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Detection and Monitoring of Temporal Changes and Distribution of Cultivable Lands in Shahr-e-Kord Plain; Using Landsat and Sentinel-2 Data

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The use of accurate and up-to-date information is crucial for sustainable resource management in agriculture. Satellite imagery provides the opportunity for the comprehensive monitoring of resources, and enables precise planning not only for rural development and agricultural sectors but also for national development programs and the implementation of food and water security policies in the country. It also helps prevent land use changes and their degradation. In this research, an attempt has been made to calculate the cultivable land area in Shahr-e-Kord Plain located in Chaharmahal-va-Bakhtiari Province. The imagery data of Landsats 7-8 and Sentinel-2 satellites were obtained in the form of NDVI index during the period from 2013 to 2022, which processed and validly classified using unsupervised algorithms in GIS environment. All existing features was differentiated based on digital number values and green area surfaces identified for different time periods. The sound and secure areas of cultivation were considered based on the frequencies of plantation during the 2013-2022. Average of the agricultural lands approximated 9,392 ha. Due to recurrent water shortages in recent years, only about 2,603 ha of agricultural lands in the study region have been under permanent cultivation over the 8-year study period and the rest have been abandoned over time or left for fallow and livestock grazing. Accordingly, as a basis for the integrated land-water-crop system planning and recommending policy for conservation of permanently cultivable land resources in the agricultural system of the region, the map of their spatiotemporal distribution was prepared and presented with a pixel specific precision, by different years of cultivation.

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1. Introduction

The accurate estimation of agricultural arable lands in the world, and their extent, regions, geographical locations, types of crops, cultivation periods, and irrigation methods (whether irrigated or rainfed) is an important scientific basis for the development of water and food security policies (Xiong *et al*., 2017). By the year 2100, the world's population is expected to be 10.4 billion, more than three-quarters of which residing in developing countries. To raise the food production capacity with the current agricultural practices, an additional two billion ha of arable land are estimated to be required (FAO, 2023). Nowadays, due to global warming and recurrent droughts (Mehrabi, 2022), the reduction of agricultural areas, soil salinization in many parts of the world as a result of urbanization and industrialization (World Resources Institute, 2019), access limitations, and the necessity to prevent further expansion of agricultural lands for biodiversity conservation and carbon sequestration (FAO, 2023), it has become an increasingly unattainable purpose to achieve further increases in food production through expanding arable land or allocating more water resources for agriculture. Also, maintaining sufficient food production and food security in many regions around the world is faced with significant challenges. Despite the emergence of biotechnology and precision agriculture as recent solutions to agricultural problems, progress has not been fast enough to ensure global food security in the coming decades (Foley *et al*., 2011).

The preservation of essential production resources such as cultivable land and available water resources is of paramount importance to ensure food security for a growing population. Without these fundamental resources, production is not possible through any of the mentioned methods. In fact, having an accurate map of agricultural lands serves as a baseline for the study of higher-level issues, such as land under cultivation, types of crops, irrigation methods (e.g., irrigated or rain-fed), crop health, crop productivity per unit of land, and water productivity. This information is crucial for the proper management of food production systems and their interrelations with geopolitical, socio-economic, health, environmental, and ecological issues.

The traditional methods of collecting this information involve census and ground-based surveys, which have multiple limitations such as inconsistencies, time and energy consumption, and difficulties in timely data acquisition. Remote sensing offers a new standard alternative method that provides a broad, efficient, and reliable view of agricultural areas and can make preliminary predictions for production and future planning (Manteghi and Rahmatabadi, 2021). Remote sensing techniques are widely used for research and monitoring across a wide range of natural and socio-economic processes and phenomena occurring in terrestrial systems (Dziob *et al*., 2020). One important application of remote sensing is mapping and monitoring agricultural lands. In fact, many technological and cognitive foundations of remote sensing were initially developed to support the need for the better monitoring of agricultural lands on local, regional, and global scales (Friedl, 2018). The use of remote sensing data is crucial for optimizing the management of agricultural spatial resources to improve resource efficiency in the face of limited resources. Having accurate data about the spatial distribution of agricultural lands is essential for assessments at a global level (discussing food security) and for formulating necessary land-use policies (Massey etal., 2018). In this context, various research studies have been conducted on estimating the extent of agricultural lands in different parts of the world and their changes over time. Some of those studies are reviewed below.

