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Land cover classification in an arid landscape of Iran using Landsat 8 OLI science products: Performance assessment of machine learning algorithms

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Abstract
The spatial variation of several dynamic chemical soil characteristics is greatly influenced by land cover and land use. High-accuracy land use and land cover (LULC) classification have enormous promise for temporal scale evaluation of soil characteristics. The study aims to evaluate the performance of linear and non-linear classification methods in determining land cover classes by using remotely sensed time-series Landsat 8 OLI satellite data in an area where semi-arid agricultural activities are active. Four LULC classes were identified, and Landsat 8 images were classified using three supervised machine learning classifiers. When the producer's accuracy, user's accuracy, overall accuracy, and Cohen kappa coefficient were taken into account, it was observed that support vector machines (SVMs) and random forest (RF) algorithms produced more accurate results than multinomial logistic regression (MNLR). The SVMs had the highest overall classification accuracy of 96.00 % and a kappa coefficient of 0.93 on the test set. It is recommended to compare the efficiency of satellite data with different spectral and spatial resolutions.

1. Introduction

Analysts and decision-makers in government, civil society, industry, and finance rely on land use/land cover (LULC) maps to keep tabs on global environmental change and assess the risk to long-term livelihoods and development (Karra et al. 2020). Typically, land use classification schemes include agricultural areas, forests, grassland, water, and artificial regions. Land-use type information is critical for the spatial study of soil attributes because it reflects the different effects of organism-associated factors on soil (Yigini et al. 2018; Shi et al. 2021). Land cover/land use maps can be beneficial for constructing land-use sensitive contextual indicators of soil and ecosystem health that are valid for spatially explicit monitoring of ecosystem health (Vågen et al. 2016). Land use maps are an important determinant in the spatial prediction of soil organic carbon in Mediterranean biogeography (Schillaci et al. 2017) Land use data collected during soil sampling can serve as training examples for land use classification. With this format, the land use maps that are eventually produced can be beneficial for the qualitative assessment of soil scientists.

In different geographies, machine learning algorithms enabled the generation of large-scale spatial maps with the integration of remote sensing, taking into account a certain number of field observations (training data) to map land use and land cover classes (Shih et al. 2019). In this regard, considering the complexity of geography, algorithms that have the potential to reveal linear and nonlinear relationships are studied comparatively and their results are evaluated (Bouaziz et al. 2017).

This research focused on the application and evaluation of different classification algorithms in obtaining LULC in Northeast Iran. It was conducted to test the potential of machine learning algorithms to classify LULC in areas where active agricultural production is maintained in arid regions.

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2. Method

2.1. Study area

The investigated area was located in northeastern Iran. This area was selected because of the importance of agriculture in this region. Rain harvested water collection ponds, which are particularly useful in Iran's dry regions and may be found in abundance in the study area, also play a significant role in the study. This covers an area of approximately 85 km² located between the coordinates of UTM Northern Zone 40, epsg:32640, 3992370 to 4005540 North, and 668891 to 687491East (Fig. 1). The climate is characterized as semi-arid with a mean daily temperature of 14.5 °C and mean annual precipitation of 233.7 mm.

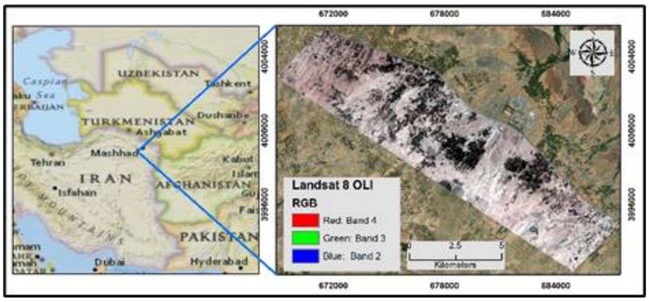

Figure 1. Location of the study area: Landsat 8 natural colors (right); Geographical location in Iran (left)

2.2. Remote sensing data

The Landsat 8 OLI science products multispectral data used in this study was acquired from https://earthexplorer.usgs.gov on 30 June 2018, 03 July 2019, 21 July 2020, and 25 August 2021. Before using data from Collection 2 Landsat Level-2 surface reflectance, a scaling factor must be applied. Landsat Collection 2 has a scale factor of SR 0.0000275 and an extra pixel offset of -0.2. (Sayler and Zanter 2021). ArcGIS 10.8-Arctoolbox-related tools (ESRI, 2021) were utilized for the visualization in this study.

2.3. Data collection

Observational data from the ground were gathered from the study region. In addition, the dataset was determined by photo-interpreting the "historical images" in Google Earth®, which was then used to classify the dataset. A total of 1323 observations representing four land cover types were gathered (Table 1). The land cover class was determined using the CORINE level 1 classification nomenclature (CLC 2018; Kozstra et al. 2019). The land use map was created using band 2-7 averages of four linked Landsat 8 OLI images. We used Multinomial logistic regression (Venables and Ripley 2002), Support vector machines (Meyer et al. 2020), and Random Forest (Liaw and Wiener 2002) algorithm from machine learning algorithms that give reliable results in producing land cover or land use maps.

