

A scalable framework for agricultural drought hazard mapping in data-scarce arid regions: Case study of Jiroft plain, Iran

Hossein Malekinezhad

malekinezhad.h@gmail.com

Yazd University <https://orcid.org/0000-0002-1733-220X>

Mina Eghtedarnezhad

Yazd University

Elham Rafiei-Sardooi

university of Jiroft

Eric J. R. Parteli

University of Duisburg-Essen

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A scalable framework for agricultural drought hazard mapping in data-scarce arid regions: Case study of Jiroft plain, Iran

Mina Eghtedarnezhad¹, Hossein Malekinezhad^{*2}, Elham Rafiei-Sardooi³, Eric J. R. Parteli⁴

1. Department of Rangeland and Watershed Management, Faculty of Natural Resources, Yazd University, Yazd, Iran. (eghtedarnezhad.m@stu.yazd.ac.ir)

2. Department of Rangeland and Watershed Management, Faculty of Natural Resources, Yazd University, Yazd, Iran. (hmalekinezhad@yazd.ac.ir)

3. Department of Ecological Engineering, Faculty of Natural Resources, University of Jiroft, Kerman, Iran. (ellrafiei@ujiroft.ac.ir)

4. University of Duisburg-Essen, Faculty of Physics, Lotharstraße 1, 47057 Duisburg, Germany (eric.parteli@uni-due.de)

*** Corresponding Author**

Abstract

Agricultural drought is a major challenge in arid regions, especially where data from weather stations are limited. In such areas, remote sensing offers a useful way to monitor soil moisture at a regional scale. However, using remote sensing data to map agricultural drought hazard (ADH) is still not well developed, particularly in places with few ground observations. This study presents the first ADH assessment for the Jiroft plain, Iran — a dry region with limited hydro-meteorological data. We used MODIS NDVI and land surface temperature (LST) from 2007 to 2022, combined with in-situ soil moisture data at 1 km² resolution, to estimate surface soil moisture (0–30 cm). We then calculated the relative departure of soil moisture (RDSM) during eight severe drought events and used this as a basis for ADH mapping. We applied three machine learning models — support vector machine (SVM), regression trees, and multivariate discriminant analysis — to predict ADH based on ten environmental variables. Our results show that SVM performed best, with an AUC of 0.95. Plant available water capacity (PAWC), together with soil moisture, was found to be the most important factor in the model. The approach allows for spatially detailed ADH mapping even in data-scarce regions. We show how the model can be used to predict future drought events in the Jiroft plain. The study provides a practical method for drought risk assessment in arid areas where monitoring data are limited. The results can support early warning systems and help improve land use planning in similar regions around the world.

Keywords: Soil moisture, Drought hazard, Spatial modeling, MODIS NDVI and LST, Iran.

1 Introduction

Agricultural drought constitutes one of the most pressing challenges of the 21st century, particularly due to its profound impacts on food production and water security (FAO, 2020). Drought events are shaped by regional climate patterns, with their frequency, intensity, and spatial distribution reflecting long-term deficits in precipitation and soil moisture (Wilhite et al., 2000; McKee et al., 1993). When precipitation deficits exceed a threshold, water supply fails to meet environmental and societal demand (Svoboda et al., 2012), leading to cascading impacts across ecosystems and economies. While drought characteristics vary across regions due to differing hydroclimatic and environmental conditions (Alley, 1985; Dai et al., 2004; Keyantash and Wilhite, 2000), droughts are commonly classified by their onset and impact: meteorological (precipitation deficit), hydrological (streamflow and groundwater depletion), agricultural (crop stress), and socioeconomic (commodity shortages) (Kaur and Sood, 2019; Shi et al., 2018; Rahimi et al., 2019).

A critical variable in agricultural drought monitoring is soil moisture, which is directly influencing plant physiological processes and crop productivity (Wang et al., 2011; Mannocchi, 2004). The spatial and temporal dynamics of soil moisture are essential for assessing drought risk, yet in situ observations are often sparse and unevenly distributed. Remote sensing offers a viable alternative for regional-scale soil moisture estimation, leveraging electromagnetic radiation from the Earth's surface (Ochsner et al., 2013). Satellite products such as AMSR (Jackson et al., 2004), SMOS (Ma et al., 2019), ASCAT (Bartalis et al., 2007), and SMAP (Burgin et al., 2017) provide valuable data, but are limited by coarse spatial resolution. To overcome this, studies have combined surface reflectance with ground observations to enhance spatial resolution (Sandholt et al., 2002). In particular, remote sensing-based indices such as the Temperature Vegetation Dryness Index (TVDI) (Rahimzadeh-Bajgiran et al., 2012) and Apparent Thermal Inertia

(ATI) (Qin et al., 2013) estimate soil moisture using NDVI and LST. The NDVI, derived from visible and near-infrared reflectance, quantifies vegetation health (Peters et al., 2002), while LST is a key variable in hydrological and climate studies (Li et al., 2013; Halder et al., 2021). MODIS-derived NDVI and LST are widely used to estimate soil moisture at higher resolution than satellite soil moisture products (Yang et al., 2015; Baldwin et al., 2017), and are frequently applied to downscale soil moisture data (Song et al., 2013; Colliander et al., 2017). Chen et al. (2025) developed an interpretable machine-learning drought index by integrating soil moisture, LST, water balance, and solar-induced chlorophyll fluorescence, demonstrating that complementary remote-sensing variables can provide a more comprehensive representation of drought conditions. Similarly, Zubair et al. (2025) and Kumar et al. (2025) demonstrated the effectiveness of remote sensing and machine/deep learning in agricultural drought assessment and forecasting, particularly by capturing nonlinear environmental relationships and reducing reliance on extensive field observations. Jahanbakhsh and Akhondzadeh (2026) demonstrated the potential of remote sensing and machine learning for agricultural drought monitoring in Iran, while highlighting the limited use of soil-moisture deficits and soil properties such as PAWC in spatial drought hazard mapping, particularly in arid regions.

Numerous drought indices have been developed, including the Standardized Precipitation Index (SPI) (McKee et al., 1993; Tsakiris & Vangelis, 2004), Soil Moisture Drought Index (SMDI) (Narasimhan and Srinivasan, 2005; Wambua, 2019; Hou et al., 2022), Soil Wetness Deficit Index (SWDI) (Martínez-Fernández et al., 2015), Palmer Drought Severity Index (PDSI) (Yan et al., 2016), and Standardized Precipitation Evapotranspiration Index (SPEI) (Begueria et al., 2014; Li et al., 2020). However, these indices rely on interpolated station data, introducing uncertainties in spatial representation (Phillips & Marks, 1996; Fernández et al., 2013; Svoboda et al., 2015). Phuc et al. (2025) combined SMAP and CYGNSS data with environmental variables and machine learning to produce 1-km daily soil-moisture estimates and agricultural drought maps.

Therefore, agricultural drought hazard (ADH) mapping is a critical component of drought risk assessment (Rahmati et al., 2020a). While hazard maps exist for floods (Islam et al., 2021), landslides (Merghadi et al., 2020), land subsidence (Rafiei Sardooi et al., 2022), and erosion (Ahmadpour et al., 2021), ADH mapping remains underdeveloped, particularly in data-scarce regions. ADH mapping for such regions is challenging primarily due to the lack of high-resolution, long-term soil moisture observations for model calibration, the complex interplay of environmental drivers in arid regions, and the limited integration of multi-source data into predictive. Machine learning (ML) models—such as boosted regression trees (BRT), support vector machine (SVM), random forest (RF), multivariate discriminant analysis (MDA), flexible discriminant analysis (FDA), and classification and regression trees (CART)—have shown promise in hazard modeling but are rarely applied to ADH mapping.

This study presents a novel method for agricultural drought hazard mapping in data-scarce arid regions, using MODIS NDVI and LST combined with in-situ soil moisture observations. We apply ML models to estimate soil moisture and predict ADH in the Jiroft plain, Iran—a region highly vulnerable to drought but lacking dense monitoring infrastructure. Our objectives are: (1) identify key environmental drivers of ADH; (2) estimate soil moisture using NDVI and LST; (3) validate model accuracy; (4) create drought inventories based on relative soil moisture departure (RDSM); (5) predict ADH using ML; and (6) evaluate model performance. We demonstrate that SVM achieves the highest accuracy (AUC = 0.95), and that plant available water capacity (PAWC) is a dominant factor. The proposed framework offers a scalable, data-driven approach for drought risk assessment in arid regions with limited hydro-meteorological data.

2 Material and methods

2.1 Study area

Jiroft plain covers an area of 2239 km² and is located within Kerman province in southeastern Iran, with latitude between 28°10' N and 28°55' N and longitude between 58°10' E and 57°25' E (Fig. 1). The average annual rainfall in the study region is 167.5 mm, the average annual temperature is 16.7 °C to 25.8 °C, being associated with arid and semi-arid climate (Jiroft Municipal Statistics Bureau 2016). The minimum and maximum elevations in the area are 497 m and 1326 m above sea level, respectively. Furthermore, Jiroft plain has a broad range of vegetation species, inclusive irrigated orchards, annual irrigated cultivated crops and natural vegetation. Irrigation of cultivated crops – wheat, barley, corn, watermelon, cucumber, potato, onion and tomato – constitute the most water-intensive type of land use. Orchards are mostly covered by citruses, while natural vegetation, which colonizes a large part of the area

under investigation, is applied for livestock grazing type of land-use. The total cropland area of about 673 km² (Agricultural Organization of Jiroft County 2017) constitutes one of the most important means of subsistence for the population in the study area, which relies fundamentally on the agricultural sector.

