APPLICATION OF LANDSCAPE METRICS AND OBJECT-ORIENTED REMOTE SENSING TO DETECT THE SPATIAL ARRANGEMENT OF AGRICULTURAL LAND

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Manuscript received: July 12, 2021
Revised version: Decemebr 11, 2021

Safdary R., Soffianian A., Purmanafi S., 2022. Application of landscape metrics and object-oriented remote sensing to detect the spatial arrangement of agricultural land. *Quaestiones Geographicae* 41(1), Bogucki Wydawnictwo Naukowe, Poznań, pp. 25–35. 3 figs, 3 tables.

Abstract: This study aims to investigate crop selection and spatial patterns of agricultural fields in a drought-affected region in Isfahan Province, central Iran. Based on field surveys portraying growth stages of the main crops including wheat, alfalfa, vegetables and fruit trees, three Landsat 8 operational land imager (OLI) images were acquired on March 15 (L1), June 27 (L2) and October 1 (L3), 2015. After performing radiometric and atmospheric corrections, Normalized Difference Vegetation Index (NDVI) maps of the images were produced and introduced to the Multi-Resolution Segmentation algorithm to delineate agricultural fields. An NDVI-based decision algorithm was then developed to identify crops devoted to each field. Finally, a set of landscape metrics including Number of Patches (NP), mean patch size (MPS), mean shape index (MSI), perimeter-to-area ratio (PARA) and Euclidian Nearest Neighborhood Distance (ENN) was utilized to evaluate their respective spatial formation. The results showed that nearly 46% of fields are devoted to wheat indicating that the landscape has been dramatically shifted towards wheat monoculture farming. Moreover, the farmers' inclination to grow crops in large fields (approximate area of 1 ha) with more regular geometric shapes are considered as an effective way of optimising water use efficiency in areas experiencing significant water shortage.

Keywords: crop type, segmentation, landscape metrics, Iran

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Introduction

Land use planning and management are fundamental to sustainable development (Godschalk 2004) and this task can be well accomplished if decisions are supported by reliable and updated information (Collier 2015, Van Knippenberg et al. 2015). In this case, an important milestone was reached in the second half of the 20th century when space-borne Remote Sensing (RS) and computer-based geographical information system (GIS) techniques were remarkably advanced and integrated, which can produce huge quantities of spatial data from local to global levels in a short time (Aronoff 2005). These quickly and accurately processed data are specifically beneficial for the

https://doi.org/10.2478/quageo-2022-0002
ISSN 2082-2103, eISSN 2081-6383

management of highly spatially and temporally dynamic land uses such as agricultural land use (Nikolaos 2015, Asgarian et al. 2016, Hassan et al. 2017). Agriculture, is one of the first and most important types of land use, which consumes the largest portion of the world's freshwater supply, with nearly 80% (Ding et al. 2007), and more than other uses of land are in direct interaction with environmental parameters such as soil, water and climate (Bedada et al. 2016). The world's population growth is estimated to continue at its high rate until the mid-21st century and it will inevitably add additional pressure on agricultural land resources to produce more food (Ma, Ma 2017).

These descriptions indicate an alarming signal concerning agricultural activities, especially in arid and semi-arid regions of developing countries where the unavailability of reliable data serves as an important barrier in achieving agricultural land use planning objectives (Rhee et al. 2010). Accordingly, raising the knowledge about the location and type of crop cultivated as well as the spatial pattern of agricultural fields are essential to outline a sustainable agricultural land use planning paradigm (Saroinsong et al. 2007, Rahman, Saha 2008). In this regard, RS techniques have allowed land-use managers and decision makers to identify cropping pattern systems (Khan et al. 2010, Foerster et al. 2012), forecast yield before harvest time (Bolton, Friedl 2013), improve agricultural and crop marketing performance (Howitt et al. 2014) and, in some cases, determine the performance of crop production concerning site-specific soil and water resources (Bandyopadhyay et al. 2009). In addition to data provided by RS techniques, they also require information about the spatial pattern of agricultural fields to better formulate agricultural land use plans. In the context of agricultural land use planning, White and Roy (2015) and Pishgar-Komleh et al. (2012) discuss that the degree of mechanisation and fuel energy consumption should be optimized according to the size of agricultural fields.

