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Integration of Sentinel-1 and Sentinel-2 for Classification of Small Urban Areas in Rural Landscape aided by Google Earth Engine

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Abstract: Rapid economic development and population growth lead to fast urban expansion in both urban and rural landscapes. Accurate and updated mapping of urban expansions is essential in urban and territorial planning for sustainable and strategic urban development. Using Earth Observation (EO) technologies, the classification of urban areas in a rural landscape is more challenging than big cities. In this regard, in this paper, we aim at assessing the integration of Sentinel-1 and Sentinel-2 satellite data for classifying small urban areas in rural landscape in Google Earth Engine (GEE). Images of close dates from Sentinel-1 and Sentinel-2 were selected, preprocessed, and integrated to develop a machine learning classification through a Support Vector Classification (SVM) classifier. We have also added vegetation indices to the investigated dataset. As a study area, the Strumica-Radovish Valley in the Republic of North Macedonia has been selected. The results showed that the integration of Sentinel-1 and Sentinel-2 performed better than Sentinel-2 alone, with accuracy higher than 90%. For future studies, we recommend testing the dataset to different study areas and adding different EO data for obtaining even higher accuracy.

Keywords: Remote Sensing; Google Earth Engine; Urban Areas; Rural Landscape; Sentinel.

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1. Introduction

Urban expansion has been prompted by the rapid economic development and the significant population growth in the last few decades. The population in the urban areas has risen drastically causing environmental concerns. Even though this situation is more obvious in the big cities, urban growth is also affecting the rural landscapes, causing changes in the land cover [1]. In order to understand the changes and their consequences, timely mapping and monitoring of the urban sprawl in the rural landscapes is as important as the one in the big urban areas [2]. Remote sensing data and techniques have been successfully used in the past few decades for the extraction of urban areas [3]. However, since the urban areas in the rural landscapes are significantly smaller and the urban objects are sparsely built, the extraction of small urban areas such as villages, small towns, ect., is challenging. The relatively coarse spatial resolution often cannot meet specific project requirements of urban land-use/landcover classification, especially in a complex urban-rural interface. For this task, for accurate classification, researchers use high-resolution imagery (< 5m). Taking in consideration that high-resolution imageries are not of open-source character, not many studies can be found in the literature on the particular topic [4,5].

Even though researchers have agreed that extracting urban areas in the rural landscape can be challenging using medium-resolution satellite imagery, taking into consideration the latest developments in the remote sensing field, in this study we use Sentinel imagery integrated into Google Earth Engine, a cloud computing platform designed to store and process huge data sets for analysis and ultimate decision making [6].

Sentinel, a middle-resolution Earth Observation (EO) satellite constellation, is offering open-source satellite imagery. Starting from 2014, Sentinel-1, a Synthetic Aperture Radar (SAR) platform, collects 5 m by 20 m imagery from all over the world at any weather condition. On the other hand, Sentinel-2, an optical satellite platform, collects multispectral imagery in 13 bands (10, 20, and 60 m), since 2015. Since their launch, Sentinel-1 and Sentinel-2 have been successfully used in a number of applications [7].

Since its inception in 2010, GEE has been used in different areas of research, such as vegetation mapping and monitoring [8,9], landcover mapping [9], agricultural applications [10], disaster management and earth sciences, and many more.

In this paper, we integrate Sentinel-1 and Sentinel-2 within GEE for classifying small urban areas in rural landscape. Images of close dates from Sentinel-1 and Sentinel-2 were selected, preprocessed, and integrated to develop a machine learning classification through a Support Vector Classification (SVM) classifier. Also, several vegetation and urban area extraction indices have been added to the investigated datasets. As a study area, the Strumica-Radovis valley located in the structural basin of the Strumica River in the Republic of North Macedonia has been selected.

2. Materials and Methods

2.1 Study area

The Strumica-Radovis Valley is located in the southeastern part of the Republic of North Macedonia, along the upper and middle part of the Strumica river basin, in the areas around the cities of Strumica and Radovish. The altitude in the valley ranges from 200 m to 1,881 m. The valley is formed tectonically, by descending the land along the fault lines between the mountains Belasica in the south, Ograzden, Plachkovica, and Goten in the north, and Plaush and Smrdesh in the west.