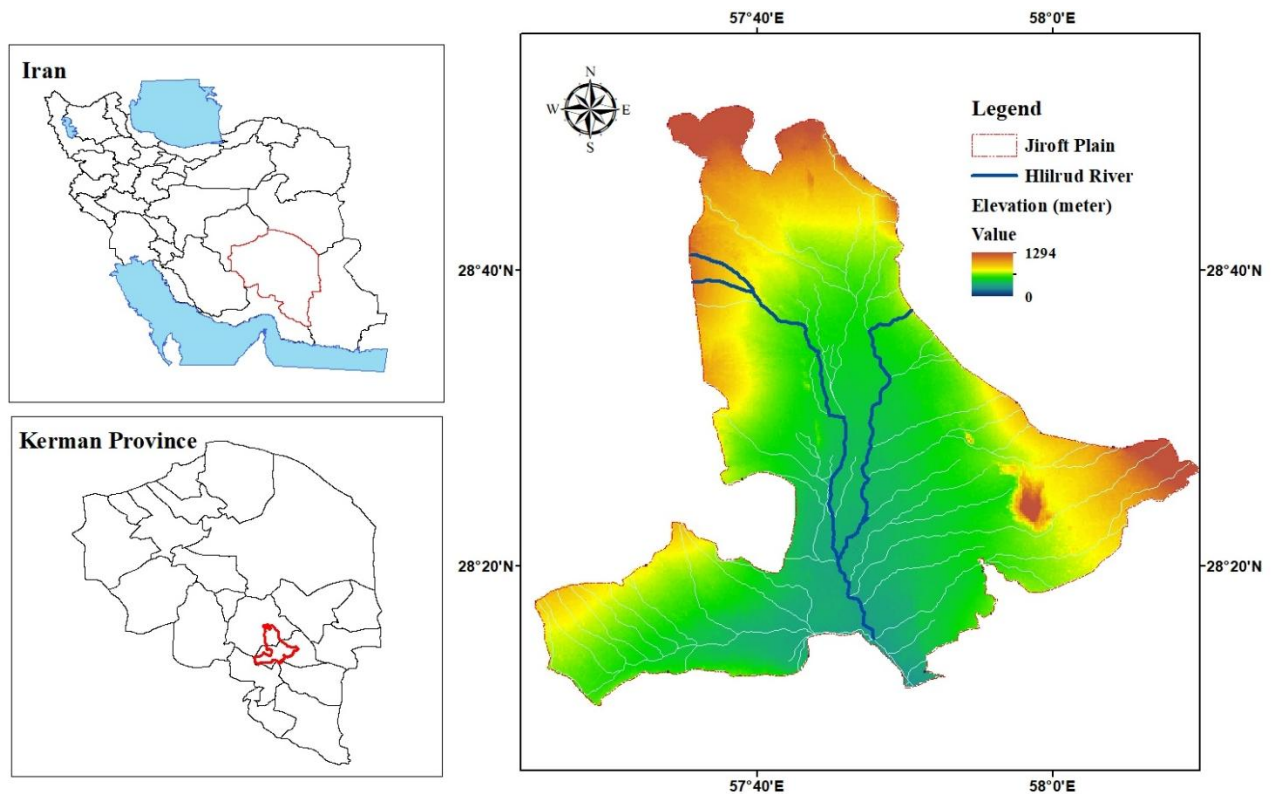


Fig. 1 The study area is located in Kerman province, Iran.

2.2 Methodology

In the present section, we present the maps associated with the environmental factors causative of droughts in the study area, as well as the machine learning models employed in the computation of the agricultural hazard map. Fig. 2 displays a research design flowchart.

2.2.1 Environmental factors for drought incidence and distribution

The pre-processing of the data layers and the selection of the conditioning factors constitute a crucial step in predictive modeling (Crozier 1986). However, there are no universal guidelines for the selection of such factors (Ayalew et al. 2005), because this selection is generally dependent upon the interplay of geology, geography, climate and environmental conditions in the study region (Glade et al. 2005).

However, in consistence with previous studies conducted on arid areas threatened by drought with characteristics similar to Jiroft plain (Rahmati et al. 2020 a, b), ten environmental factors can be considered as effective factors for the spatial distribution of drought in our study region. These factors, associated with topography (elevation, slope percent and topographic wetness index, i.e., TWI), soil properties (sand content, clay content, silt content and Plant Available Water Capacity, i.e., PAWC), mean annual precipitation, Normalized Difference Vegetation Index (NDVI), Land surface temperature (LST) and drainage density, are discussed in the following subsections.

2.2.1.1 Topographic agents (elevation, slope percent and TWI)

Elevation and slope affect soil moisture and agricultural productivity. High elevations are generally associated with lower soil moisture than low elevations (Aniya 1985) owing to gravity-driven, downhill water flows, which also lead

to lower levels of soil moisture on steeper slopes than over flat areas (Shekhar and Pandey 2015). In the present work, the spatial distribution of elevation and slope percent layer has been computed from a digital elevation model (DEM) with pixel size of 30 × 30 m (Fig. 2 a, b).

Moreover, Topographic Wetness Index (TWI) is used as a topography-based proxy for soil moisture (Winzeler et al. 2022). TWI provides a quantitative measure for terrain-driven variation in soil moisture and indicates the flow direction of soil (Rodhe and Seibert 1999). It can be calculated as follows:

$$TWI = \ln\left(\frac{\alpha}{\tan\beta}\right) \quad (1)$$

where α is the basin region (m^2/m) and β is the slope gradient (in degrees). In the study region, TWI was obtained from the digital elevation model (DEM) with a spatial resolution of 30 m using the SAGA software. The TWI map in the study region is shown in Fig. 2c.

2.2.1.2 Soil properties (sand, clay and silt contents; plant available water)

Coarse soils with high content of sand particles are generally associated with a lower capacity of water retention compared to fine soils, which contain higher amount of smaller-sized clay particles (Abdulkadir 2016). Because silt particles have size intermediate to sand and clay, soils with a large fraction of silt particles have intermediate water-holding capacity to sand and clay soils.

The sand, clay and silt content maps for the study area are available for the year of 2022 and for three depth-distances: 0–5 cm, 5–15 cm, 15–30 cm (source: <https://soilgrids.org>). Here, we compute an average over the three depths to obtain a single-value representation for the distribution of sand, clay and silt layers in Jiroft plain (Dayal et al. 2018). The corresponding maps for the sand, clay and silt content are shown in Figs. 2d, 2e and 2f, respectively. Furthermore, soil porosity, texture and structure affect the Plant Available Water Capacity (PAWC), which is obtained from the difference in water content between the field soil capacity (FC) and the permanent wilting point (PWP) – see, for instance, the discussion by Łabedzki (2017). Therefore, PAWC provides an important indicator of soil characteristics that complement the information associated with particle size. The PAWC map for Jiroft plain has been obtained using data available from the global soil database (extracted from soilgrids.org), by applying the following equation (de Ridder and van Keulen 1995),

$$PAW = FC - PWP \quad (2)$$

where FC ($cm^3 cm^{-3}$) and PWP ($cm^3 cm^{-3}$) denote the values of water content at field capacity and wilting point, respectively. These parameters are acquired using (de Ridder and van Keulen 1995)

$$FC = [(0.37 - 0.0035 \cdot S) \cdot Bd]/100 \quad (3)$$

$$PWP = [(0.007 + 0.0039 \cdot Cl) \cdot Bd]/100 \quad (4)$$

with S and Cl standing for the sand and clay percentages, respectively, and Bd denoting the bulk density of the soil ($g cm^{-3}$). Figure 2g shows the PAWC map of the study area.

2.2.1.3 Precipitation

Precipitation is the most effective factor in the inception of a drought (Martínez-Fernández et al. 2015). Here, the average annual precipitation map for Jiroft plain, shown in Fig. 2h, was prepared based on the data available from 17 meteorological stations of the study area using the kriging method. As can be seen from this map, the average annual precipitation (1989–2019) decreases from 180 mm in the northern part to 155 mm in the southern part of the study area.

2.2.1.4 Normalized Difference Vegetation Index (NDVI)

NDVI provides a measure to characterize the current distribution of vegetation in the region. In addition, vegetation provides an excellent proxy for soil water availability, as vegetation growth is favored by abundant content of soil moisture (Benedetti and Rossini 1993). In this study, MODIS Vegetation Index Product (NDVI) at a 1 km scale was extracted from <https://search.earthdata.nasa.gov/>. Fig 2 i shows the associated NDVI map of the study area.

2.2.1.5 Drainage density

Regions experiencing more intense drainage have higher soil moisture and are less affected by drought occurrence than other areas in which drainage is scarce or inexistent. To calculate the drainage map for Jiroft plain, we processed the river map based on DEM 30m in SAGA-GIS by applying the line density command in ArcGIS 10.8 to obtain the drainage distribution (Fig 2j).

2.2.1.6 Land Surface Temperature

Land surface temperature (LST) is one of the most important variables for application in hydrological processes, drought monitoring and climate change (Li et al, 2013 & Halder et al, 2021). Using satellite data of land surface temperature (LST) in soil moisture estimation can provide crucial information about the moisture conditions of the land surface. On the other hand, LST data have high spatial resolution for soil moisture estimation (Song et al, 2013 & Colliander et al, 2017). In this study, Land Surface Temperature (LST) at a 1 km scale was extracted from <https://search.earthdata.nasa.gov/>.

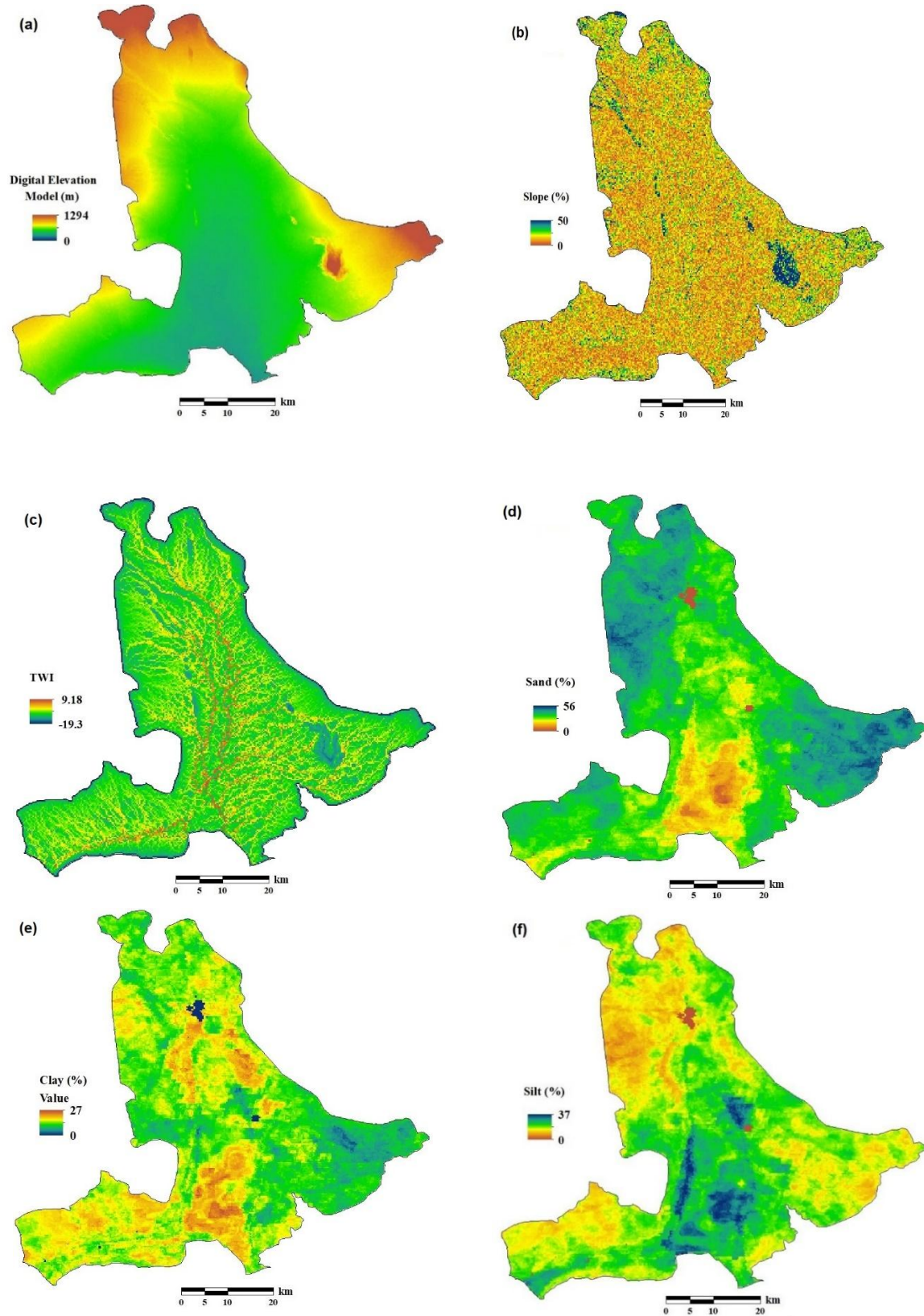


Fig. 2 (a) Digital Elevation Model (DEM), (b) Slope percent, (c) topographic wetness index (TWI), (d) sand (%), (e) clay (%), (f) silt (%), (g) Mean annual precipitation, (h) Plant Available Water Capacity (PAWC), (i) Normalized Difference Vegetation Index (NDVI), and (j) drainage density in the study area.