Object-based image analysis (OBIA) is one of the most precise techniques of delineating land use and land cover (LULC) maps from air- and spaceborne imagery data (Blaschke 2010). Initially, this technique attempts to aggregate neighbouring pixels into a cluster, also known as an object or a segment, based on some similar spectral and/or spatial characteristics and, in contrast to other traditional techniques, it relies on the characteristics of the objects (not pixels) to conduct an image classification task (Blaschke 2010). In our case, Peña et al. (2014), Aguilar et al. (2015) and Li et al. (2015) have tested the performance of OBIA techniques in the identification and classification of crop types using various image sources and in different locations and found that OBIA techniques, as a new technique in RS, are highly successful in crop type mapping. Following that, other studies such as Abraham (2015) attempted to extract more spatial information from the objects such as the size, geometry (structure) and overall spatial formation of fields in a landscape through the application of landscape metrics (also known as spatial metrics). Landscape metrics are algorithms for quantifying the spatial properties of patches, classes, or mosaics of the entire landscape. Landscape metrics are a suitable tool for designing and finding the exact relationship between the structure and performance of different land uses (Abraham 2015). To date, a broad range of landscape metrics have been developed and used to quantify almost every facet of the distribution and structure of land parcels and have been widely utilised in various scientific disciplines (Farina 2008, McGarigal 2017).

Based on the above-mentioned descriptions, an attempt is made in this research to identify and classify crop types and quantify the spatial pattern of fields in a drought-affected agricultural landscape in central Iran which suffers from a lack of updated and reliable data for appropriate implementation of agricultural land use plans. Accordingly, an OBIA technique with the use of multi-temporal Landsat 8 imagery data was first utilised to classify the main crop types into four classes including wheat, alfalfa, fruit tree and vegetable. In doing so, an attempt was also made to analyse in a way that a given object reflects a certain field. This was of great help to further investigate the composition, structure and configuration of agricultural fields devoted to each crop type.

Material and methods

Study area

Segzi Hydrological Unit in Isfahan Province, central Iran was selected as the case study area.

This region spans over 32°40′ to 32°65′ N longitude and 51°49′ to 52°26′ E latitude and covers an area of about 90,870 ha. One of the most notable characteristics of this area is the Zayandeh-Rood River which enters the region from the west and after traversing approximately 80 km inside the study area and reaches the Gavkhooni Wetland in the east. This river is the main water source for agricultural, municipal and industrial activities in the Segzi Hydrological Unit. In central parts, this region consists of deep, moderately drained and fertile, fine to moderately grained soils with loam, clay loam and, in some small parts, sandy texture (Soffianian et al. 2013). Based on the agricultural land suitability model developed by Makhdoom Farkhondeh (2013) for Iranian territories, these characteristics represent a medium potential for irrigated crop production.

From a climatic point of view, this region is characterised by an arid and semi-arid climate with cold winters and dry, hot summers. Precipitation is rare but mostly occurs in late fall and winter and ranges from 50 to <150 mm (Iranian Bureau of Statistics 2011). Crop production is the main use of land, located exclusively near the river. More than 160 thousand people have inhabited this area which due to its adjacency to the Isfahan city – the third-most populated city of Iran near the northwestern boundary of the region – are growing at a high annual rate of 1.6% (Iranian Bureau of Statistics 2011). Due to the recent multi-year severe drought in central Iran and the consequent sharp decrease in freshwater supplies, agricultural activities have now massively shifted towards crops with fewer water requirements such as wheat. Figure 1 illustrates the layout of the Segzi Hydrological Unit in Isfahan Province, central Iran.

Crop type mapping

Field investigation

Wheat, barley, alfalfa, fruit trees and vegetables (including sugar beet, lettuce and cabbage) were recognised as the main crop types through field surveys and interviews of local farmers and experts. From the standpoint of growth stages, wheat and barley (hereafter only termed wheat) and alfalfa begin to grow clearly in early March when the mean daily temperature reaches above 10°C. Soon after in mid-March, fruit trees start to grow new leaves. In late April, alfalfa and fruit trees reach their full growth. Wheat matures by mid-June and is totally harvested across the region. In July, some new fields are selected to grow vegetables. At the beginning of fall, farmers start to harvest vegetables and then fruit trees and alfalfa start hibernating for the winter season. This cropping system is repeated annually in this region (Iranian Bureau of Statistics 2011).