The valley is divided into three parts: Strumica, Radovis, and Damjansko Pole. The flat part has a length of 200 to 500 m and covers an area of 29,000 ha (290 km2). The highest is Damjansko Pole, and the lowest is Strumica.

To the north, towards the mountain Ograzden, the lowest part of the valley rises. In the west, the valley is connected with the small fields Popchevsko and Kosturinsko along the valley of Bela and Trkajna Reka. To the east, Strumica Field narrows and east of Novo Selo, between Belasica and Ograzden, the width is about 2 km, and then the river Strumica through the Key Strait enters the Petrich Valley.

The valley gives high yields of early vegetable crops thanks to the built irrigation systems. Of particular importance is the Strumica Field, which is very fertile and rich.

Along the entire length at the foot of the mountains, there are fossilized diluvial deposits, on which there are several villages and two cities, Strumica and Radovish.

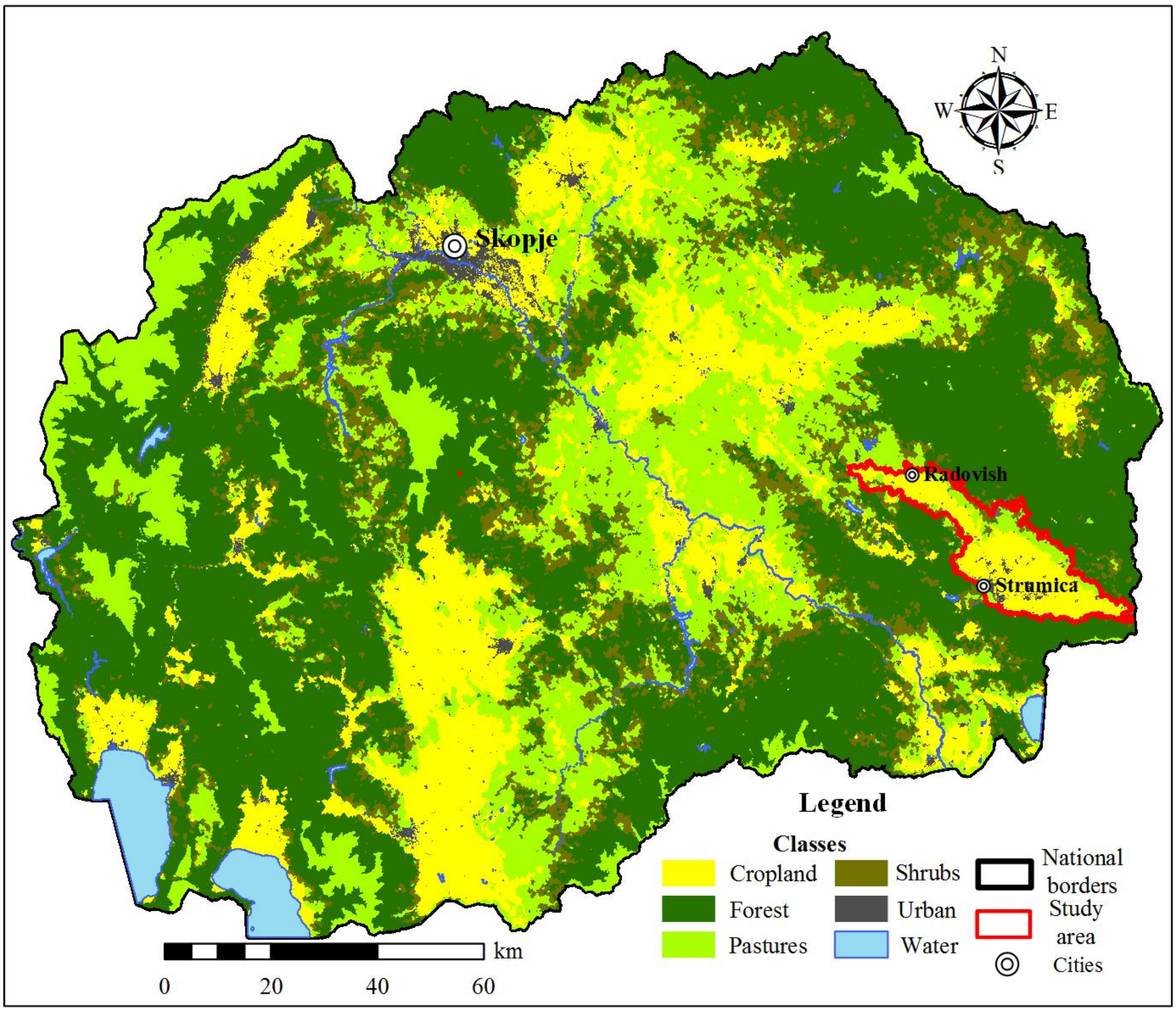

Figure 1. Study area; location of Strumica-Radovis valley, North Macedonia (Land cover map by G.K.)

2.2 Materials and methods

In order to classify small urban areas in a rural landscape within the study area, the integration of Sentinel-1 and Sentinel-2 data aided by the cloud computing platform, GEE has been investigated. For this purpose, image collections of both Sentinel-1 and Sentinel-2 satellite data were used. In order to get cloud-free imagery, image collection from 07 July 2020 – 01 September 2020, setting a cloud filter for the Sentinel-2 images to be less than 25%, obtaining 26 Sentinel-2, and 45 Sentinel-1 images. Furthermore, the obtained images were reduced to a single image, calculating their median values. All 10 and 20-m Sentinel-2 bands, and the two Sentinel-1 polarizations (VV, VH) were used for the classification, compiling several different datasets and combinations. In addition to the mentioned bands, three spectral indices calculated from Sentinel-2 data were added to the investigation; Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Urban Index (UI) [11]. Details and equations of the indices are given in Table 1.