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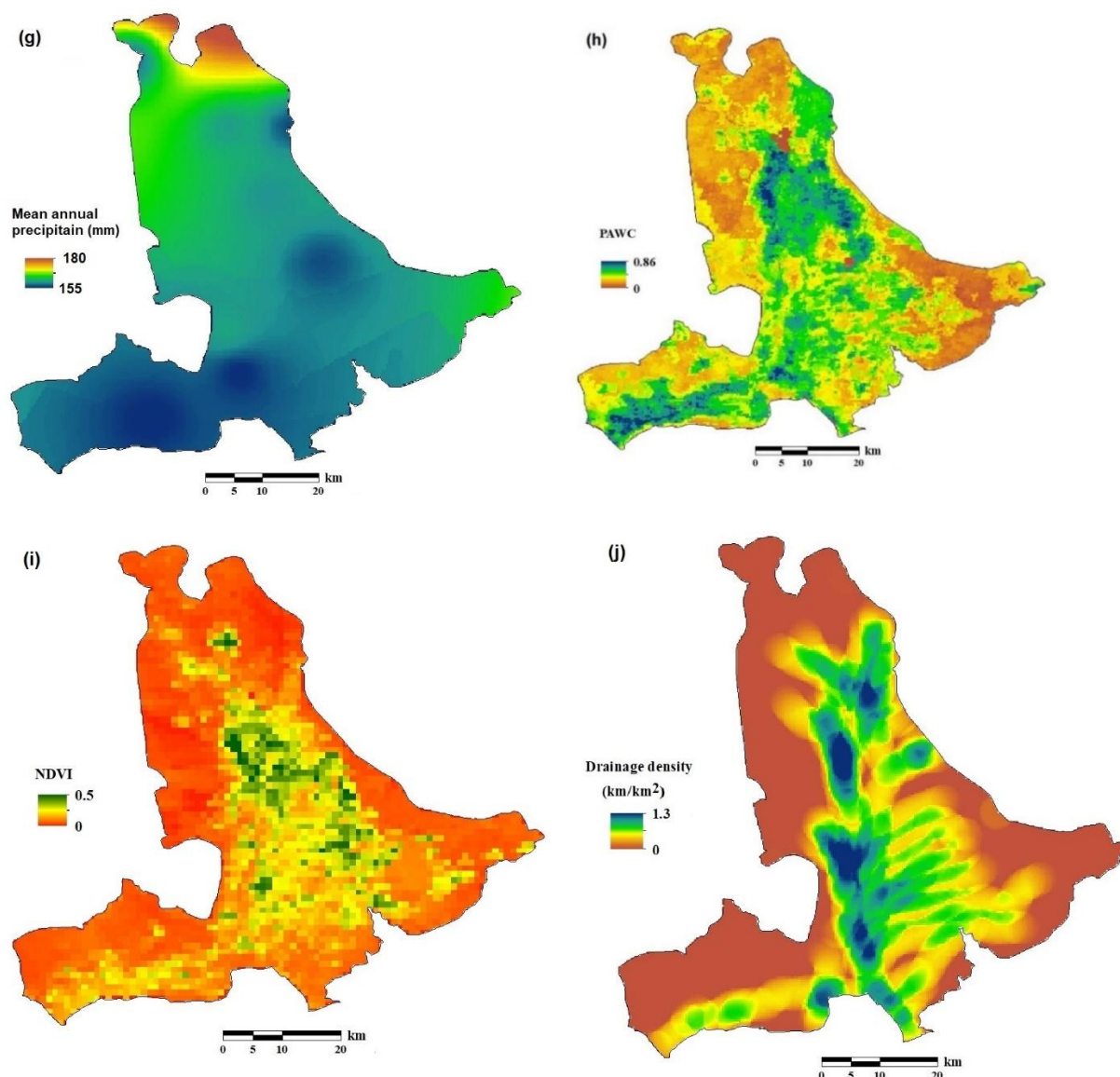


Fig 2 Continued

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2.2.2 Multi-collinearity between independent variables

Existing collinearity among variables decreases the model accuracy (Ghorbanzadeh et al. 2020). Therefore, following Greene (2000), we use the tolerance coefficient (TOL) and variance inflation factor (VIF) to test for variable multi-collinearity (see also O'Brien 2007). The application of the TOL and VIF coefficients for assessing collinearity between the independent variables in Section 2.2.1 is discussed later in Section 3.

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2.2.3 Soil Moisture Estimation Using Remote Sensing

In the present study, we estimate soil moisture using Terra MODIS data, which have a much higher spatial resolution (1 km). To this end, we develop an algorithm that combines optical/IR data with ground measured soil moisture, building on the so-called "universal triangle" relationship (Carlson et al. 1994; Gillies et al. 1997; Zhan et al. 2002) between soil moisture, land surface temperature (LST) and the Normalized Difference Vegetation Index (NDVI). As

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depicted in Fig. 3, this relationship can be represented by means of an “universal triangle” (Chauhan 2003), because soil moisture, land surface temperature, and the Normalized Difference Vegetation Index (NDVI) are interconnected, thereby leading to a triangular or trapezoidal pattern in a scatter plot. Such triangular relationship is used in remote sensing to estimate soil moisture and evapotranspiration, and has been extensively verified and corroborated in previous work. This previous work used a soil vegetation-atmosphere-transfer (SVAT) model based on the following variables,

$$T^* = \frac{T - T_o}{T_s - T_o} \quad (5)$$

$$NDVI^* = \frac{NDVI - NDVI_o}{NDVI_s - NDVI_o} \quad (6)$$

where T and $NDVI$ are the observed surface temperature and normalized difference vegetation index, respectively, the subscripts o and s represent the minimum and maximum values, respectively.

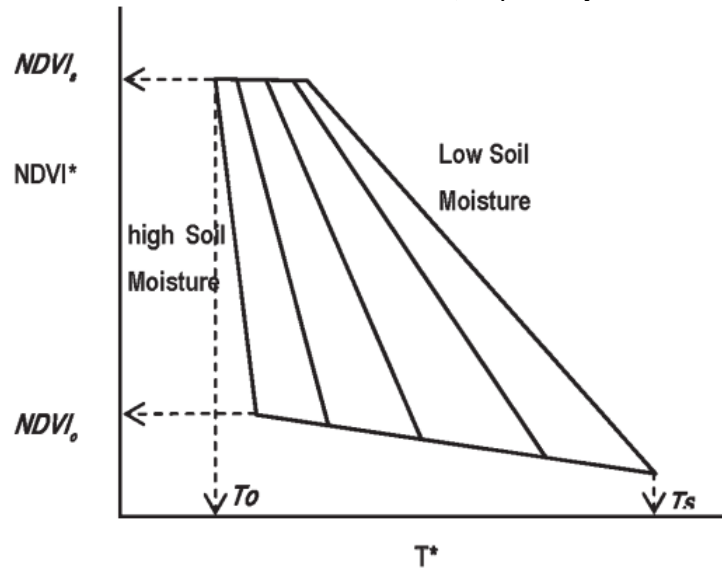


Fig. 3 Universal Triangle Relationship between NDVI, temperature and soil moisture (Chauhan 2003). Here, T stands for LST, while the subscripts o and s specify minimum and maximum values.

Soil moisture (M) is then estimated through a regression equation (Carlson et al. 1994):

$$M = \sum_{i=0}^n \sum_{j=0}^n a_{ij} \cdot (NDVI^*)^i \cdot (T^*)^j \quad (7)$$

which has been written by Chauhan (2003) as a second-order polynomial:

$$M = a_{00} + a_{10}NDVI^* + a_{20}NDVI^{*2} + a_{01}T^* + a_{02}T^{*2} + a_{11}NDVI^*T^* + a_{22}NDVI^{*2}T^{*2} + a_{12}NDVI^*T^{*2} + a_{21}NDVI^{*2}T^* \quad (8)$$

In this study, the Universal Triangle Relationship between NDVI and temperature (LST) is used to estimate soil moisture. To this end, two years (2021–2022) of NDVI and LST products from Terra MODIS are blended with ground-based measurements of soil moisture to characterize and validate regression relationships at a 1 km scale. MODIS data include 16-days dataset of vegetation index (MOD13A2) to derive NDVI, and 8-days dataset of land surface temperature (MOD11A1) for extraction of LST at 1 km resolution. The datasets are accessed at <https://search.earthdata.nasa.gov/>. Using the results obtained from the referred regression analysis, soil moisture maps at 1 km resolution are then produced for the study region.

Here, we apply a multiple linear regression method to estimate the soil moisture from Vegetation Index (NDVI) and Land Surface Temperature (LST) data at depth of 0-30 cm for the time period from 2007 to 2022 (Bai et al. 2020). The soil volumetric water content (SMC in $\text{m}^3 \text{m}^{-3}$) associated with the samples is calculated using (Bai et al. 2020):

$$\text{SMC} = b_0 + b_1 \text{LST} + b_2 \text{NDVI} \quad (9)$$

where the regression coefficients b_0 , b_1 and b_2 are obtained using the ordinary least squares (OLS) method (Mahara et al. 2016) implemented in ArcGIS 10.8. Soil moisture maps at a depth of 0-30 cm are prepared using the regression model with spatial resolution of 1 km^2 , for the period from 2007 to 2022.

However, given the sparse distribution of meteorological stations throughout Jiroft plain and the rare soil moisture database for the study region, to obtain observed soil moisture at the soil depth of 0-30 cm, about 73 soil samples were collected from different areas across Jiroft plain in both years of 2021 and 2022. Thereafter, the soil moisture maps of 2021 and 2022 were interpolated using the Kriging method available in ArcGIS 10.8, whereas both maps were averaged to produce the final soil moisture map. Indeed, Bai et al. (2020) collected in situ soil moisture in five layers (0–10, 10–20, 20–30, 30–50 and 50–70 cm) and estimated soil moisture using MODIS products over the various depth levels. The results obtained by Bai et al. (2020) indicated that soil moisture models at 0-30 depth yield the highest accuracy, thus justifying our choice for the 0-30 depth level in the present study.