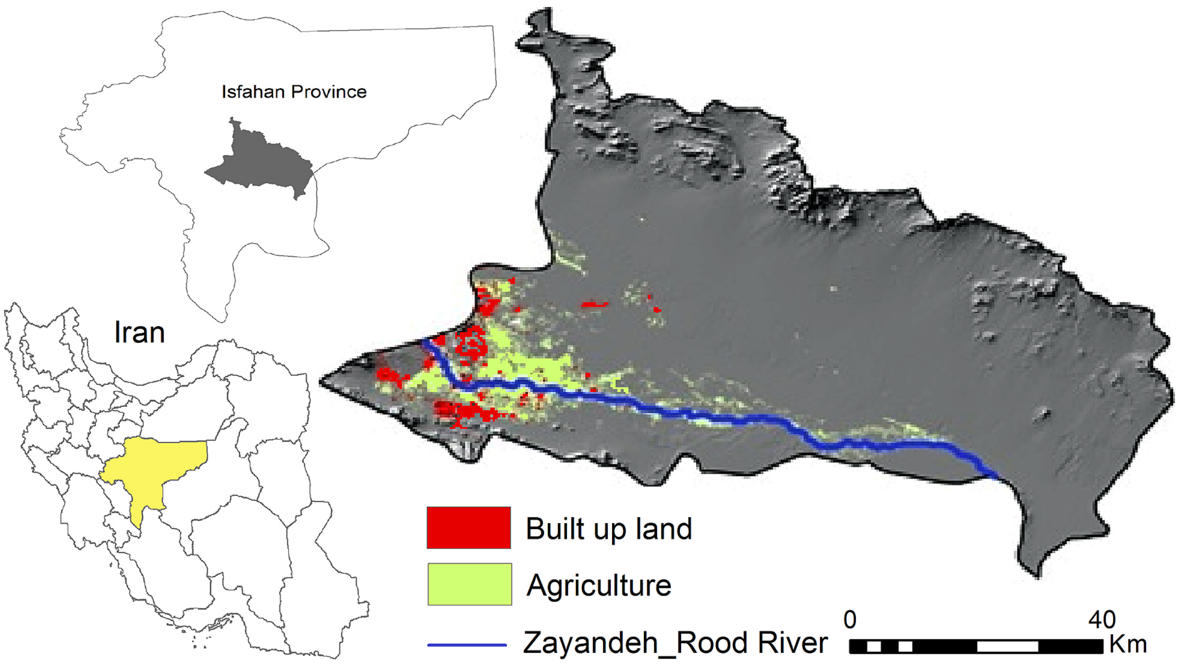

Fig. 1. The layout of the Segzi Hydrological Unit in Isfahan Province, central Iran.

The steps taken in this study are summarised below.

1. Identifying the area of agricultural lands using multi-time segmentation techniques,
2. Designing a decision tree for allocating any type of cultivation to agricultural lands,
3. Using land features to quantify the structure and spatial arrangement of crops.

Image selection and preparation

Operational Land Imager (OLI) is the most advanced sensor of the Landsat satellite series. This sensor is carried on Landsat 8 (launched in February 2013) and, similar to its antecedent sensors (TM: Thematic Mapper/ETM+:Enhanced Thematic Mapper Plus), is designed to identify and monitor the earth's green surface like agricultural land areas (Roy et al. 2014). Image acquisition in a 16-day time interval and the accordance of its spatial resolution (pixel spacing of 30 m) with the size of agricultural fields of the study site (approximately 1 ha) were the main reasons for using Landsat 8 OLI images.

Selecting satellite images in terms of the time and season in which they have been taken is very important, and the proper time and season should be chosen considering the phenology of the crops. Synchronisation of imaging with the stage of vegetation growth is crucial. Changes in chlorophyll concentration of leaves of some plants occurred in periods. Therefore, the difference in chlorophyll concentration leads to the difference in their reflections. Therefore, this period can be an appropriate criterion to distinguish the cultivated plant types. The quality of images and atmospheric conditions should be also considered in choosing the images. According to the crop growing patterns depicted in Section 'Field investigation', three Landsat 8 OLI tiles were acquired on March 15 (L1), June 27 (L2) and October 1 (L3), 2015.