Taking into consideration the main aim of the study, classification of small urban areas, two classes were determined in the study area, urban and other. In order to be able to use the training samples in the classification, and in the accuracy assessment, approximately 2,000 samples were collected over the study areas, 1,000 samples for each class. However, 70% of the samples were used in the classification, while 30% were used for the accuracy assessment where overall accuracy and kappa statistics were calculated.

The investigation was done over six different datasets. First, Sentinel-1 and Sentinel-2 were assessed separately, and then their integration was assessed. In addition to the integrated Sentinel-1 and Sentinel-2 data, a combination of the spectral indices was added.

The sample training was done over the 10-m Sentinel-2 data, using a Library for SVM (LIBSVM) classifier.

Table 1. Spectral indices used in the investigation.

	Index	Used Bands	Sentinel-2 bands	Equation
1	NDVI	Red, NIR	B4, B8	B8 – B4 / B8 + B4
2	NDWI	Green, NIR	B3, B8	B3 – B8 / B3 + B8
3	UI	NIR, SWIR-2	B8, B12	B12 – B8 / B12 + B8

3. Results and Discussion

The results of the analyses are given in Table 2 and Figure 2. For the accuracy analyses, 30% of the training samples were used for calculating the validation overall accuracy and the kappa statistics (Table 2). The results showed that with the use of Sentinel-2 alone, the urban area in rural landscape cannot be classified with high accuracy (49%). The use of Sentinel-1 alone showed significantly higher accuracy, of 80%. The integration of Sentinel-1 and Sentinel-2 improved the results of the Sentinel-1 dataset for only 3.7%, or 83.7. However, the use of spectral indices as an addition to the integration of the two satellite data showed significant improvement in the results. Thus, the use of NDVI, improved the results to 88.7%, while the use of the NDVI, UI, and NDWI, boosted the results by over 90%. From all of the investigated datasets, the integration of Sentinel-2, Sentinel-1 VV band, and NDVI, gave highest accuracy with a kappa of 91.8, and validation accuracy of 98.1.