Dewan and Yamaguchi (2008) investigated land-use and land cover changes in the city of Dhaka, Bangladesh, from 1960 to 2005. They used topographic maps and remote sensing data from Landsat and IRS-1D satellites to assess these changes. The accuracy of the data was validated using SPOT, IRS, IKONOS images and field measurements. The results indicated that, from 1960 to 2005, urban areas had increased by approximately 15,924 ha, while agricultural lands, vegetation, and wetlands and plains had decreased by 7614, 2336 and 6,385 ha, respectively. (Oliphant *et al*., 2019) used the time series satellite imagery data from Landsats 7-8 for the years 2013 to 2016 to assess the extent of agricultural lands in 64 countries, including significant regions in Europe, the Middle East, Russia, and Central Asia. To mitigate the impact of cloud cover on the image quality and enhance the coverage, the images were acquired over four periods in a three-year span. The images were analyzed with the Google Earth Engine, and a combination of 10 Landsat bands was used along with the slope and elevation data obtained from GDEM (Global Digital Elevation Model). In the concluding part of the research, the results were compared with reports from the United Nations Food and Agriculture Organization and other national agricultural land statistics, demonstrating the high accuracy of the findings.

(Pajoohesh *et al*., 2020) investigated the spatial changes in land use trends in the Beheshtabad watershed of Ch&B Province using Landsat 5 TM and Landsat 8 OLI satellite data for three time periods, considering five categories of rangelands, urban areas, agricultural lands, orchards, and bare lands. Subsequently, the trend of land use changes was determined for the two study periods. Findings indicate that the area of rangelands decreased, while urban areas showed an increasing trend. Agricultural lands experienced a decrease and an increase respectively. Orchards exhibited an increasing trend, whereas bare lands showed a fluctuation trend.

Javaheri and Tarahi (2021) conducted a study using Landsat images to examine land-use changes in Kamyaran County from 1984 to 2019. After raw data were obtained from Landsat TM, ETM, and OLI sensors, land-use classes were identified through field observations and Google Earth images. Then, a neural network method was employed to supervise the classification of images using the ENVI 5.3 software. The results revealed that forests and pastures had decreased by 11.64% and 19.12%, respectively, over three-time intervals (1984, 2000, 2019). Meanwhile, residential areas, water bodies, and orchards showed an increasing trend at the growth rates of 27.2%, 57.3%, and 98.3%, respectively. This research underscores the importance of utilizing remote sensing data to monitor land-use changes, which can be invaluable for planning and policy-making in the fields of agricultural resource management and global food security.

(Devkota *et al*., 2023) conducted a study using Landsat images to examine the land-use changes in the major cities of Nepal from 1990 to 2020. The selected urban areas were classified into five categories including vegetation, agricultural lands, barren areas, water bodies, and built-up lands. This was done with the Random Forest algorithm. The results indicated a continuous increase in the built-up areas and a decrease in the agricultural lands over the three decades, while the areas with a vegetation cover had different trends during each of the three decades.

In a study conducted by Mosleh Ghahfarokhi and Bagheri Bodaghabadi (2023), temporal and spatial changes in vegetation cover of agricultural lands in Sistan Plain over ten years of 2011 to 2020 were investigated using Landsat 8 images, based on NDVI index. Findings indicate that the central regions of Sistan Plain have experienced a reduction in vegetation cover, whereas the northern and eastern areas have shown an increase. The vegetation covers of Sistan Plain decreased by 19,260.4 hectares, while it increased by over 25,633.2 hectares over the time.

Undoubtedly, accurate statistics on the extent of agricultural lands in a country underlies any decision-making and policymaking for rural and agricultural development programs in that country. Studies of this nature, due to the high precision of their results alongside other national statistics, can greatly contribute to the corresponding endeavors. Moreover, the constraints of agricultural lands and water resources, which significantly limit agricultural production, necessitate strict regulations for the preservation and maintenance of agricultural lands as well as the prevention of their destruction and alteration. Achieving this goal is only possible with a complete awareness of the area and the location of these lands within the country. These principles serve as a basis in this study to calculate the extent of the agricultural lands in the main sections of Shahr-e-Kord Plain, located in the central part of Chaharmahal-va-Bakhtiari Province. This is done with time series satellite images taken from 2013 to 2022. The images were collected from Sentinel-2, Landsats 7-8 satellites. The study aims to provide an accurate map of the geographical location of the agricultural lands.