Radiometric and atmospheric corrections were performed to improve the quality of the images' bands. To conduct radiometric correction, Equation 1 was first used to calculate Top of Atmosphere (TOA) reflectance without correction for solar angle (ρ_λ) where Q_{cal} represents pixel values (Digital numbers) and M_ρ and A_ρ are band-specific multiplicative and additive rescaling factors, respectively (Markham et al. 2014). Afterwards, equation 2 was utilised to correct the solar angle where ρ_λ is TOA reflectance and θ_{SE} denotes the sun elevation angle in the center of the image scene (Markham et al. 2014). All numerical values of the parameters used in these equations are provided in the product metadata file.

$$\rho_\lambda = M_\rho Q_{cal} + A_\rho \tag{1}$$

$$\rho_\lambda = \frac{\rho_\lambda}{\sin(\theta_{SE})} \tag{2}$$

The dark pixel subtraction method (Chavez 1996) was then employed to correct the effect of aerosols on TOA reflectance. Based on the assumption of this method, for each image, the lowest reflectance value of the darkest pixel in the near-infrared band (841–876 nm) was detected (i.e. minimum reflectance value of deep-water pixels over the Zayandeh-Rood Dam's reservoir), and then, the resulting value was deducted from the TOA reflectance values of all bands to correct for atmospheric distortions. It should be noted that Landsat L1T products have been automatically ortho-rectified using GCPs (Ground Control Points) and DEM (Digital Elevatin Model) layers and thus no geometric calibration is performed (Roy et al. 2010).

The following types of software, namely version 5.1 of ENVI (Environment for Visualizing Images (image processing software; Research Systems, Inc.)) and version 4 of eCognition were used to identify lands under cultivation and their cultivation patterns, and for separation of agricultural lands under object-oriented methods (land segmentation), respectively. Finally, to quantify the area of agricultural lands and compare them with each other, the landform measures embedded in version 4.1 of Fragstats software were used.

Crop identification and classification

Multi-temporal segmentation analysis was used to delineate agricultural fields. This method is basically designed to detect objects representing high temporal-spectral variability, such as croplands (Anders et al. 2013). Previous research findings showed that multi-temporal segmentation analysis leads to better segmentation results when relying on a small subset of bands (Tong Yang et al. 2015) or some spectral indices

(Dutrieux et al. 2016). According to these suggestions and due to the importance of vegetation cover in this research, the Normalised Difference Vegetation Index (NDVI) maps were produced from the images and used to inform the segmentation algorithm (three NDVI maps). NDVI is one of the most well-known and widely used vegetation indices which in its ability in detection and monitoring of croplands have been well justified in the scientific communities (Mulla 2013). This index is calculated by replacing the pre-processed red (Red: 0.63–0.69 μm) and near-infrared bands (NIR-0.76–0.90 μm) into Equation 3 (Aronoff 2005).

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{3}$$

A multi-resolution segmentation algorithm (Baatz, Schäpe 2000), which controls colour, scale and shape parameters was used to extract objects from the NDVI layers (Bihamta Toosi et al. 2020). The mean of NDVI values was considered as the color parameter. The value of 1 ha reflecting the approximate size of agricultural lands across the study location was considered as the scale parameter. This value is selected based on long-term field surveys and interpretation of aerial photographs, but some studies such as Möller et al. (2007) and Weidner (2008) showed that this parameter can be also identified through some quantitative techniques. In the case of the shape parameter, our objective was to generate rectangular objects with lengths three times greater than the width (Asgarian et al. 2016).

Crop types were classified relying on the mean of NDVI values. Estimating the NDVI threshold was done according to the parameters of shape, texture, and adjacent complications and the extracted values. In each NDVI map, objects with a mean NDVI value of >0.185 were coded 1 as cropped fields and coded 0 otherwise. Taken all NDVI layers together, objects with mean NDVI values >0.185 in the L1, L2 and L3 images were coded 111, and coded 000 otherwise. Based on the results of field investigation and phenological stages given in section 2.2.1, objects with code 110 show areas under wheat cultivation because, in comparison to the other crop types, wheat has a significant vegetation cover in the L1 and L2 images (code 11*) and at the time of the L3, it has been completely harvested across the region (code **0). Objects coded 111 represent alfalfa fields which are green over the whole time period. Code 011 and 001 indicate fruit tree and vegetable classes which begin their vegetative growth before the acquisition time of the L2 and L3 images, respectively. Table 1 shows a summary of the classification scheme used in this research.

Table 1. The classification scheme is used to recognise crop types.

Crop type	Object code			Final code
	L1	L2	L3	
Wheat	1	1	0	110
Alfalfa	1	1	1	111
Fruit tree	0	1	1	011
Vegetable	0	0	1	001

Finally, a polygon-level confusion matrix was constructed to assess the accuracy of the image classification process. Several studies showed that polygon-level accuracy assessment provides more reliable results since it tends to remove errors made by pixel-level accuracy assessment such as positional error (Lunetta, Lyon 2004). Validation was performed using the control points which were recorded during the field survey using GPS (Global Positioning System) (Garmin 629sc). We totally collected 860 control points for different crops, from which 50% were randomly selected and used as training samples for image processing, and the remaining 50% were used for validation. As mentioned, during the field survey, we collected >100 control points by GPS for each type of cropland. They have included 222 points for wheat, 137 points for alfalfa, and 543 points for other croplands. To identify agricultural lands, we utilised the recorded control points and Google earth imageries.

