.3.273

Vicente-Serrano, S. M., Cabello, D., Tomás-Burguera, M., Martín-Hernández, N., Beguería, S., Azorin-Molina, C., et al. (2015). Drought variability and land degradation in semiarid regions: assessment using remote sensing data and drought indices (1982–2011). *Remote Sens.* 7 (4), 4391–4423. doi:10.3390/rs70404391

Zargar, A., Sadiq, R., Naser, B., and Khan, F. I. (2011). A review of drought indices. *Environ. Rev.* 19 (NA), 333–349. doi:10.1139/a11-013

Zhang, X., Chen, N., Li, J., Chen, Z., and Niyogi, D. (2017). Multi-sensor integrated framework and index for agricultural drought monitoring. *Remote Sens. Environ.* 188, 141–163. doi:10.1016/j.rse.2016.10.045