2. Materials and Methods

2.1. Study area

The study area is in the central part of Shahr-e-Kord County and covers approximately 18,536 ha. Geographically, it extends from 44°50' E to 59°50' E and from 08°32' N to 26°32' N. It encompasses the main parts of Shahr-e-Kord Plain, covering approximately 41.6% of the total area of the plain. The elevation of the region above sea level is about 2050 meters. Based on the meteorological data from the synoptic weather station in Shahr-e-Kord, the average annual precipitation in the region over a 60-year statistical period (from 1961 to 2020) was 323 mm. However, the average annual precipitation for the farming year 2020-2021 was 188.2 mm, which shows a 32% decrease compared to the long-term average for a similar period (I. R. of Iran Meteorological Organization. Ch&B province site, 2021). Furthermore, the average annual temperature over the years from 1955 to 2014 was 12.5°C. Shahr-e-Kord Plain has a total of 758 authorized wells (492 agricultural wells, 53 drinking water wells, 213 industrial wells), 79 active qanats (i.e., underground aqueducts), and 37 seasonal springs as well as 124 permanent springs. The predominant land use in the region is livestock farming and the cultivation of crops such as wheat, barley, alfalfa, and forage corn.

2.2. Methodology

To identify agriculturally significant lands in the study area, remote sensing data were used in the form of NDVI index, which was calculated for each year using the median filter in the EO Browser platform, as:

$$\mathrm{NDVI} = \frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+\mathrm{RED}} \tag{1}$$

Where NIR and RED indicate infrared and red bands, respectively. NDVI values vary from +1 to -1. Values close to +1 indicate vegetation, zero indicates land without vegetation (soil), and values close to -1 indicate moisture. These outputs were derived from the images captured in the range of visible and near-infrared wavelengths. The data were obtained from the Earth Observation (EO) Browser platform and included images from Landsats 7-8 sensors for the farming years 2014-2016 to 2017-2020 and from the Sentinel-2 sensor for the farming years 2019-2020 to 2023-2024.

The images obtained from the EO Browser platform were first geometrically corrected to ensure their accuracy. The acquisition dates of the images were also standardized to mid-June for each time series. This timing was chosen because it corresponded to a period with minimal atmospheric disturbances, which could cause geometric distortions in the images. Consequently, the images required no additional specialized corrections. The details of the sensors used and their image characteristics, organized by each farming year, are provided in Table 1.

Table 1. Specifications of the sensors used and their images

cropping year	Satellite / sensor	Spatial resolution	Index calculation method NDVI
2013 2015	Landsat-8_L2	30 meters	(B05-B04) / (B05+B04)
2016	Landsat-7_ETM+_L1	30 meters	(B04-B03) / (B04+B03)
2018 2019 2020 2021 2022	Sentinel-2_L2A	10 meters	(B8-B4) / (B8+B4)

Based on the research ever conducted and the analysis of the images captured in mid-June, the quantity of forage and rangeland shrubs decreases significantly due to dry weather conditions and notable reduction in soil moisture. Consequently, forage and rangeland shrubs mix up with cultivated plants to a minimum. Around that date, alongside autumn crops, spring crops and vegetation emerge too. Therefore, this date was chosen as a reference date in this study. To download the images, a specific area was selected from the Earth Observation (EO) Browser platform. It covered the boundaries of Shahr-e-Kord Plain. Figure 1 illustrates the extent of this plain located in Shahr-e-Kord County, Chaharmahal-va-Bakhtiari Province.