Some points with randomly selected fields were digitised by google earth imageries and used to construct the confusion matrix. Kappa coefficient, Overall Accuracy, Omission error and Commission error were calculated to evaluate the performance of image classification (Aronoff 2005).

Quantifying the structure and spatial pattern of croplands

In this section, a set of class-level landscape metrics was used to explore the composition, spatial structure and configuration of fields devoted

Table 2. Description of landscape metrics used in this research, adapted from Leitão et al. (2012).

Landscape metric	Acronym	Aspect of pattern	Range [unit]
Number of patches	NP	Composition	NP > 0, without limit [−]
Mean patch size	MPS	Composition	MPS > 0, without limit [ha]
Mean shape index	MSI	Structure	MSI > 1, without limit [−]
Perimeter-to-area ratio	PARA	Structure	PARA > 1, without limit [−]
Euclidian nearest-neighbor distance	ENN	Configuration	ENN > 0, without limit [m]

to the cultivation of each crop type. Landscape metrics were chosen based on literature review (Southworth et al. 2002, Hendrickx et al. 2007, Leitão et al. 2012) and also the interpretation of their ability in measuring various spatial aspects. Additionally, based on the literature review, the used metrics were selected based on similar studies that used similar metrics with low correlation (Bozorgi et al. 2020). The number of patches (NPs) and mean patch size (MPS), as non-spatial landscape metrics, were selected to measure the composition of cropped fields. In the case of spatial structure, mean shape index (MSI) and perimeter-to-area ratio (PARA) was used to produce information about the geometry of agricultural fields allocated to each crop type, and Euclidian Nearest Neighborhood Distance (ENN) was used to evaluate the spatial configuration of fields. The metrics are fully described by McGarigal et al. (1995) and embedded in the free Fragstats software. Table 2 gives a brief description of the landscape metrics used in this research.

Results

After performing radiometric and atmospheric corrections, NDVI layers were introduced to the Multi-Resolution Segmentation to delineate agricultural fields. Wheat, alfalfa, fruit tree and vegetable classes were identified based on the mean NDVI values of objects and information provided