Moreover, the model accuracy is evaluated here by means of different statistical indicators, including standard error (SE), t-statistics (t-stat), Akaike information criterion (AIC), p-value, variance inflation factor (VIF) and R^2 . These indicators are briefly summarized below.

- a) The coefficient of determination (R^2) (Krause et al. 2005) describes the linear correlation of the dependent variable (soil moisture) and multiple explanatory variables in the multivariate linear regression,

$$R^2 = \left[\frac{\frac{1}{n} \sum_{i=1}^n (s_i - \bar{s})(o_i - \bar{o})}{\sigma_s \cdot \sigma_o} \right]^2 \quad (10)$$

where o_i and s_i are the observed and anticipated data, respectively, with $\bar{o}$ and $\bar{s}$ denoting their respective average values, while σ_s and σ_o denote the associated standard deviation values. The R^2 measure can take values from 0 to 1, whereas model performance is considered the better the closer R^2 is to unity.

- b) The certainty level p indicates the level of significance of the regression equation. A p-value smaller than 0.01 (0.05) indicates 99% (95%) confidence level.
- c) Moreover, the Akaike information criterion (AIC) is an estimator of forecast error and provides, thus, a relative measure for the quality of statistical models for a given set of data (Cavanaugh 1997). There is no value for AIC that can be considered “good” or “bad”, but the model with the lowest AIC offers the best fit (Sen & Shitan 2002).
- d) The variance inflation factor (VIF) provides a measure of the amount of multi-collinearity in regression analysis (Miles 2014). Multi-collinearity occurs when there is a correlation between multiple independent variables in a multiple regression model. This can negatively impact the regression results. Values of VIF > 10 indicate that there exists collinearity between the variables (Thompson et al. 2017).
- e) The t-statistic is the proportion of the deviation of the estimated value of a parameter from its assumed value to its standard error. It is utilized in hypothesis testing via Student's t-test (Box et al. 1978). The t-statistic is utilized in a t-test to determine whether or not to support the null hypothesis. A good t-statistic is one that is statistically significant, meaning that the difference between the two-sample means is unlikely to have happened by chance. By and large, a t-statistic of 2 or higher is considered statistically significant (Kim 2015).

- f) The standard error (SE) of a statistic is the standard deviation of its sampling distribution, i.e., an estimate of the real standard deviation. The standard error measures the amount of difference that can be expected in a sample estimate compared to the true value in the society (Altman & Bland 2005). Hence, the smaller the standard error, the better the model. A standard error of zero (or close to it) would show that the estimated value is exactly equal to the true value (Hanley 1987).

2.2.4 The inventories of agricultural drought

Soil moisture constitutes a key indicator of agricultural drought (Martínez-Fernández et al. 2016; Wu et al. 2018). The relative departure of soil moisture (RDSM) is frequently employed as a means to quantitatively assess agricultural drought throughout a wide range of average annual precipitation levels (Rahmati et al. 2020 a, b; Gao et al. 2023). RDSM is computed using (Rahmati et al. 2020 a):

$$\text{RDSM} = \frac{s_i - \bar{s}}{\bar{s}} \cdot 100 \quad (11)$$

In Eq. (11), s_i denotes the average annual soil moisture for the given year, while $\bar{s}$ is the average annual soil moisture during the base period. Eight severe agricultural drought events (2007, 2009, 2011, 2013, 2015, 2017, 2019, and 2022) were mapped and analyzed. The RDSM was normalized from the initial value to a range between 0 to 1 using fuzzy logic. Following Dayal et al. (2018) and Rahmati et al. (2019a), a threshold value of 0.5 ($\text{RDSM} < -0.5$) was applied to determine the points of agricultural drought occurrence. Furthermore, a total of 267 drought points were randomly selected and divided into two groups using resampling technique of subsampling: 70% RDSM drought points ($n=187$) used as the training data, and 30% RDSM drought points ($n=80$) used as validation data to evaluate the generated drought hazard map.

Moreover, points (locations) associated with non-occurrence of drought were chosen at random and away from drought locations (i.e., using the criterion $\text{RDSM} < -0.5$). For the mapping purpose, drought and non-drought locations were labeled using 1 and 0, respectively.

2.2.5 Machine learning models

In the following subsections, we briefly describe the Machine Learning tools applied in the present work to generate the agricultural drought hazard map based on the information specified in the aforementioned sections.

Support vector machine (SVM): Machine Learning algorithms relying on SVM constitute supervised learning methods, in which the optimized solution is obtained through structural risk minimization (SRM), with a linear or non-linear Kernel being employed in the learning process of a classification model (Vapnik 1999).

Boosted Regression Trees (BRT): Such models combine decision tree algorithms with a model-averaging method called boosting, in which the training and testing datasets are selected at random (Elith et al. 2008). Decision trees are fitted to the training data to increase the performance of the model, whereupon the fitted model is used to predict the test data. BRT models offer a powerful tool in applications involving various variable types, allowing the user to manage different predictor variables by automatically distinguishing interactions among these predictors (Aertsen et al. 2011).

Multivariate discriminant analysis (MDA): Multivariate discriminant analysis consists in a classification method to predict categorical responses. MDA models are employed to distinguish among two groups of variables by means of the Fisher discriminant analysis based on Bayes' theorem (Adnan Aziz and Dar 2006), where the conditional probability and the predictors are presumed to conform a multiple normal distribution. In MDA, the collection of parameters is considered to be part of the closest group in which the distance is calculated under the assumption that the parameters follow a normal distribution. The variability and correlation between parameters are assumed to be same (Lombardo et al. 2006). Hereby, a quadratic (QDA) or linear (LDA) discriminant analysis can be applied for the binary responses, when boundary between classes is presumed linear or non-linear, respectively (Rossi et al. 2010).

In this study, we run the ML algorithms implemented using the built-in packages of the R software 3.5.3, utilizing the radial basis (RBF) Kernel along with the SDM (Species Distribution Modelling) package explained by Naimi & Araújo (2016). To appraise the performance of the ML models, the receiver operating characteristics (ROC) curve

provides one of the most well-known indicators. Indeed, the ROC indicator has been applied in many environmental studies such as susceptibility modeling of groundwater, landslide, erosion and flood – see, for example Marjanović et al. (2011), Rafiei-Sardooi et al. (2021) and references therein.

In the drought map, each observation belongs to the positive (drought occurrence) or negative (drought nonoccurrence) class of the drought classification. The positive and negative pixels that have been correctly categorized are called true positives (TP) and true negatives (TN), respectively. By contrast, false positives (FP) and false negatives (FN) denote wrongly categorized pixels (Merghadi et al. 2020). In the ROC curve, the x-axis shows the specificity and y-axis indicates the sensitivity, defined as

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (12)$$

$$\text{Specificity} = \frac{TN}{FP + TN} \quad (13)$$

The area under the ROC curve (AUC-ROC) ranges from 0 to 1, with higher values indicating excellent model function (Van Phong et al. 2020; Pham et al. 2017).

We remark that, in the present study, training and test data were separated using resampling technique for subsampling, so that cross-validation and hyperparameter tuning were not applied in the machine learning models considered in our calculations.

3 Results and discussion

3.1 Spatial distribution of soil moisture estimated from remote sensing data and ground observations

Figures 4 and 5 display snapshots of the NDVI and LST distributions throughout Jiroft plain for three different years (2007, 2014 and 2022), as well as their respective trends within the time span from 2007 to 2022. To produce these maps, we divided the time span from 2007-2022 into two periods. In the first period, from 2007 to 2020, a remote sensing-based algorithm (Wang et al. 2007; Bai et al. 2020) was used to estimate soil moisture from MODIS LST and NDVI products at a 1 km² resolution, given the data scarcity associated with the observed time series of soil moisture. For the second time period, encompassing the years of 2021 and 2022, multiple linear regressions were performed among the available soil moisture data from ground observations and the NDVI and LST time series data utilizing OLS method.

The general trend of the spatial and temporal changes of simulated soil moisture is shown in Fig. 6, while table 1 presents the results from the soil moisture estimation (0–30 cm) using the OLS method. Our results show that the model prediction for both independent variables, NDVI and LST, is significant at the 99% level (p-value < 0.01). Moreover, the associated VIF values are smaller than 10, thus indicating absence of collinearity between the independent variables. This model quality assessment is, indeed, consistent with the results of the other tests performed in our study, which yield low standard error, a t-statistic value higher than 2, and a high value of R². Specifically, in Fig. 7, simulated and observed soil moisture in the years of 2021 and 2022 are displayed in separated linear plots. As can be seen from Fig. 7, the value of R² amounts to 0.74 for the year of 2021 and 0.8 for 2022. These high values of R² obtained in our model are compatible with the good model performance reported by Bai et al. (2020), who applied MODIS NDVI and LST datasets to estimate the soil moisture distribution in the upstream of the Heihe River basin, Northwest China. Our results confirm the conclusions of Bai et al. (2020) that the remote sensing model is suitable for regions of complex topography, heterogenous soil conditions and assorted vegetation types, which are characteristics inherent to the study area considered in the present study.

Table. 1 Results obtained with the OLS method for soil moisture estimate (0–30 cm).

Variable	<i>Ordinary Least Squares Model</i>
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	Cofficient (a)	St- Error	T-stat	p-value	VIF
Intercept	3.76	1.8	3.31	0.005	-
LST	-0.13	0.11	2.25	0.003	3.12
NDVI	8.8	2.03	4.3	0.0012	2.12
R ²	0.78				
AIC	166.2				

AIC: Akaike Information Criterion, $p < 0.05$ level.