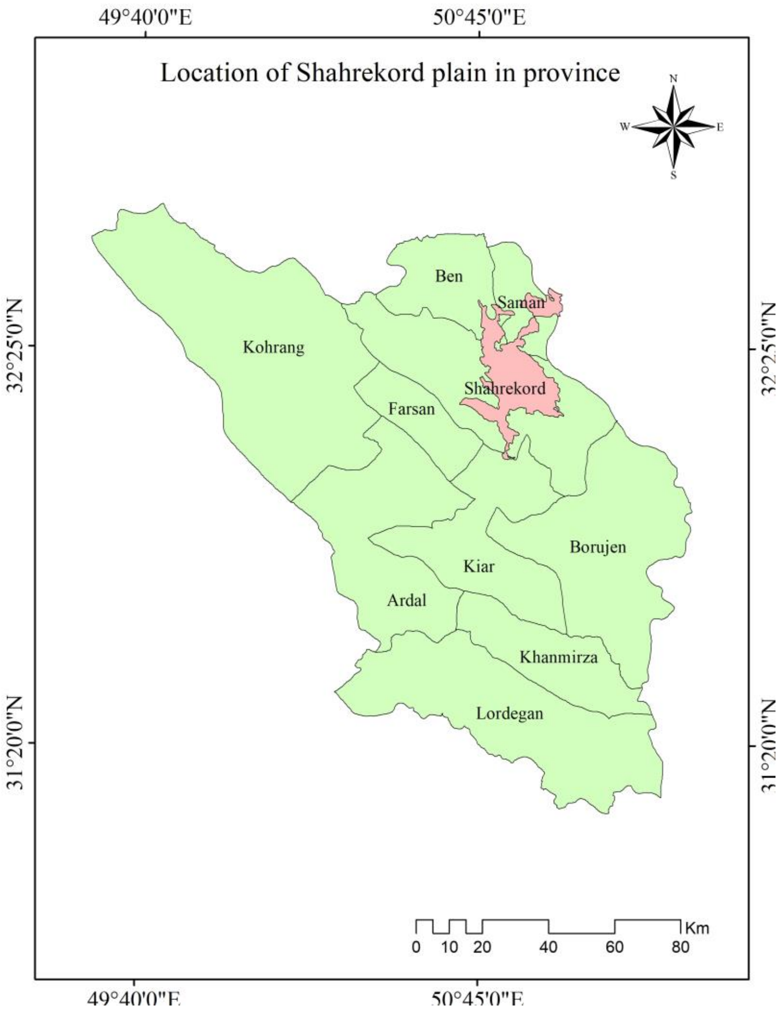

Fig. 1. Geographical location of the Shahr-e-Kord plain

After the suitable satellite images of the study area were downloaded, they were transferred to the ArcMap space in a raster file format. The raster data fed into the ArcMap consisted of digital satellite images in the visible spectrum (used as background reference for the validation of operations conducted on the raster data) and the images captured at near-infrared wavelengths in the form of normalized difference vegetation index (NDVI) outputs. In addition, the analysis process benefited from vector data about the extent of Shahr-e-Kord Plain and the administrative boundaries of the surrounding counties and urban-rural areas. These data were utilized for data alignment and synchronization with the raster data. Due to Landsat ETM sensor images were received with gaps due to Scan Line Corrector (SLC) failure, the Landsat toolbox plugin was utilized to address this error in the images. Due to the differences in spatial resolution between Landsat sensor images (30 meters) and Sentinel-2 sensor images (10 meters), the images were not seamlessly consistent within the study area's coverage. To address this issue, the "resample" command was applied to standardize the pixel size across all the images. Also, to align and prepare digital images from different time periods in the study area, the "Extract" command served to separate the portions in the study boundary from the other areas. The digital images were used in the subsequent analyses. Subsequently, classification and reclassification were performed to distinguish green areas and cultivated lands from the other features. Due to the significant spectral variability in even a single crop type induced by various factors as well as the rather large size of the study area, an unsupervised classification technique was used for data classification. Upon completing the unsupervised classification and assigning the samples to the obtained categories, the researcher separated the target land cover types from the other features through reclassification. Given that the data distribution was non-uniform, the reclassification process was performed based on the natural breaks in the data.

The features in the satellite images of the study area were categorized into five classes. Three classes were for agricultural lands and two for non-agricultural. Since the importance and the cropping patterns varied over the time, the lands were classified into three categories. The accuracy of the final classification was evaluated using three different methods. Firstly, continuous comparison was made between the raster dataset after classification and the visible imagery background. Secondly, some other classification methods were performed, and their results were compared with the selected method (natural breaks). In general, available methods for reclassification include equal interval, quantile, natural breaks, and standard deviation methods. The equal interval (or equal step) classification method divides the range of characteristic values into classes of equal size. Quantitative classification method places equal number of observations in each class. The natural break classification (or Jenks) method uses an algorithm to group values into classes that are separated by distinct break points. Finally, the standard deviation classification method forms each class by adding and subtracting the standard deviation from the mean of the data set. Here, the method of natural fractures was chosen, which is used for data that is unevenly distributed but not skewed, and validated by 120 control points in Google Earth, as the centroids of the fields, with good resolution and distribution within the plain extent. The classified images were tested using field data, and the accuracy of vegetation cover maps evaluated by calculating overall accuracy and kappa statistics, based on the error matrix. The former is an average classification accuracy that shows the ratio of correctly identified pixels to all identified pixels, mathematically:

$$OA = \sum_{i,j=1}^{n} \frac{xij}{N} \quad (2)$$

Kappa coefficient also compares the classification accuracy with the completely random classification by eliminating the chance effect, as the degree of conformity with the reality on the earth. One of the most famous estimations is (Congalton, 1991):

$$K=N\sum_{i=1}^{n} xXii - \frac{\sum_{i=1}^{n}(Xio\times Xoi)}{N^2} - \sum_{i=1}^{n}(Xio - Xoi) \quad (3)$$

When the accuracy of the visible categories was confirmed, the raster files were converted into vector files for further calculations. Since urban and rural green spaces and grasslands were also identified in the classifications but were not the focus of this study, the boundaries of pastures, cities, and major villages in the study area were digitized using Google Earth and transferred to ArcMap. Then, the "Erase" command served to remove these residential and pasture areas from the polygon of the plain. After the agricultural land raster was converted into a vector file, this area was separated from the new plain layer to include only the productive agricultural surfaces in the calculations.

As a pure land layer was obtained for Shahr-e-Kord Plain, the area of each final layer was calculated with the geometric calculators available in the software tools mentioned in the descriptive table. To create a map of the lands cultivated from 2013 to 2022, a reliable and consistent part of the cultivated lands was selected within the study area. Since the lands were not all cultivated uniformly during the selected time frame and some areas were cultivated only once while the others were cultivated every year, the extent of the reliable and consistent lands was determined through comparing the agricultural maps prepared in different years, and the agricultural lands were classified based on the times of cultivation times during the selected time period. The complete steps of the task are illustrated in the figure below.

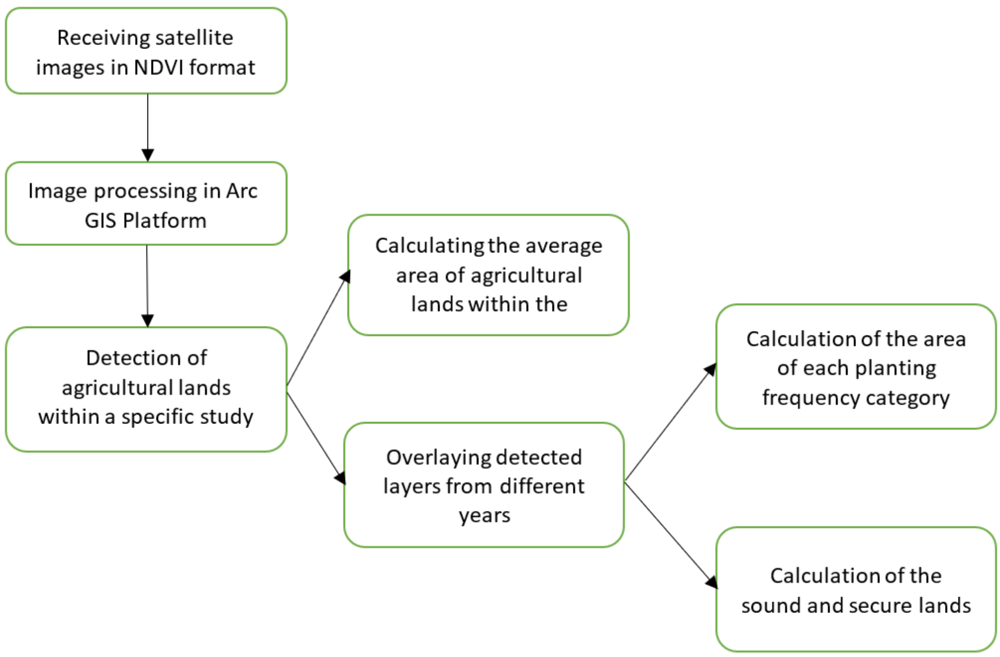

Fig. 2. The steps of the study method

3. Results and discussion

As explained in the methodology the features in the satellite images of the study area were categorized into five classes. The validation of the classification using the three mentioned methods indicated its high accuracy in all the time series. The results of the overall accuracy and Kappa coefficient for Landsat-8, 7 and Sentinel-2 images are presented in table 2.