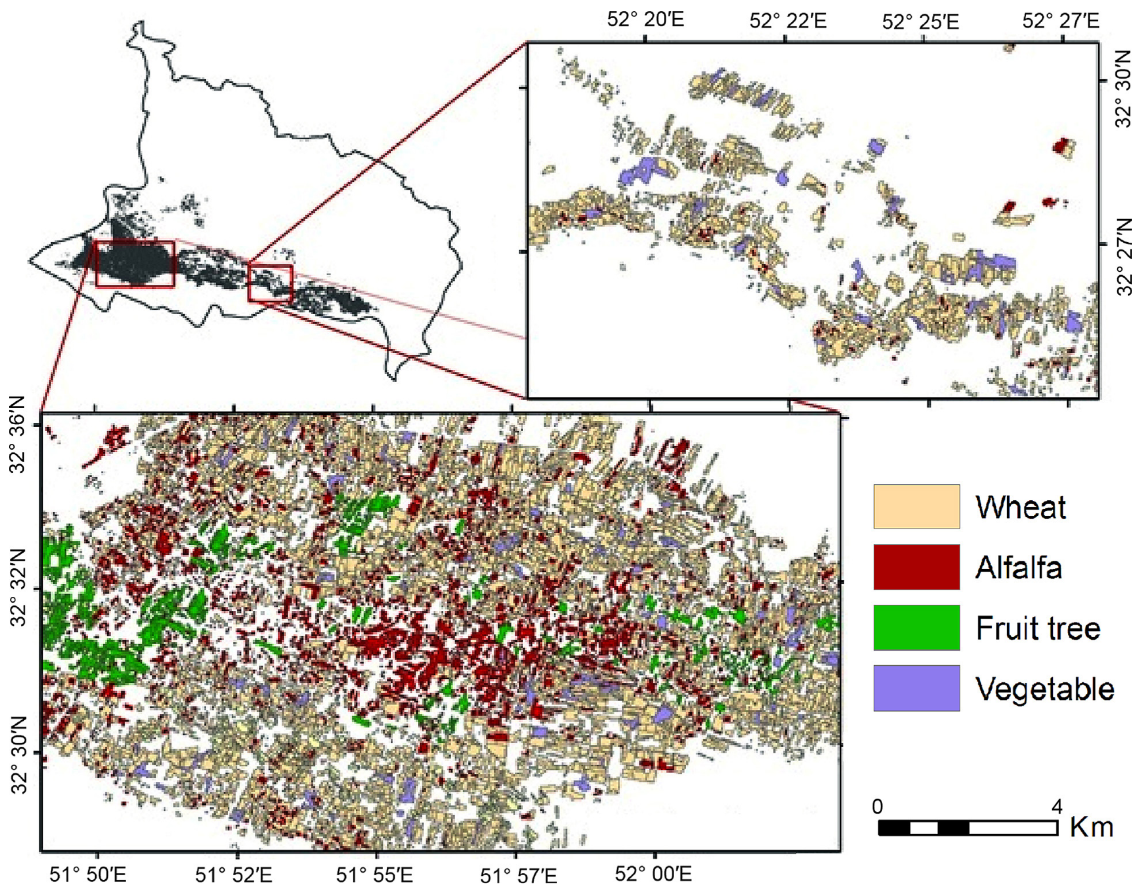

Fig. 2. Crop type map produced from image classification.

in Table 1. The spatial distribution and area of crops are respectively given in Figure 2 and Table 3. Wheat, with an area of about 21,800 ha, occupied the largest agricultural land area (approximately 62%) while the smallest land area was devoted to vegetables (2816 ha – 8% of the agricultural landscape). Kappa Coefficient and Overall Accuracy were respectively estimated to be 82.84% and 87.41% reflecting the acceptable accuracy of the crop type classification. The errors of omission and commission were relatively higher for alfalfa (above 15%) indicating that alfalfa is the most difficult crop type to identify and classify. This is largely due to the periodic harvest of alfalfa exhibiting a significant variation in its reflectivity. The accuracy statistics calculated from the confusion matrix are given in Tables 2 and 3.

The results of quantifying the structure and spatial pattern of fields allocated to each crop type are given in Figure 3. According to the results, the

Table 3. The area of crops and the results of accuracy assessment.

Crop type	Area]	Number of reference polygons	Omission error	Commission error
	[ha]	[−]	[%]	
Wheat	21,803	214	6.59	14.01
Alfalfa	4892	137	17.02	15.59
Fruit tree	5561	162	8.43	9.87
Vegetable	2816	99	7.36	11.11
Kappa Coefficient = 82.84%			Overall Accuracy = 87.41%	