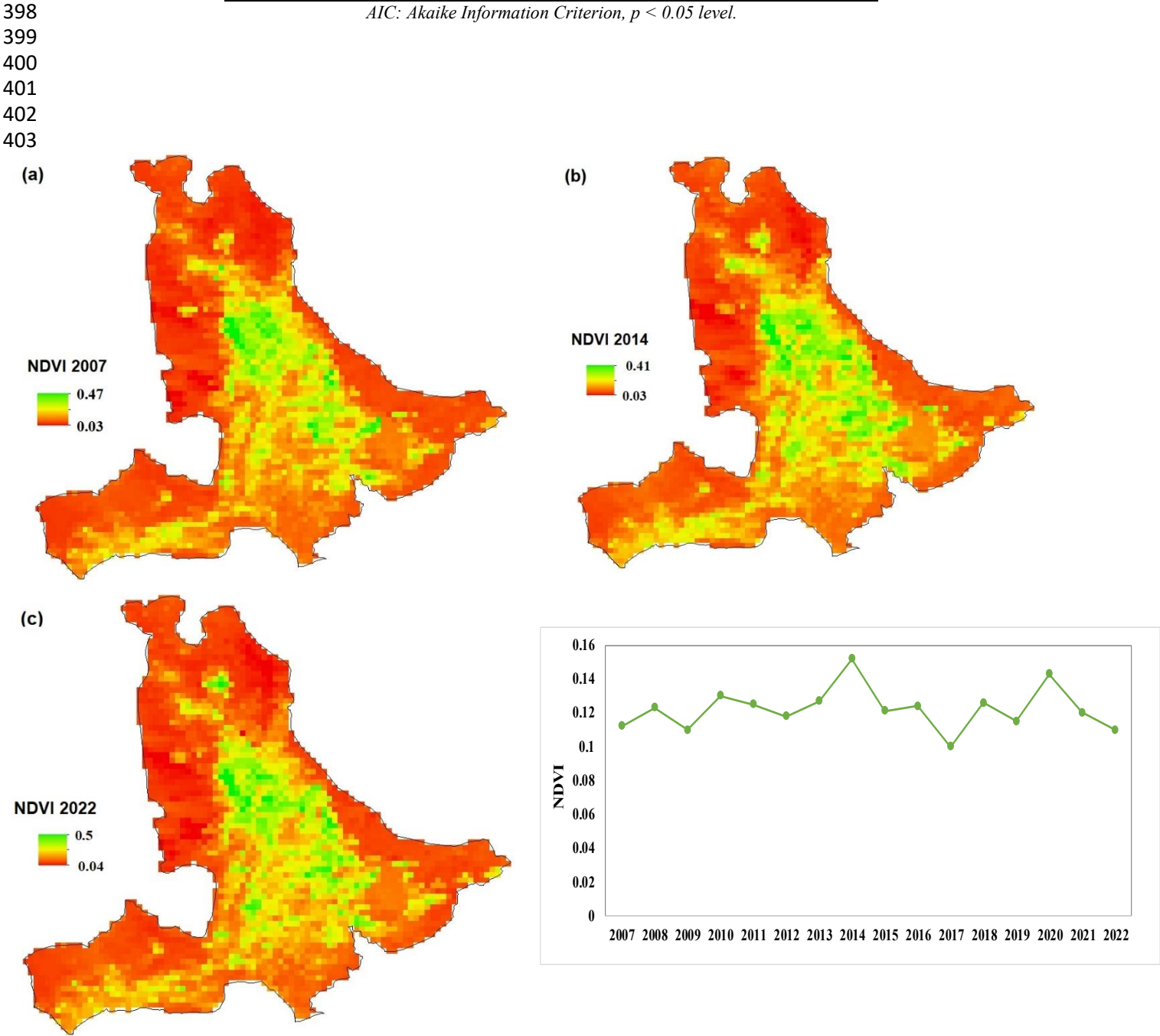


Fig. 4 NDVI maps for (a) 2007, (b) 2014 and (c) 2022, along with the time series over the time span from 2007 to 2022.

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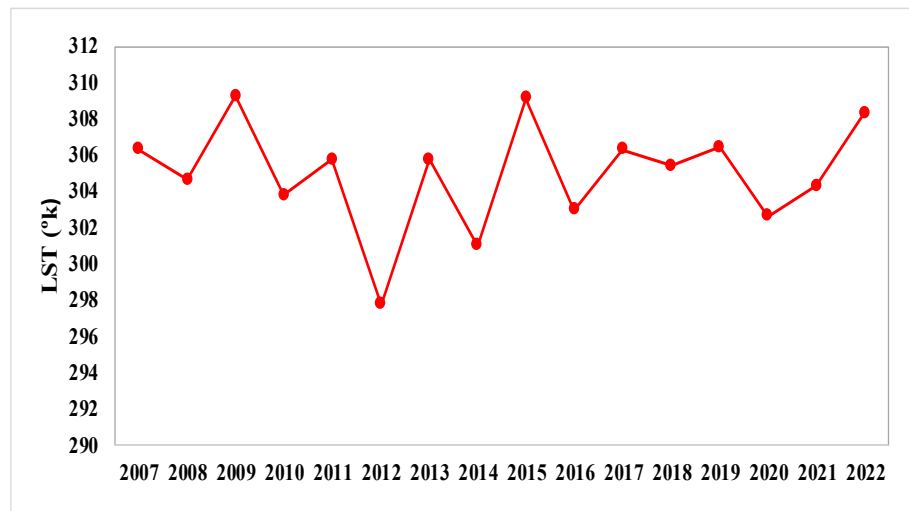
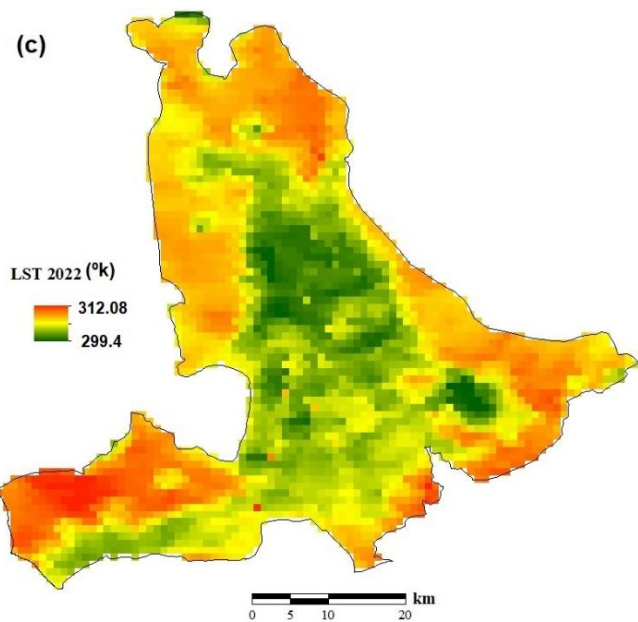
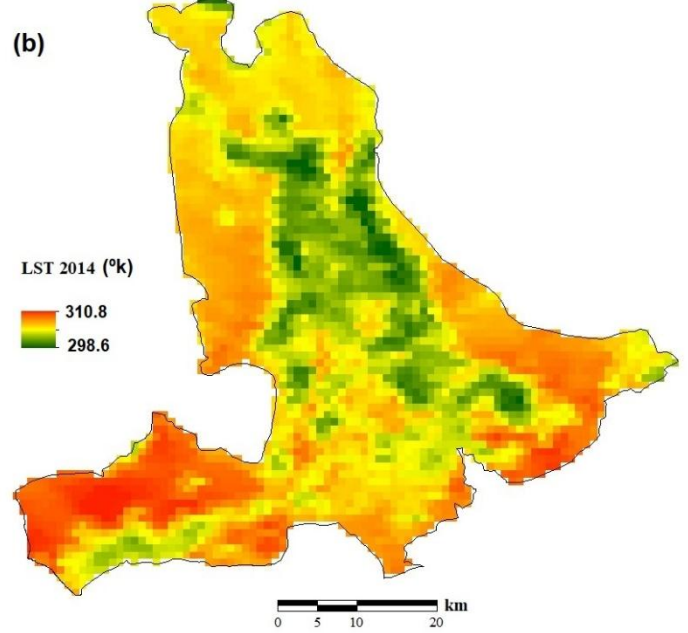
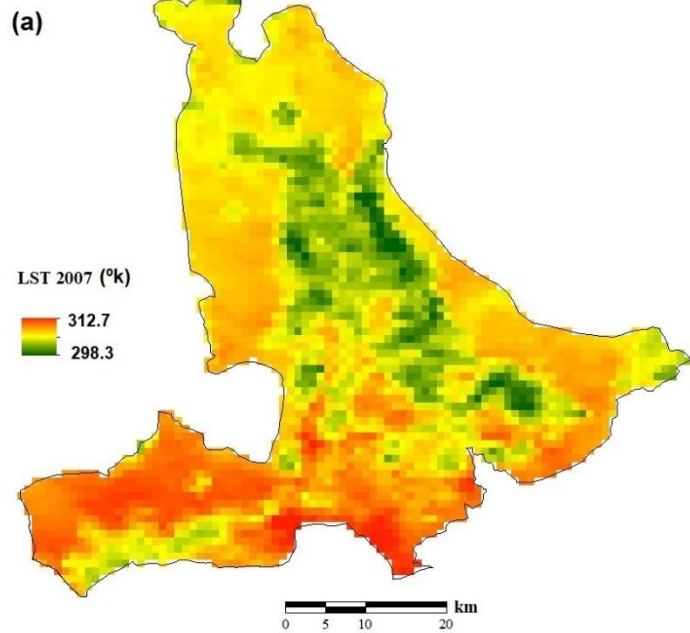


Fig. 5 LST maps for (a) 2007, (b) 2014 and (c) 2022, along with the time series over the time span from 2007 to 2022.

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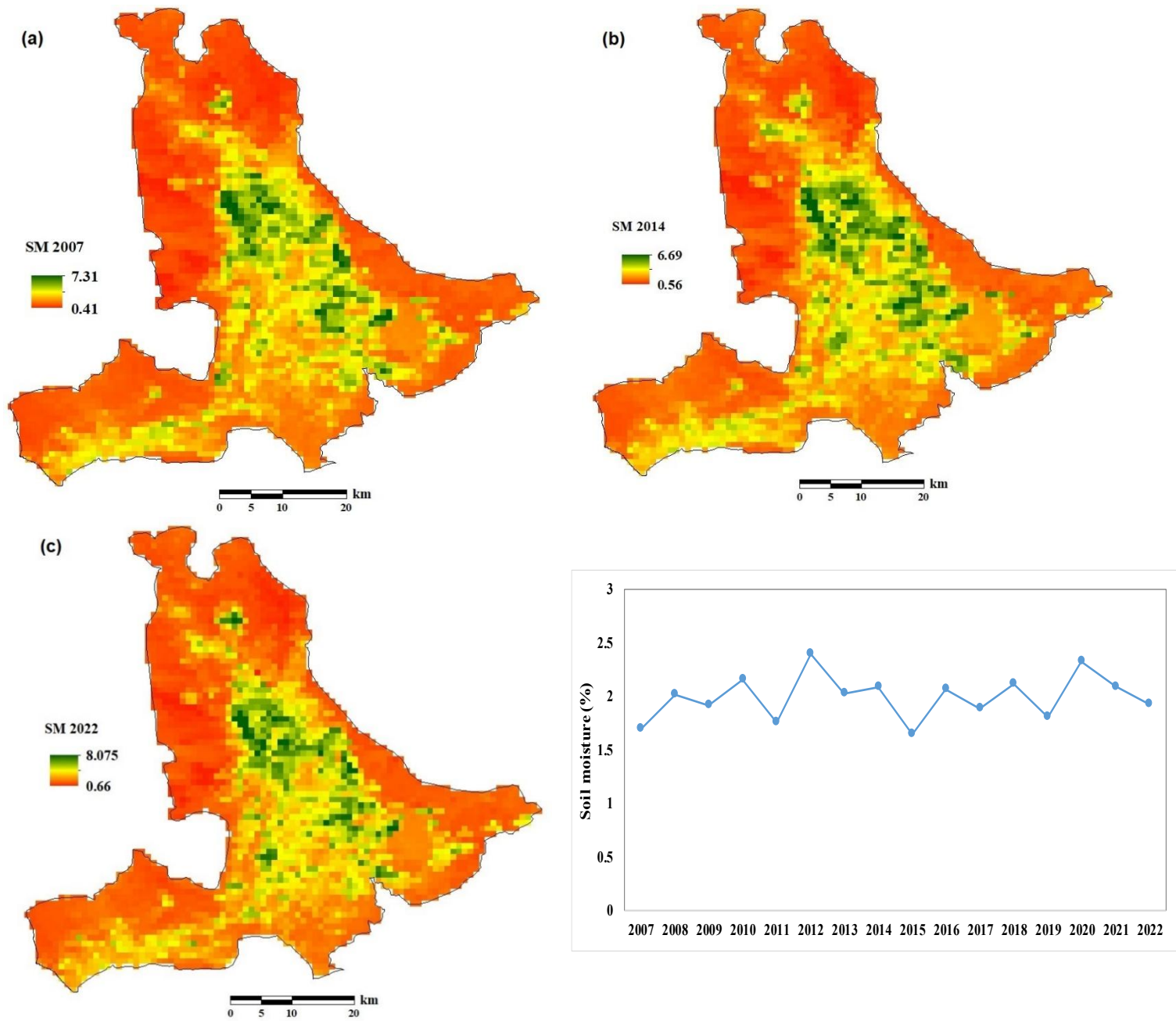


Fig. 6 Soil moisture maps for (a) 2007, (b) 2014 and (c) 2022, along with the time series over the time span from 2007 to 2022.