Table 2. This is a table. Tables should be placed in the main text near to the first time they are cited.

No	Dataset	No of Bands	Validation OA	Kappa
1	S2 + S1VV + S2NDVI	12	98.1	91.8
2	S2 + S1VV+ S1VH + S2NDVI + S2Ui + S2NDWI	15	97.8	91.1
3	S2 + S1VV+ S1VH + S2NDVI	13	97.2	88.7
4	S2 + S1VH + S1VV	12	95.5	83.7
5	S1 VH + S1 VV	2	94.8	80.2
6	S2	10	83.7	49.1

In addition to the statistical accuracy, a visual accuracy has also been performed. In Figure 2, the results of dataset 1, 3, 5, and 6 are presented. From the figure, it can be seen that although all of the results classified the urban areas accurately, the noise or mistakenly classified areas are present in dataset 5 (Figure 2.c), and dataset 6 (Figure2.d). In these two datasets, cropland areas with greenhouses, or orangeries, have also been mistakenly classified as urban areas.

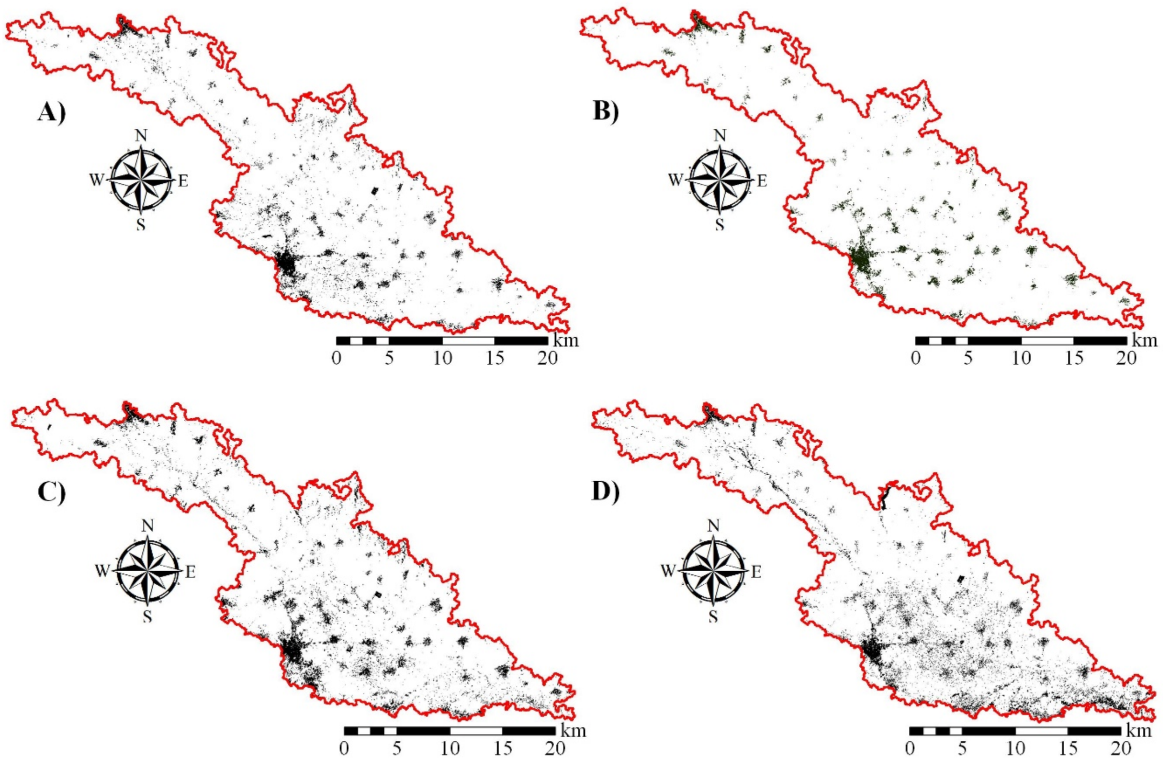

Figure 2. Results; a) Dataset – 1 (S2 + S1VV + S2NDVI); b) Dataset – 3 (S2 + S1VV+ S1VH + S2NDVI) ; c) Dataset – 5 (S1 VH + S1 VV) ; d) Dataset – 6 (S2).