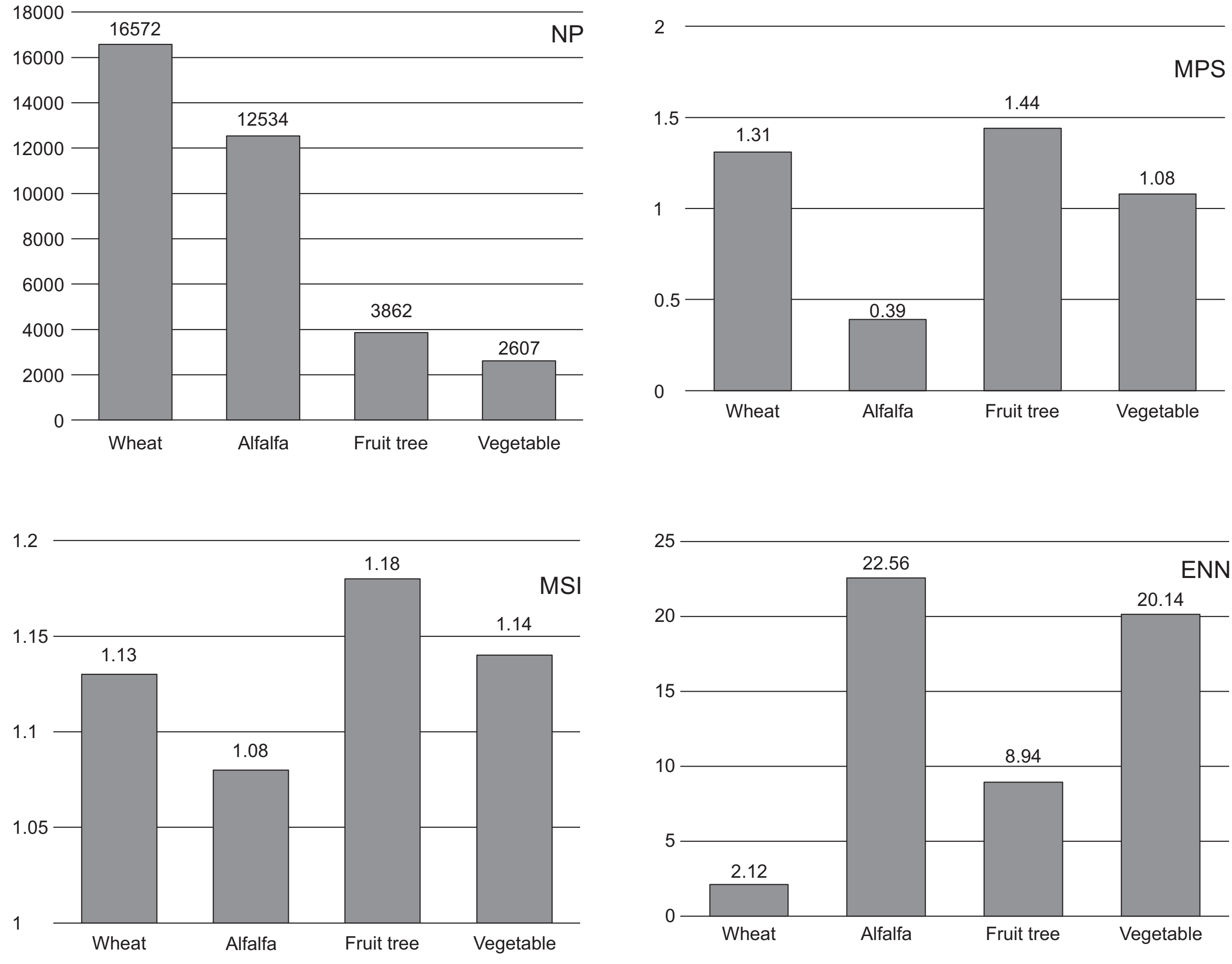

Fig. 3. The results of landscape metrics analysis for each crop type.
NP – Number of patches, MSI – mean shape index, MPS – mean patch size, ENN – Euclidian Nearest Neighborhood Distance.

landscape is composed of over 35,500 fields. The largest number of fields, over 16,500, was allocated to wheat cultivation (approximately 46% of the total fields) and vegetables, as the least selected crop type, occupied nearly 2600 fields (<8% of the total fields). The results of MPS showed that fruit tree fields have the largest mean size (MPS of 1.44 ha) while alfalfa was cultivated in very small fields (MPS of 0.39 ha). The results of spatial structural metrics (MSI and PARA) showed that, on average, the landscape is built by simply shaped fields where the largest MSI and PARA values, belonging to the fruit tree class (1.18 and 0.81 respectively), were quite low. The results of ENN showed that wheat is cultivated in adjacent fields (ENN of 2.12 m) and alfalfa and vegetable fields are located at a far mean distance from each other (ENN of >20 m).

Generally, the results of metrics analysis showed that the pattern of agricultural appearance in the study area was a large NPs of wheat and alfalfa. Wheat patches had a larger area and were located close to each other, while the patches of Alfalfa fields had a small area and were far from each other, indicating their dispersion across the landscape.

Discussion

Principally, in this study, multi-temporal images of Landsat satellite (8) were used to identify agricultural products, especially two important crops, i.e. wheat, and alfalfa. Due to the successful results of the developed method, it can be used for the Zayandeh Rud watershed, and also the central regions of Iran, where main crops are wheat, barley, and alfalfa. Also, this method can be used to identify and map cultivation patterns in different regions of the world. It can be performed using multi-temporal satellite images, considering phenology of different vegetation types, and using spectral information and geometric features such as shape, compaction, and information obtained from field surveys. Using multi-temporal images is one way to reduce uncertainty in this area. Because by increasing time period, the probability that two different, adjacent agricultural lands show different reflections increases.

The results of this research in identifying the type of crop show the dominance of wheat crop over other crops, which can indicate the movement of the land landscape towards the monoculture pattern, which is one of the factors threatening the environment. (Asgarian et al. 2016, Chen et al. 2016). The most common cause of this condition is the significant decrease of freshwater supplies in this region imposing farmers to rely on crops with fewer water requirements such as wheat. Direct water withdrawals from the Zayandeh-Rood River, especially in western parts, have left the minimum possible amount of water for agricultural activities in the eastern parts and, as shown in Figure 2, monoculture is more intensified in this area.