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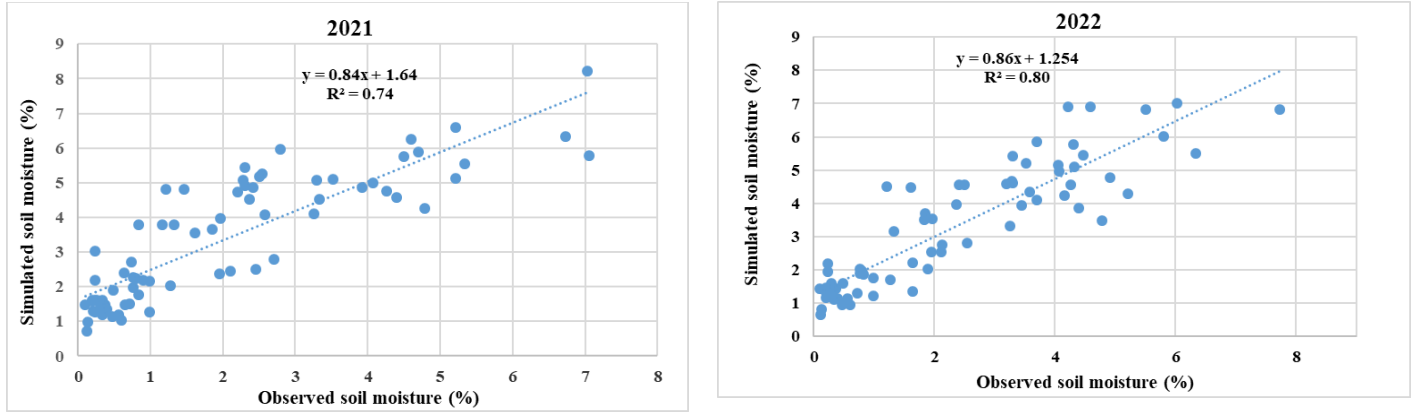


Fig. 7 Comparison of simulated and observed soil moisture values in the years of 2021 and 2022.

3.2 Relative departure of soil moisture (RDSM) and inventory maps

In this study, the relative departure of soil moisture (RDSM) was applied to create the inventories of agricultural drought. Figure 8 shows the RDSM maps derived with MODIS products from 2007 to 2022. Hereby, eight severe agricultural drought events (i.e., 2007, 2009, 2011, 2013, 2015, 2017, 2019, and 2022) were mapped and analyzed. A threshold value of 0.5 ($RDSM < -0.5$) was applied to specify the points of agricultural drought occurrence. As can be seen from Fig. 8, the spatial pattern of RDSM is similar for all years, the central regions of the study area being associated with a smaller RDSM and experiencing less drought. In this study, the RDSM values of all years were averaged to produce the final representation in the RDSM layer based on the drought inventories.

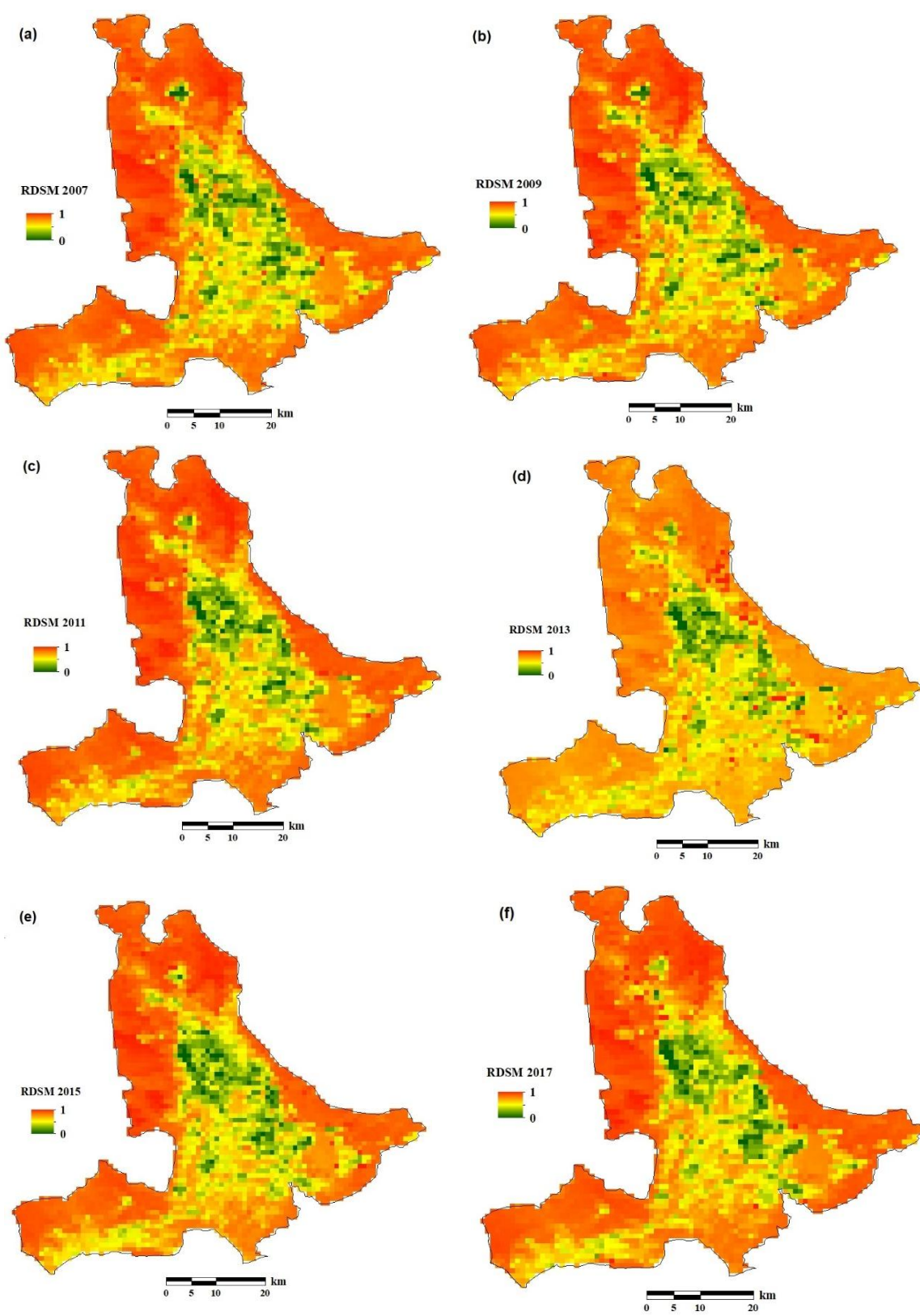


Fig. 8 Standardized value of the relative departure of soil moisture (RDSM) in the surface layer (0-30 cm), obtained using the fuzzy membership functions bounded to $[0, 1]$ in the years of (a) 2007, (b) 2009, (c) 2011, (d) 2013, (e) 2015, (f) 2017, (g) 2019, and (h) 2022.

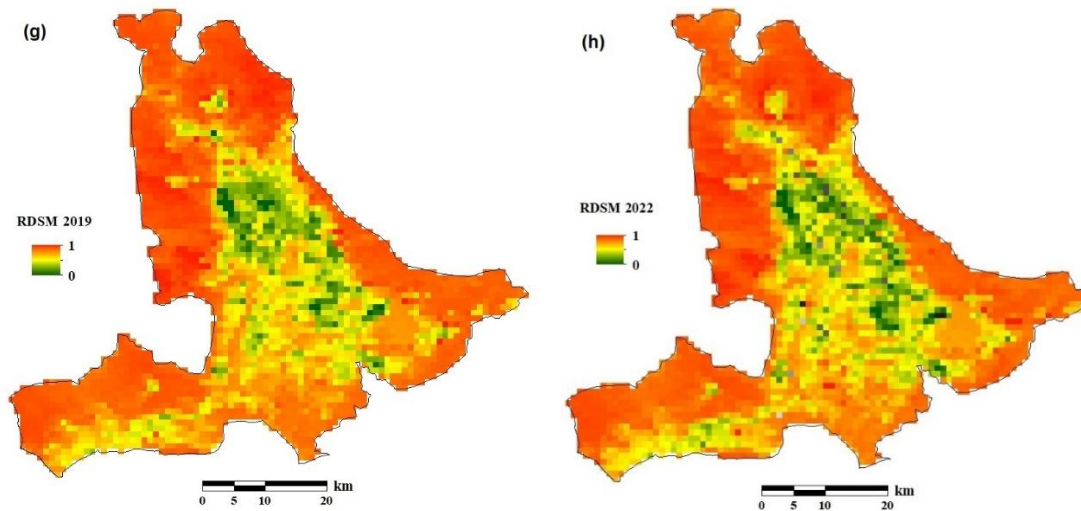


Fig. 8 Continued.

3.3 Multi-collinearity tests

The variance inflation factor (VIF) and the tolerance factor (TOL) provide indicators for collinearity between the explanatory variables. Specifically, the multi-collinearity test suggests the occurrence of collinearity between the predictor variables (presumed to be independent) when $TOL < 0.1$ and $VIF > 10$. Table 2 displays the results of VIF and TOL associated with the drought predictors considered in our study. As can be seen from this table, we can conclude that there is no significant collinearity between the predictor variables.

Table. 2 Results from the multi-collinearity test between conditioning factors, using VIF and TOL as indicators of collinearity.

Factors	TOL	VIF
NDVI	0.61	1.89
Drainage density	0.59	1.94
Precipitation	0.52	2.13
PAWC	0.74	1.32
TWI	0.67	1.45
Sand content	0.39	3.06
Clay content	0.48	2.48
Silt content	0.44	2.95
Elevation	0.32	3.27
Slope percent	0.21	3.64

3.4 Agricultural drought hazard maps

The agricultural drought hazard (ADH) maps of the study region created by the three Machine Learning models discussed in Section 2.2.5 are displayed in Fig. 9. All three maps share various aspects of spatial distribution, with low ADH in the central parts of the study region. Moreover, the ROC curves and corresponding AUC values associated with the three models are presented in Fig. 10 and Table 3, while Table 4 displays the statistics of simulated ADH maps.