Table 2. The results of the overall accuracy and Kappa coefficient for Landsat-8, 7 and Sentinel-2 images

Cropping year	Satellite / Sensor	Kappa coefficient	Overall accuracy
2013 2015	Landsat-8_L2	.97	98.40
2016	Landsat-7_ETM+_L1	.97	99.67
2018 2019 2020 2021 2022	Sentinel-2_L2A	.98	98.32

Following the classification, the extent of the agricultural lands from 2013 to 2022 was determined (Table 3). In addition, to assess the changes in the area under cultivation in Shahr-e-Kord Plain, the cultivated lands were measured separately for the selected time periods. Figure 3 illustrates the status of the cultivated area in different years. It is evident that the area fluctuated significantly during the selected time period. To accurately determine the changes, the cultivated land area was calculated separately for each time period. The results of the calculations are presented in Table 3.

Table 3. Area of cultivated lands during the period of 2013 to 2022 in terms of ha

Cropping year	Cultivated lands (Both sound & and peripheral crops)	Uncultivated lands	Total area
2013	12697.5	5838.8	18536.3
2015	11969.8	6566.5	18536.3
2016	8912.6	9623.7	18536.3
2018	7714.0	10822.3	18536.3
2019	9900.8	8635.5	18536.3
2020	9144.6	9391.7	18536.3
2021	7682.2	10854.1	18536.3
2022	7115.6	11420.7	18536.3
Average	9392.1	9144.1	

Based on the results, the average area of the agricultural lands in the study region over eight time periods (from 2013 to 2022) were approximately 9,392 ha. The remaining land area (9,144 ha) includes the fields that have been abandoned for various reasons or left for fallow and livestock grazing. Some have also experienced severe water shortages and pests. According to the statistics of the Agricultural Jihad Organization, over the past 10 years, the average area of the agricultural lands in Shahr-e-Kord County has been 22,340 ha. Considering that the study area covers approximately 6.41% of Shahr-e-Kord Plain and that the agricultural statistics are reported by county rather than by plain, it appears that the results of this research are consistent with the actual conditions in the region.

As shown in Table 3, the area of the cultivated lands in Shahr-e-Kord Plain has significantly decreased during the selected time period. This decrease is mainly due to water scarcity in the region as a result of the noticeable reduction in underground water reserves, which have been the primary source of water supply. This situation has even pushed the plain into a critical crisis in recent years. If precautions are not taken soon, the plain may turn into a vast desert. According to the studies conducted, this problem has caused a decrease in the level of agricultural land not only in this province but also in the whole country. The obtained results are consistent with the studies (Mousavi *et al*., 2013) and (Eskandari Damneh *et al*., 2022). While the study of Akbari and Farpour (2022) in the Laleh-Zar region of Kerman shows an increase in the size of agricultural land, although the growth of agricultural activity does not match the growth of the population. While the easiest solution to this problem is to stop cultivating the lands, it is not a sustainable option. This is because the major occupation of a significant portion of the population in the province is agriculture, and this province is considered a hub for agricultural production and livestock in the country.