As previously mentioned, the agricultural landscape has been highly fragmented due to the direct effect of freshwater shortage. Such a spatial pattern, however, was of great help to accurately disentangle agricultural fields from their neighbors using the segmentation algorithm. It should be noted that fields devoted to similar crops tend to represent different spectral behaviors since crop production in this region is not mechanised and farmers conduct their own farming practices in which crops are managed to grow under various planting and harvest dates and irrigation frequencies. Furthermore, due to various combinations of trees or vegetables, each fruit tree or vegetable field has also its own unique spectral signature different from other fields classified in a certain class, and in turn, such diversity of spectral behavior has substantially allowed the segmentation algorithm to properly identify agricultural fields across the region.

Integration of the segmentation algorithm with an innovative NDVI-based decision tree classifier formed a basis to better recognise the type of crop grown in each field. The results of the accuracy assessment also confirmed the performance of the proposed multi-temporal object-based classification procedure used in this research. This procedure was more beneficial for the classification of alfalfa. At any time, alfalfa may exist in its various growth stages from harvested to well grown and such a variation pattern is a technical problem to appropriately classify alfalfa from a single image. Previous research such as Khan et al. (2010) and Foerster et al. (2012) have also indicated that temporal spectral profiles could result in better identification and classification of crop types across agricultural landscapes especially in large areas where a specific crop is grown under various practices.

To our knowledge, this study is the first attempt of producing data about the structure and spatial pattern of agricultural fields in central Iran. Based on the results, this region is composed of a large number of agricultural fields with a mean area of nearly 1 ha which, in comparison to other regions, could be ranked as high acreage fields found in Iran (Asgarian et al. 2016). The relatively long distance between agricultural fields (on average over 13 m) denotes a massive agricultural land abandonment. A large share of such fragmented landscape is due to the significant decrease of freshwater supplies and it is little related to the natural and human-made barriers such as Zayandeh-Rood River, roads and human settlements. The very low values obtained for PARA and MSI are due to the regular geometric shape of agricultural fields in this region. As Turner et al. (2015) depicted, the farmers' inclination to grow crops in bigger fields with more regular shapes are an effective way of optimising water use efficiency in areas experiencing significant water shortage.

One of the most notable results of this research is the very small mean size of alfalfa fields. One possible explanation for this may be due to the cultivation of alfalfa mostly for meeting small scale livestock purposes, not for economic reasons and accordingly, farmers select small fields to cultivate alfalfa. The longer distance between alfalfa fields could be also due to the dispersed distribution of livestock units across the region. Fruit tree fields were mostly located in the western parts, at a mean distance of <9 m from each other, where agricultural lands are less faced with water shortage and are more expensive due to adjacency to Isfahan city while vegetables were more sporadically cultivated and showed a mean distance of >20 m from each other.

Providing information on the composition of agricultural lands and the type of cultivation of each farm provides very important information for the management and planning of agricultural lands to decision-makers. Different experiences in the field of satellite image processing have shown that relying solely on a specific algorithm prevents the researcher from using the appropriate algorithm at the right time to achieve the desired goal (Lillesand et al. 2015). Therefore, to obtain accurate information about agricultural lands, the present study emphasised utilising both methods (object-oriented and pixel-based) for data extraction and interpretation. The suggested procedure then can be used for different times and locations by considering these two important approaches.

Conclusion

Integration of the results of a segmentation algorithm with a temporal NDVI-based decision algorithm led to better identification of agricultural fields and crop types. Furthermore, the application of landscape metrics has provided further information about the spatial structure and spatial pattern of agricultural fields devoted to each crop type. Based on the results, agricultural lands in central Iran are experiencing a massive shift towards wheat monoculture, especially in eastern parts where agricultural activities suffer from the unavailability of water. The results of this research effort and other similar studies, in this case, are of great help to develop more effective and strong land use plans and policies. It is also recommended to carry out further research relying on high spatial resolution imagery data and a broader range of landscape metric to provide more accurate data for proper agricultural land use management.

Competing interests

The authors declare that they have no competing interests.

Acknowledgments

We are grateful to all experts for their help with data analysis and gathering information. We also thank the reviewers and the editors for their comments and suggestions.

Author's contribution

R.S. conceived and designed the study; R.S. and A.S. analyzed the results and contributed to the respective discussion; R.S wrote the manuscript. A.S. and S.P. conceived and provided useful suggestions to the manuscript. All the authors have reviewed and approved the submitted version of this manuscript and have agreed to be accountable for the author's own contributions.

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