As can be seen from the results in Tables 3 and 4, the SVM model yields the highest accuracy among all three models ($AUC=0.95$ and $STD=0.146$). Indeed, SVM has been found to yield the highest accuracy in previous studies too, this behavior being attributed to the method's capability for good generalization and rapid learning (Rafiei Sardooi et al. 2022). Moreover, our findings that SVM yields the highest model accuracy are in line with the conclusions of Pourghasemi et al. (2020), who compared the performance of SVM with the one of BRT and MDA, based on different types of spatial modeling phenomena associated with the construction of sediment control check dams.

We can classify drought hazard in Jiroft plain using five classes, i.e., very low (0–0.2), low (0.2–0.4) medium (0.4–0.6), high (0.6–0.8), and very high (0.8–1) drought hazard – Fig. 11 presents the drought hazard map obtained by applying SVM with natural break classification. We note that this choice for the ranges associated with each class is empirical but takes inspiration on the classification scheme adopted in a broad range of previous studies, which adopted 5 classes for the dependent variable, uniformly distributed from 0 to 1. However, using this classification scheme, according to the SVM model (Table 5), we find that about 17.2% and 54.5% of the study region can be classified as zones of high and very high drought hazard, respectively, thus providing a reasonable model for representing the observations in RSDM displayed in Fig. 8. Furthermore, the areas of moderate, low and very low drought hazard correspond to 10.4%, 6.1% and 11.8% of the study region, Low ADH and very low ADH classes occur in the central part of the study region.

The hazard mapping method developed in the present study offers substantial advantages compared to previous approaches. Drought monitoring based on weather stations and interpolation is often associated with high levels of uncertainty throughout the interpolated regions (Swain et al. 2011). Moreover, index-based methods lack consideration of the complex relationship between drought occurrence and the conditioning factors, consequently yielding little information about the physics underlying the spatial distribution of the mapped variable (Ahmadalipour et al. 2017, Hao and Singh 2015). The remote-sensing-method proposed in our study offers a means to overcome these deficiencies. Specifically, the associated algorithm (Wang et al. 2007; Bai et al. 2020) encompasses a physics-based relationship between MODIS NDVI and LST and observed soil moisture, and incorporates spatial modeling of soil moisture as a function of physical variables regarded as causative factors (Section 2.2.1). Therefore, our method provides a helpful tool for investigating the physics of agricultural drought occurrence by building on the understanding of how the different conditioning factors contribute to land surface characteristics (in particular, soil moisture) and the concatenated distribution of drought events.

Since the conditioning factors and their spatial patterns depend fundamentally on local climatic, geographic and geological conditions of the environmental setting considered, we anticipate that the method proposed here will be relevant for a broad range of hazard mapping studies, being, moreover, not limited to physical conditions characteristics of Jiroft plain.

Table. 3 Statistics of the probability values derived from the three Machine Learning models considered in the present study.

Model	Drought prediction values	
	Mean	Standard deviation
SVM	0.77	0.146
MDA	0.71	0.30
BRT	0.67	0.35

Table. 4 Area Under Curve (AUC) of ROC.

Methods	AUC	
	Training	Testing
SVM	0.987	0.95
MDA	0.982	0.923
BRT	0.969	0.911

Table. 5 Areas (%) of ADH for each class and classification method.

Hazard class	Area (%)		
	SVM	MDA	BRT
Very low	11.8	14.9	8.6
Low	6.1	5.1	7.8
Moderate	10.4	5.3	11.5
High	17.2	8.2	24.4
Very high	54.5	66.5	47.8

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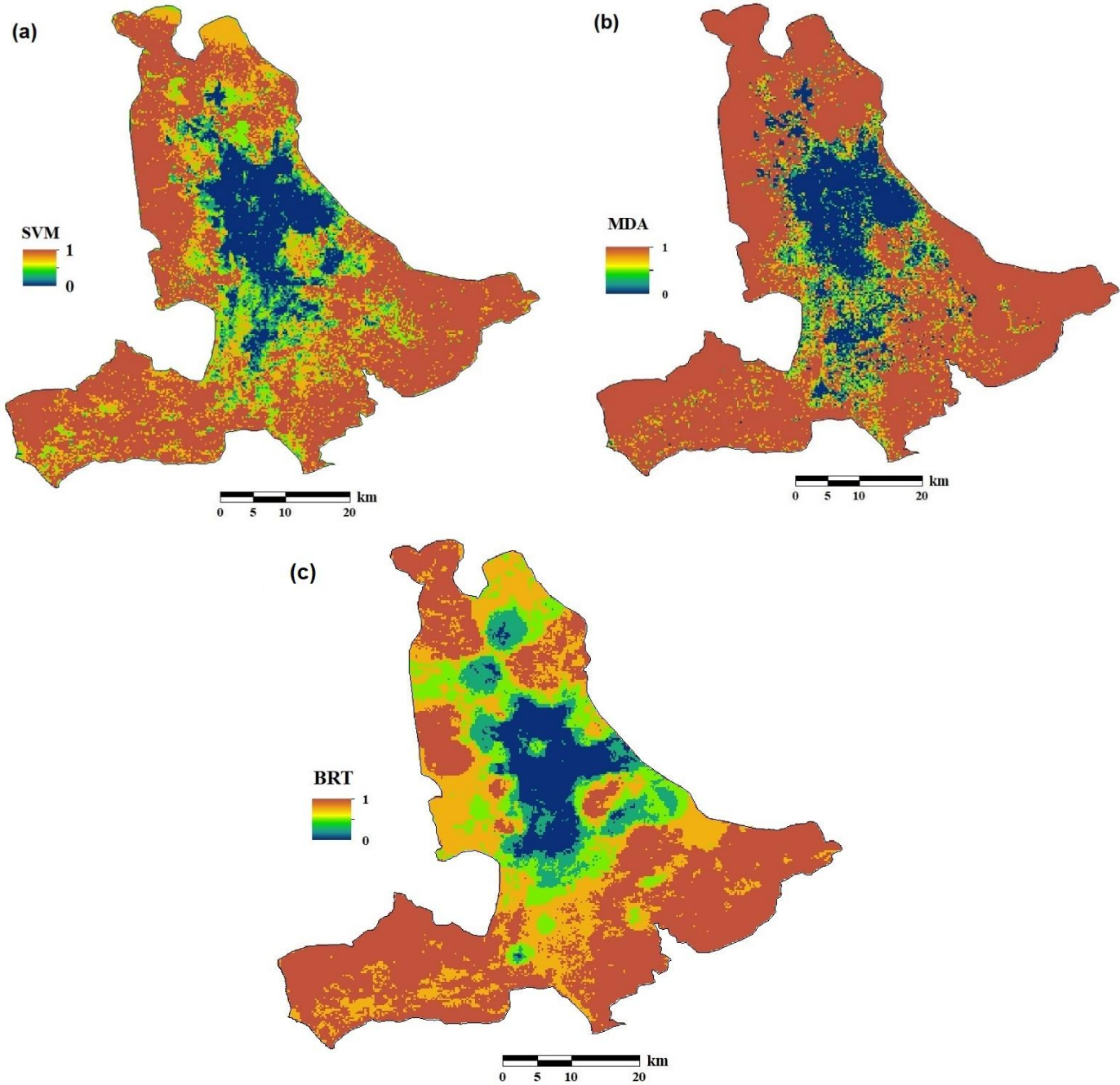


Fig. 9 Agricultural drought hazard maps based on the (a) SVM, (b) MDA, and (c) BRT models.

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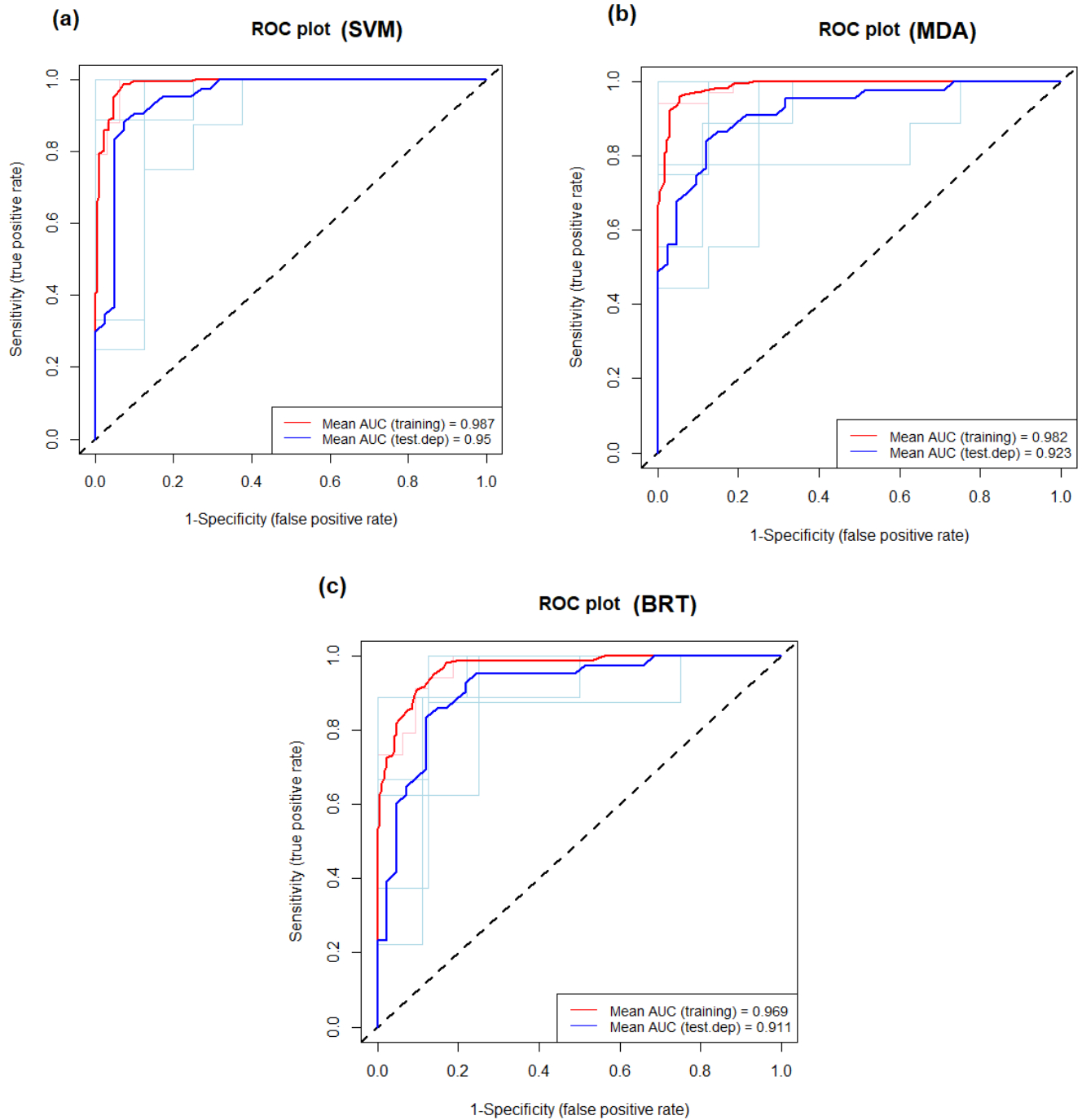


Fig. 10 Area under curve (AUC) of the ROC curve associated with the (a) SVM, (b) MDA, and (c) BRT models.