5. Conclusions

This paper investigated the potential of Sentinel-1 and Sentinel-2 for extracting urban areas in rural landscapes within GEE. The study area, the Strumica-Radovis Valley, located in the southeastern part of the Republic of North Macedonia, contains two major cities and over thirty small villages. The area is mainly used for agriculture, and there are large areas of greenhouses that can be misclassified with urban areas. The results of the study showed that Sentinel-2 alone is not capable of extracting these areas, but the integration of Sentinel-1 and Sentinel-2 gives high accuracy. The addition of several spectral indices showed to give the highest accuracy (91.8).

The methodology and the results can be used in several applications, from urban sprawl monitoring to planning and managing of rural landscapes. For future studies, we recommend testing the methodology on different study areas with similar characteristics and adding more classes to the classification.

Author Contributions: G.K. and M.A. conceived and designed the experiments; M.A. performed the experiments; G.K. and M.A. analyzed the data; G.K. wrote the paper.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations are used in this manuscript:

EO: Earth Observation
GEE: Google Earth Engine
SVM: Support Vector Classification

NDVI: Normalized Difference Vegetation Index
NDWI: Normalized Difference Water Index
UI: Urban Index

References

1. Prestia, G.; Scavone, V. In Enhancing the endogenous potential of agricultural landscapes: Strategies and projects for a inland rural region of sicily, International conference on Smart and Sustainable Planning for Cities and Regions, 2017; Springer: pp 635-648.
2. Zhu, Y.; Wang, C.; Sakai, T. Remote sensing-based analysis of landscape pattern evolution in industrial rural areas: A case of southern jiangsu, china. Sustainability 2019, 11, 4994.
3. Hou, L.; Wu, F.; Xie, X. The spatial characteristics and relationships between landscape pattern and ecosystem service value along an urban-rural gradient in xi'an city, china. Ecol. Indic. 2020, 108, 105720.
4. Lu, D.; Hetrick, S.; Moran, E. Land cover classification in a complex urban-rural landscape with quickbird imagery. Photogrammetric Engineering & Remote Sensing 2010, 76, 1159-1168.
5. González Díaz, J.A.; Celaya, R.; Fernández García, F.; Osoro, K.; Rosa García, R. Dynamics of rural landscapes in marginal areas of northern spain: Past, present, and future. Land Degradation & Development 2019, 30, 141-150.
6. Kumar, L.; Mutanga, O. Google earth engine applications since inception: Usage, trends, and potential. Remote Sensing 2018, 10, 1509.
7. Kaplan, G.; Avdan, U. Evaluating the utilization of the red edge and radar bands from sentinel sensors for wetland classification. Catena 2019, 178, 109-119.
8. Schmid, J. Using google earth engine for landsat ndvi time series analysis to indicate the present status of forest stands. Georg-August-Universität Göttingen: Basel, Switzerland 2017.
9. Huang, H.; Chen, Y.; Clinton, N.; Wang, J.; Wang, X.; Liu, C.; Gong, P.; Yang, J.; Bai, Y.; Zheng, Y. Mapping major land cover dynamics in beijing using all landsat images in google earth engine. Remote Sens. Environ. 2017, 202, 166-176.
10. Xiong, J.; Thenkabail, P.S.; Gumma, M.K.; Teluguntla, P.; Poehnelt, J.; Congalton, R.G.; Yadav, K.; Thau, D. Automated cropland mapping of continental africa using google earth engine cloud computing. ISPRS Journal of Photogrammetry and Remote Sensing 2017, 126, 225-244.
11. Li, H.; Wang, C.; Zhong, C.; Su, A.; Xiong, C.; Wang, J.; Liu, J. Mapping urban bare land automatically from landsat imagery with a simple index. Remote Sens 2017, 9, 249.