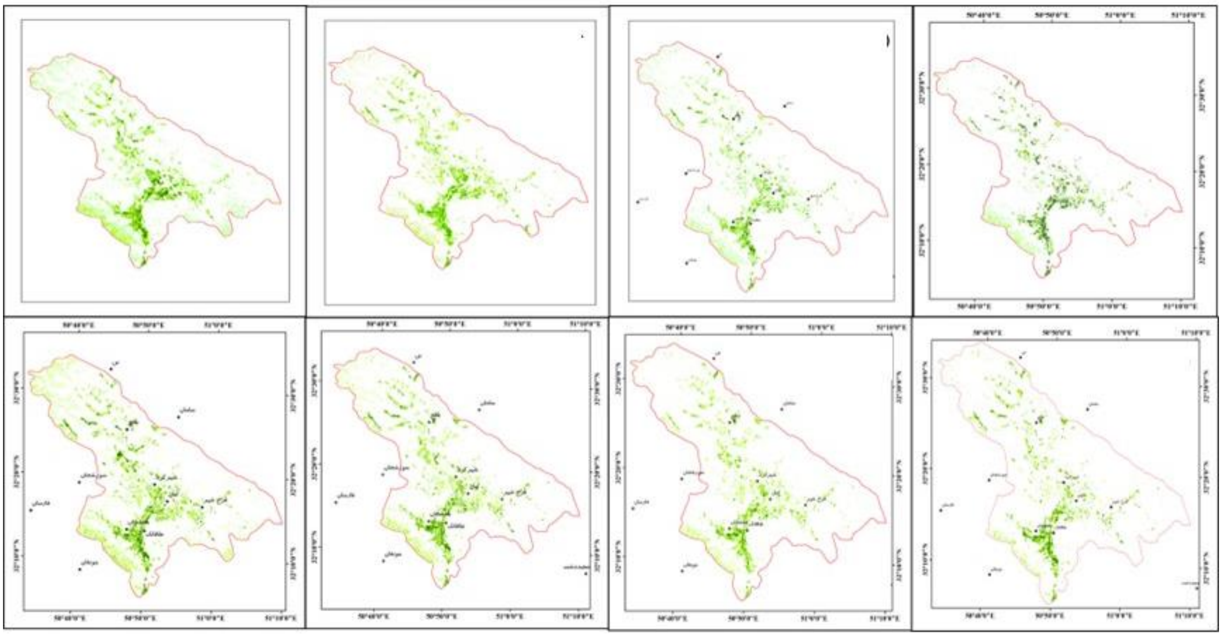

Fig. 3. Images of cultivated area revealed from 2013 to 2022

The best solution to overcome the crisis, which affects not only the studied region but also the entire province and sometimes the whole country, is to adopt policies for the preservation and maintenance of agricultural lands. What should be in the focus of agricultural planning and policymaking is the lands that are capable of being part of the annual production cycle, referred to as "productive lands." In fact, calculating the area of these lands is indicative of land resources in agriculture, and policies are designed based on these resources. To determine the boundaries and the surface areas of these lands, the map of the agricultural lands in the study area was classified based on the number of seasons or planting cycles during the research period (2013-2022). The classification aimed to identify how many times each land lot was cultivated during that period, based on which to identify the productive lands that were continuously cultivated over several years. After the agricultural lands on the map were classified based on the times of planting cycles, the area of each category was calculated separately.

As shown in Table 4, only about 2,603 ha of the lands were cultivated every year throughout the selected time period. According to the field study and the interviews with the regional water authorities and farmers, the primary reason for the low cultivation is the water scarcity in Shahr-e-Kord plain. This has made farmers unable to fully utilize the available capacity for production. The problem has been aggravated over the years due to recurring droughts and climate fluctuations. Now, based on the classification in this study, it is possible to define the area of secure agricultural lands in Shahr-e-Kord plain. Figure 4 shows the boundaries of this area.

Table 4. The cultivated land area of Shahr-e-Kord plain according to planting frequency

Planting frequency	Land area (ha)
1	2183/8
2	2189/0
3	2150/2
4	2077/2
5	2056/0
6	1760/6
7	1766/1
8	2603/1