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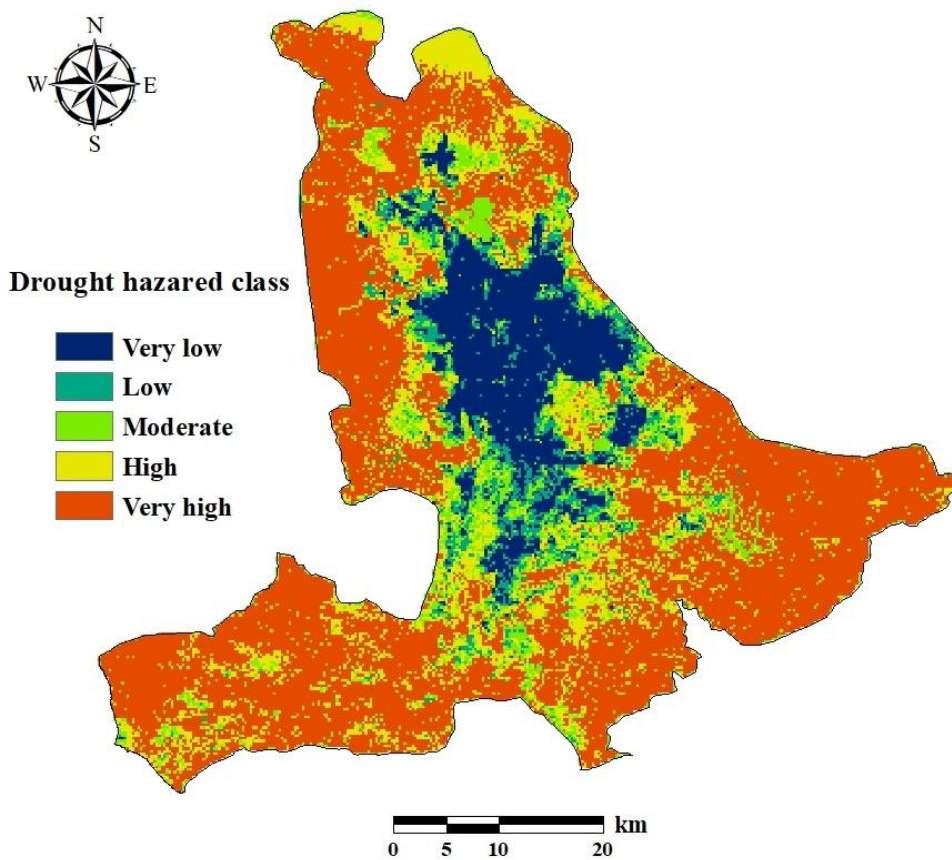


Fig. 11 Agricultural drought hazard classification map obtained with the support vector machine (SVM) model.

3.5 Evaluation of the relative impact associated with the different conditioning factors on drought occurrence in Jiroft plain

Determining the most effective factors and the investigation of the relationship between environmental parameters and drought events could be beneficial for environmental managers, and pave the way toward improved adaptation to drought with regard to an effective management of natural resources (Williams et al. 2011; Gómez and Blanco 2012). Machine learning models could provide new insights for the environmental management, by unveiling information about the connections between drought events and environmental variables (Deo et al. 2017).

In the present study, the relative importance of predictor variables was analyzed utilizing Jackknife test. To this end, we chose the SVM model, as this model displayed the highest accuracy in both training and validation steps. The result of the relative importance using the Jackknife test based on SVM model is shown in Fig. 12. We find that PAWC, TWI, NDVI and drainage density are the most influential factors for drought occurrence in Jiroft plain. PAWC affects available soil water and, consequently, ecophysiological responses of plant and crop yield (Agaba et al. 2010). As discussed by Rahmati et al. (2020 a, b), PAWC can affect soil-water availability, thereby substantially contributing to drought occurring during arid periods.

Furthermore, we see from Fig. 12 that precipitation is associated with a low AUC. This finding sounds, a priori, surprising, given the strong influence of precipitation on soil moisture and drought occurrence in arid and semi-arid districts. However, the low AUC associated with the precipitation predictor in the context of the drought hazard mapping for Jiroft plain can be understood by noting that, as shown in Fig. 2g, precipitation levels do not vary substantially over most of the study area. Specifically, maximum and minimum values of mean precipitation amount to 180 mm and 155 mm, respectively. Therefore, precipitation does not provide an effective factor for explaining the spatial distribution of drought occurrence in Jiroft plain, which explains the associated low value of AUC in the ADH modelling of the study area (Fig. 12).

The regions with highest drought hazard are those with low vegetation cover (NDVI), with sandy soils containing low PAWC and drainage density. These regions are the driest areas in Jiroft plain and display the largest values of RDSM for all drought events.

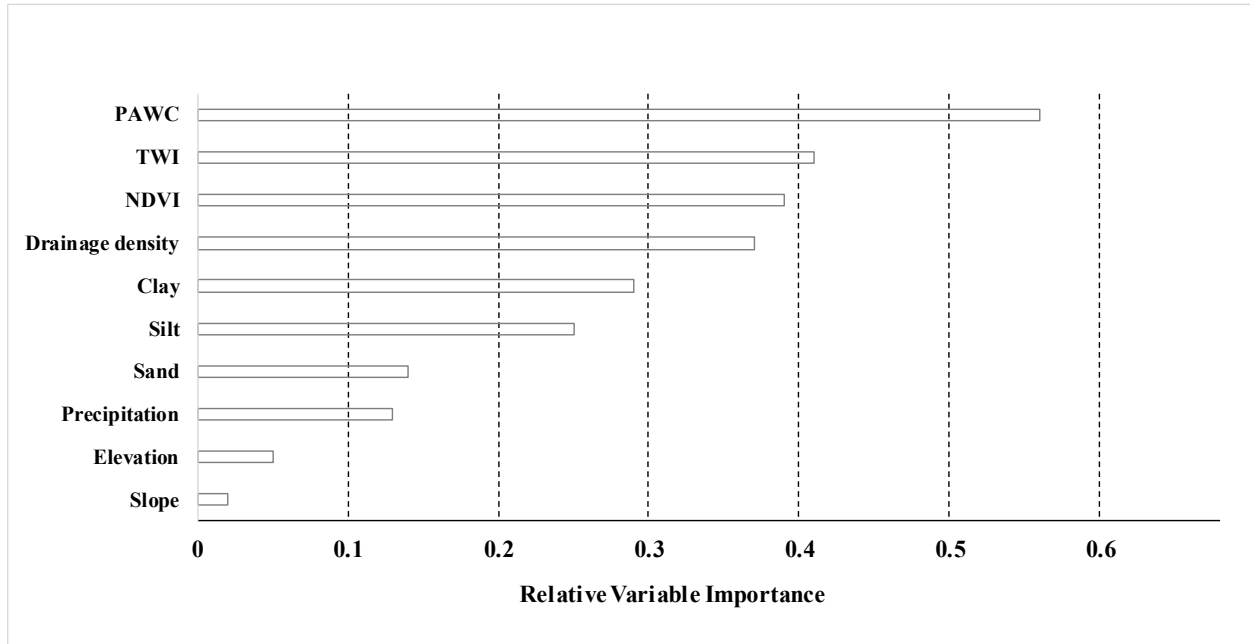


Fig. 12 Jackknife test on the relative importance (AUC) of the disparate conditioning factors in the SVM model

4 Concluding remarks and outlook

This study presents the first agricultural drought hazard (ADH) mapping for the Jiroft plain, Iran, using remote sensing data and machine learning. MODIS NDVI and land surface temperature (LST) from 2007 to 2022 were combined with in-situ soil moisture observations at 1 km² resolution to estimate surface soil moisture (0–30 cm) and derive the relative departure of soil moisture (RDSM) during eight severe drought events. These RDSM values were used to generate ADH maps, evaluated using three machine learning models: support vector machine (SVM), multivariate discriminant analysis (MDA), and boosted regression trees (BRT). The SVM model achieved the highest accuracy (AUC = 0.95), outperforming the others.

Our results indicate that plant available water capacity (PAWC), together with soil moisture, is the most influential factor in ADH modeling. This finding reflects the critical role of both water availability and soil storage capacity in determining drought vulnerability. Areas with the highest ADH are characterized by low vegetation cover (low NDVI), sandy soils with low PAWC, and low drainage density — conditions that also correspond to the driest parts of the region and the highest RDSM values during droughts.

The approach presented in our manuscript demonstrates that combining MODIS NDVI and LST with ground observations enables reliable estimation of regional soil moisture, even in periods when in-situ data are unavailable. This allows for a model extension of soil moisture time series and supports long-term drought monitoring. Unlike traditional drought indices, which often lack physical interpretability, the model captures the underlying processes driving drought occurrence by linking soil moisture to environmental predictors.

Several limitations of our model must be acknowledged. Temporal mismatches between MODIS overpasses and ground measurements may affect soil moisture estimation (Wang et al., 2007). Additionally, the spatial scale difference between point-based observations and 1 km² MODIS pixels introduces uncertainty, especially in heterogeneous landscapes. Cloud cover can also limit data availability, as MODIS operates in optical and infrared bands and cannot penetrate clouds. Despite these challenges, our study demonstrates the feasibility and value of

integrating remote sensing and machine learning for agricultural drought hazard mapping in arid regions. The model provides insights into the physical drivers of drought and supports the development of early warning systems.

Our model could be employed in future projections of drought patterns under climate change scenarios, through assessing land use impacts, and informing agricultural and water management policies. Moreover, the future application of our model has the potential to improve practical solutions for drought hazard assessment in data-scarce arid regions, through providing a scalable framework for generating ADH maps while using widely available remote sensing data and limited ground observations. This feature of our model is particularly important for regions like Jiroft, where hydro-meteorological infrastructure is limited.

The combination of ADH maps with models for predicting changes in regional soil conditions, atmospheric processes, and patterns of precipitation and temperature, could help to elucidate the effect of climate change on spatial patterns of soil moisture and drought hazard. Such perspective has promising implications for various sectors of agriculture, food production, and drought management. In a broader context, understanding regional changes of soil moisture dynamics is important for assessing climate changes impacts on regional patterns of temperature, precipitation, atmospheric geochemistry, and various components of the arid and semi-arid zones of our planet (Yazdandoost et al., 2021; Parteli, 2022). The insights presented here contribute to a growing body of work on drought risk assessment in drylands and offer a transferable methodology for other arid and semi-arid regions facing similar data limitations. With further refinement, this approach could support sustainable land use planning and climate resilience in vulnerable ecosystems.

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