2.4. Modelling process

For classification analyses, the sampled dataset was split into two subsets of training and then tested. Yigini et al. (2018) recommended splitting criterion of 70% (n = 926) for training and 30% (n = 397) for validation. Similar data splitting techniques have been common practice in land cover classification studies (Thenkabail et al. 2021). Classification results were evaluated by considering general accuracy and kappa coefficients (Congalton, 1991). R Core Environment and related packages were used for data extraction, modeling, and spatial mapping (R Core Team 2022). The methodological flow chart is present in Fig. 2.

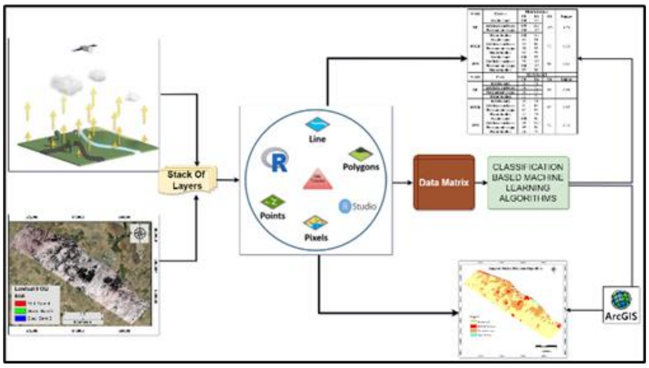

Figure 2. Flowchart of the methodology of the study

Table 1. Number of observations in the training and test sets

Class_Type	TRAINING	TESTING
Arable Lands	316	145
Artificial Surfaces	105	46
Permanent Crops	453	181
Water Bodies	52	25

The spectral signatures from the investigated classes are shown in Fig. 3, where it can be seen that arable lands and artificial surfaces have similar values, while permanent crops and water bodies have significantly lower spectral values in all bands, except for the permanent crops in band 5. The peak of the reflection in the 5th band must have occurred due to the chlorophyll content. This is an expected result for permanent crops.

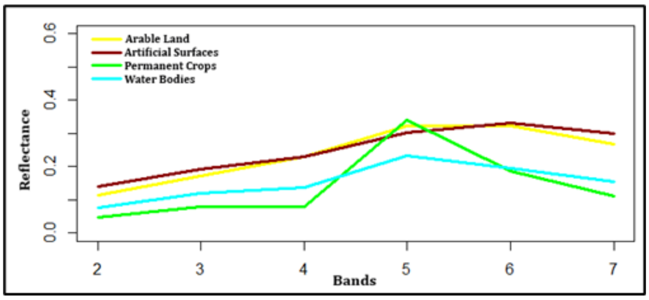

Figure 3. Spectral profile of land cover classes

3. Results

The results from the investigation made in this study are presented in Fig. 4, while the accuracy assessment results are in Table 2. In this study, we compare three different machine learning algorithms for producing land cover over the semi-arid area in Iran. For this purpose, we have classified the study area into four classes, Arable land, Artificial surfaces, Permanent crops, and Water bodies. The accuracy assessment from the training set showed high accuracy using the RF classifier, followed by SVM. MNLR performed last, especially in the water class, where the producer accuracy was 62%. The testing set, on the other hand, showed the best result with the SVM algorithm, followed by RF. Here also MNLR performed last. Permanent crops were classified with the highest accuracy in all tested models, followed by arable lands, and artificial surfaces. Water class was classified with poor accuracy.

Table 2. Comparisons of the performance of random forest (RF), support vector machines (SVM) and multinomial logistic regression (MNLR) models for the training and the validation datasets (O: Overall, A: Accuracy, P: Producer's, U: User's)

Model	Class [1]	TRAINING SET PA	UA	OA	Kappa
RF	Arable land	100	100	100	1.00
	Artificial surfaces	100	100		
	Permanent crops	100	100		
	Water bodies	100	100		
MNLR	Arable land	94	91	93	0.88
	Artificial surfaces	84	88		
	Permanent crops	98	97		
	Water bodies	62	79		
SVM	Arable land	100	97	99	0.97
	Artificial surfaces	93	100		
	Permanent crops	100	100		
	Water bodies	87	98		
Model	**Class**	**TESTING SET PA**	**UA**	**OA**	**Kappa**
RF	Arable land	96	91	93	0.88
	Artificial surfaces	74	92		
	Permanent crops	98	97		
	Water bodies	72	79		
MNLR	Arable land	96	91	92	0.87
	Artificial surfaces	81	87		
	Permanent crops	97	97		
	Water bodies	57	74		
SVM	Arable land	100	96	96	0.93
	Artificial surfaces	83	100		
	Permanent crops	99	98		
	Water bodies	76	76		

4. Discussion

In this study, we use Landsat – 8 data for land use mapping of four different classes in a semi-arid area in Iran. For this purpose, we use three different machine learning algorithms, RF, MNLR, and SVM. For the classification, we use a dataset of 1323 points collected from the field and high-resolution imagery. The dataset was divided into 70% samples for training and 30% for testing.