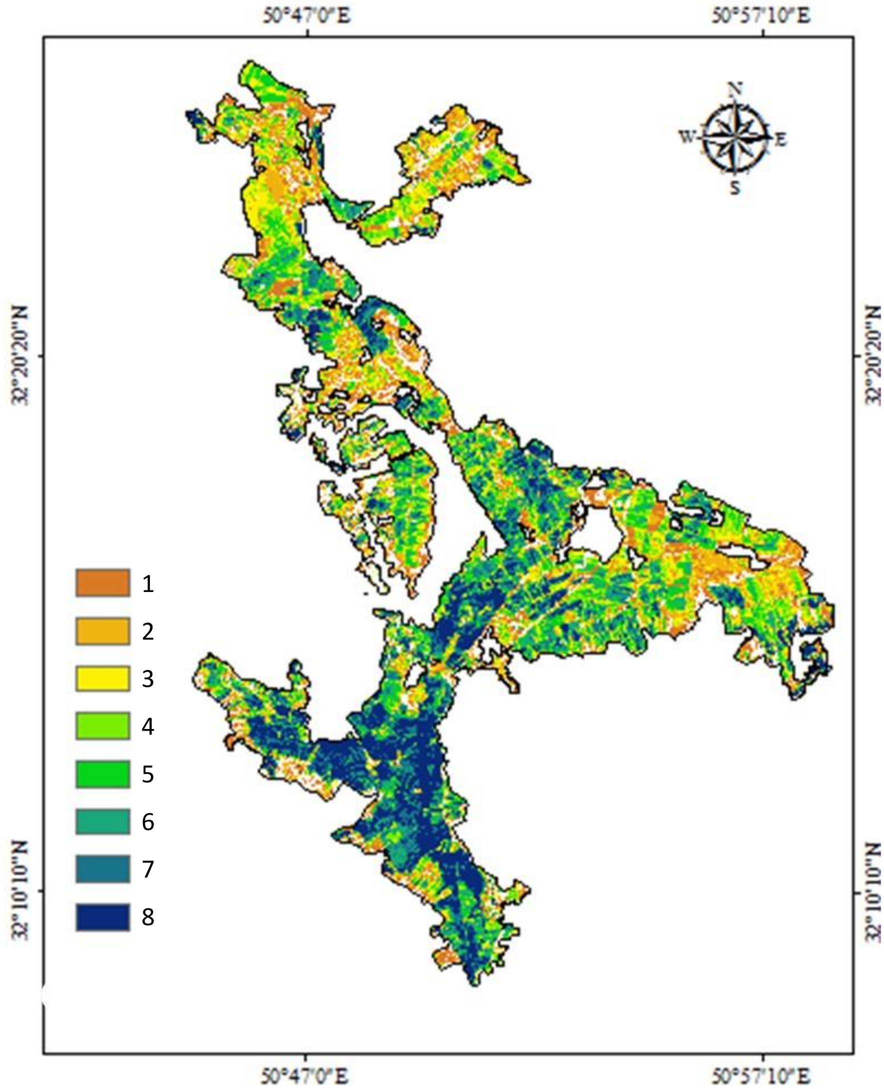

Fig. 4. Map of the arable land area and the planting frequencies of Shahr-e-Kord plain during the study period

What matters most is the preservation and maintenance of these lands as national resources and providing proper solutions to prevent their destruction, desertification, and subsequent changes in land use. This issue is of special importance for sustainable agriculture in the region and the country, ensuring food security and preserving the country's independence. It is the responsibility of not only statesmen and policymakers but also every individual in the society who is somehow connected to agriculture. This article serves as an introduction to extensive research and the policies aimed at the preservation and maintenance of lands. The existence of a national database to represent the resources and inputs in the agricultural sector is crucial for policymaking and research, and its absence makes efforts in the field foundationless. Based on this premise, the following recommendations are made:

- Presenting a proper cultivation pattern that matches the economic, social, and resource conditions in the region
- Introducing certain laws to prevent land destruction and changes in land use
- Supporting farmers and adopting incentive policies to boost their motivation
- Guiding macro-policies towards the prosperity of the agricultural sector and realizing the genuine motto of "Agriculture-Centered Development"
- Amending inheritance laws to prevent the fragmentation of agricultural lands: Many farmers abandon their land due to its small size and lack of economic viability, migrating to urban areas. Moreover, small land sizes hinder the adoption of modern agricultural technologies and solutions for increased productivity.
- Conducting research of this kind to create an accurate and up-to-date database as well as providing precise statistics on agricultural resources and inputs which can serve as a reference in policymaking

Based on the classified maps and the corresponding statistics, the overall accuracy of the results and the Kappa coefficient were found to be 98.24% and 0.95, respectively. Considering an 85% threshold for the acceptability of results, the findings can be deemed satisfactory.

4. Conclusion

A database that provides reliable information on water and land resources and agricultural inputs in a country is essential for planning and policymaking in the field of agriculture as well as implementing water and food security policies and long-term development plans. Accordingly, this study sought to calculate the size of the target region and determine the boundaries of the lands there using satellite images taken from 2013 to 2022. As the results showed, the average area of the agricultural lands in this region was approximately 1939.2 ha for eight times of imaging. Furthermore, it was indicated that the area of the cultivated lands in this region had significantly decreased during the selected time period. The area and boundaries of the secure lands, which are part of the annual agricultural production cycle and a resource in planning, were determined through classifying the map of the agricultural lands in Shahr-e-Kord Plain based on the times of the cultivation cycles within the selected time frame. According to the results, out of nearly 1939.2 ha of agricultural lands in the study region, only about 1260.3 ha were cultivated every year, and the rest was left uncultivated. This was primarily due to the water shortage in the region.

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