The results showed the significant success of both SVM and RF algorithms in the classification accuracy assessment parameters. Surprisingly, the water class was the least accurate classified class. Due to the water sensitivity in the green and NIR bands, water is usually classified with high accuracy. It is possible that the accumulated water has been inactive for a certain period and has affected the reflection as a result of the development of biological organisms due to the high organic content (Fig. 3). However, in our study area, not many water bodies can be found. Thus, the training and testing data for the water class is very limited. The water bodies might be also confused with freshly watered croplands, thus, lowering the producer and user accuracy of the water class, and affecting the overall classification accuracy. This problem might be solved using higher spatial resolution imagery, like Sentinel-2, or fusing Landsat-8 and/or Sentinel-2 with Sentinel-1, a microwave active radar sensor, which is very sensitive to water bodies. Also, for relatively small areas like the one selected in the presented study, a UAV of high-spatial resolution imagery might be considered for more accurate mapping. However, as UAV and high-resolution imagery require additional funding, and are more time-consuming for processing, the results obtained in this study are sufficient for drawing a general frame of the study area.

5. Conclusion

This study investigates different machine learning algorithms for land cover classification. We have selected a relatively small area in Iran for this purpose, using Landsat-8 imagery. The four investigated classes were Arable land, Artificial surfaces, Permanent crops, and Water bodies. Two of the investigated algorithms showed high and similar results, RF and SVM. MNLR on the other hand performed last in the overall accuracy and the single class assessment. As there are small water bodies in the study area, the accuracy of the water bodies was not as high as in the other classes. Considering that the water in the area is rain harvested water collection ponds, organic developments are expected to be high. Nature is dynamic and has a complex interaction within itself. When it comes to the detection and identification of natural objects, the selection of satellite images and band preferences affect accuracy more than classification methods. The capability of approaches based on simple mathematics or complex algorithm is controversial. For future studies, we recommend using imagery with higher spatial and temporal resolution, such as Sentinel-2, and for the water bodies, Sentinel-1 can be considered, as it is highly sensitive to water areas.

Acknowledgment

We acknowledge the usage of Landsat Collection 2 L2SP Surface Reflectance data from A subcategory of the Landsat category is Landsat 8 OLI/TIRS C2 L2, which contains the files for each sensor (160 path, 35 Row).

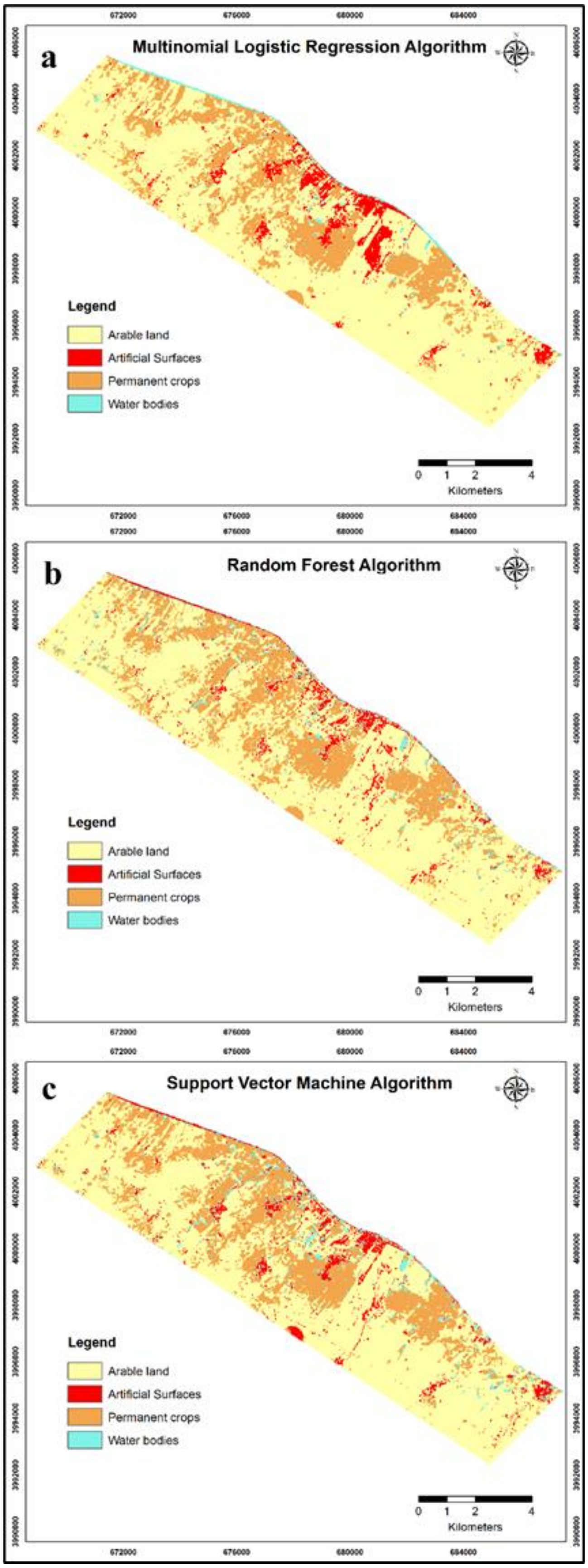

Figure 4. Comparison between a) MNLR, b) RF, and c) SVM classification results for land cover types

References

Bouaziz, M., Eisold, S., & Guermazi, E. (2017). Semiautomatic approach for land cover classification: a remote sensing study for arid climate in southeastern Tunisia. Euro-Mediterranean Journal for Environmental Integration, 2(1), 1-7. https://doi.org/10.1007/s41207-017-0036-7

CLC (2018). CORINE land cover-CLC2018 Technical Guidelines. 25 October 2017. Environment Agency Spittelauer Lände 5 A-1090 Wien, Austria.

Congalton R, (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37, 35–46. https://doi.org/10.1016/0034-4257(91)90048-B.

ESRI, (2021). ArcGIS user's guide, http://www.esri.com.

Vågen, T. G., Winowiecki, L. A., Tondoh, J. E., Desta, L. T., & Gumbricht, T. (2016). Mapping of soil properties and land degradation risk in Africa using MODIS reflectance. Geoderma, 263, 216-225. https://doi.org/10.1016/j.geoderma.2015.06.023

Karra K, Kontgis C, Statman-Weil Z, Mazzariello J C, Mathis M, Brumby S P, (2021). Global land use/land cover with Sentinel 2 and deep learning. 2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS, pp. 4704–4707. Brussels, Belgium. https://doi.org/10.1109/IGARSS47720.2021.9553499

Kosztra, B., Büttner, G., Hazeu, G., & Arnold, S. (2019). Updated CLC illustrated nomenclature guidelines. European Environment Agency: Wien, Austria, 1-126.

Meyer D, Dimitriadou E, Hornik K, Weingessel A, Leisch F, (2020). e1071: Misc Functions of the Department of Statistics, Probability Theory Group (Formerly: E1071), TU Wien. R package version 1.7-4.

R Core Team., 2022. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria

Sayler K, Zanter K, (2021). Landsat 8 Collection 2 (C2) Level 2 Science Product (L2SP) Guide LSDS-1619 Version 2.0, EROS Sioux Falls, South Dakota

Schillaci, C., Acutis, M., Lombardo, L., Lipani, A., Fantappie, M., Märker, M., & Saia, S. (2017). Spatio-temporal topsoil organic carbon mapping of a semi-arid Mediterranean region: The role of land use, soil texture, topographic indices and the influence of remote sensing data to modelling. Science of the total environment, 601, 821-832. https://doi.org/10.1016/j.scitotenv.2017.05.239

Shi, T., Hu, X., Guo, L., Su, F., Tu, W., Hu, Z., Liu, H., Yang, C., Wang, J., Zhang, J., & Wu, G. (2021). Digital mapping of zinc in urban topsoil using multisource geospatial data and random forest. Science of Total Environment. 148455. https://doi.org/10.1016/j.scitotenv.2021.148455

Shih, H. C., Stow, D. A., & Tsai, Y. H. (2019). Guidance on and comparison of machine learning classifiers for Landsat-based land cover and land use mapping. International Journal of Remote Sensing, 40(4), 1248-1274. https://doi.org/10.1080/01431161.2018.1524179

Thenkabail P S, Teluguntla P G, Xiong J, Oliphant A, Congalton R G, Ozdogan M, Foley, D (2021). Global cropland-extent product at 30-m resolution (GCEP30) derived from Landsat satellite time-series data for the year 2015 using multiple machine-learning algorithms on Google Earth Engine cloud. https://doi.org/10.3133/pp1868

Venables W N, Ripley B D, (2002). Modern Applied Statistics with S. Fourth Edition. Springer, New York Liaw A, Wiener M, (2002). Classification and regression by randomForest. R News. 2,18-22.

Yigini, Y, Olmedo G F, Reiter S, Baritz R, Viatkin K, Vargas R, (2018). Soil Organic Carbon Mapping Cookbook 2nd edition. Rome, FAO. 220 pp.