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NATIONAL LAND COVER MAPPING USING VARIOUS REMOTE SENSING DATASETS IN GEE

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Abstract: National land-cover maps are essential for the development of the countries as land-use patterns have shifted dramatically throughout the world in the previous decades. With the latest development in the remote sensing community, the power and ease of web-mapping and web-based map and GIS services have increased. This work investigates several datasets for land cover categorization on a national scale across North Macedonia (25,713 km^2) using Sentinel images within Google Earth Engine (GEE), a cloud computing platform designed to store and process huge data sets for analysis and ultimate decision making. Both single and synergetic use of Sentinel-1 and Sentinel-2 satellite images have been investigated. The basic land-cover components are generated, upon which the more detailed final land-cover/land-use data were derived and defined. Comparing the results of the datasets indicate the influence of the radar data over the optical data in land cover classification. Also, the influence of the investigated data over every class is calculated. The results showed that the various datasets lead to different overall accuracy. Also, the different datasets performed differently over single classes, even though their overall accuracy was the same. As a result, a high accuracy national-level land cover classification has been created. The results have been compared to the latest Corine data. The results can be critical to making informed policy, development, planning, and resource management decisions. This provided the standardized references from which landscape changes could be determined and quantified.

Keywords: Remote Sensing; National Map; Sentinel; GEE.

1. INTRODUCTION

National land cover maps are crutial for the countries development. Land use patterns have changed drastically in the last few decades all over the World. Some countries rely on ready-to-use data, such as CORINE Land Cover (CLC) data for detailed classification (Caetano, et al., 2009, Popovici, et al., 2013, Fernández Nogueira & Corbelle Rico 2019, Kucsicsa, et al., 2019). In North Macedonia, the land use changes are also on a high level considering the rapid urban development in the last few decades. When it comes to land use classification of North Macedonia, researchers used CLC data (Milevski, et al., 2019). Other than the CLC data, there are no other detailed land cover classifications for North Macedonia except the object-based classification using topographic and settlement data together with Landsat imagery (Kaplan 2021).

Many national land cover databases are updated using historical Landsat images to provide yearly updated national land cover datasets. Gilani et al., (2015) used Landsat images to investigate decadal dynamics in land cover changes in Buthan at the national and sub-national levels. Jawarneh & Biradar (2017) utilized Landsat images to update Jordan's national land cover database at the Level-1. Thunnissen et al., (2000) created a model for measuring the Netherlands' land cover. The requirement for more frequent, precise, and uniform national land cover classification drives the advancement of land cover monitoring (Homer, et al., 2020). Most nations create national land cover databases using middle-spatial-resolution satellite images to determine land cover changes on a national scale (Yang, et al., 2018). Kaplan (2021) created a national land cover for North Macedonia using Landsat imagery. Even though the results gave high accuracy, the study confronts several limitations, such as difficulty mapping urban areas, adding urban settlement layers etc. The recent developments in the remote sensing field, such as increasing the number of open-source satellite data and software, are promising in overcoming such difficulties.

Google Earth Engine (GEE) has been utilized in a variety of research fields, including vegetation mapping and monitoring (Huang, et al., 2017; Schmid 2017), landcover mapping (Xiong, et al., 2017, Mleczko & Mróz 2018), agricultural applications (Yang, et al., 2018, Homer, et al., 2020), disaster management, earth sciences, and many more. The data in GEE are of open-source character and include primary data used in the remote sensing community, such as Landsat legacy and Sentinel program data. Sentinel-2 offers better spatial, spectral, and temporal resolution than the Landsat data. Since the launch of the Sentinel satellites (Sentinel – 1 and Sentinel – 2), many authors have benefited from their single and fused use. Carrasco et al., combined Sentinel – 1, Sentinel – 2, and Landsat – 8 for land cover mapping and found that the combination of different datasets can boost the accuracy of the classification. Similar, Ghorbanian et al., (2020), combined Sentinel – 1 and Sentinel – 2 for mangrove ecosystem mapping and reached relatively high accuracy. Kaplan & Avdan (2019) evaluated the utilization of Sentinel – 2 red edge bands for the classification of small wetlands. The results showed that different dataset differently affects the accuracy of single classes. Clerici et al., (2017), suggested a technique for combining Sentinel-1 and Sentinel-2 photos for precise land cover mapping using OBIA. The data from the satellites was categorized independently and integrated in this study. In addition, three distinct categorization methods were compared. They determined that the Sentinel satellites' most significant benefit is their high temporal resolution of roughly 6 days. They advocate using the technique in diverse subject areas in future investigations. Thus, Delegido et al., (2011) investigated the Sentinel-2 Red-Edge bands for calculating green leaf area and chlorophyll content early on and determined that the band's inclusion is crucial. Abdikan et al., (2018) used Sentinel-1 multi-temporal data for maize crop growth in Konya, Turkey, and found more than 80% accuracy rates. Using Sentinel-1 pictures over Istanbul, Turkey, Üstüner, et al., (2017) investigated the impact of novel band combinations on LULC classification.

Sentinel-1 and Sentinel-2 have also been used for soil moisture mapping (Gao, et al., 2017). Two ways to map soil moisture are provided in the paper. The study's findings are compared to in-situ measurements, demonstrating the utility of Sentinel-1 data for future research. Chang &Shoshany (2016) employed a combination of Sentinel data to estimate the biomass of shrublands, using dual-polarization data from Sentinel-1 and NDVI values from Sentinel-2. They also contrasted the findings of single sensor studies and combination usage, concluding that the combined use of both sensors enhances the categorization of Sentinel-2 by around 14%.

Steinhausen et al., (2018) combined Sentinel-1 and Sentinel-2 using the Random Forest classifier and achieved a classification accuracy of about 91%. According to the findings of this study, the combination of Sentinel radar and optical sensor can significantly improve LULC classification results. Sentinel and other sensors were compared in specific research for wetland mapping. However, it should be noted that the mentioned studies were conducted over relatively small study areas. Large area land cover maps derived from remote sensing data are critical in many global, regional, and national assessments of land cover and land use (Knorn, al., 2009).

The primary goal of this study is to explore the integration of Sentinel-1 and Sentinel-2 within GEE for national map categorization and the success of the various datasets for multiple classes. The main objectives of this paper are: (1) exploring different datasets for land cover classification on the national level in North Macedonia; (2) assessing the accuracy of single classes using different datasets; (3) comparison of the results with CLC data. To the authors' knowledge, the efforts for land cover classification on a national level for North Macedonia in GEE using Sentinel data are first in the literature.

2. MATERIALS AND METHODS

2.1. Study Area

North Macedonia (25,713 km^2) is a landlocked mountainous country in the southern part of the Balkan Peninsula where 2% of the territory is covered by water (lakes), 19% are plains and valleys, and the greatest part of 79% is hills and mountains (Figure 1). Because of the position near the collision zone between African and Eurasian tectonic plates, the country has chequerboard topography with frequent changes of mountains and basins, resulting in a high mean slope of 15.5°, with 39.5% of the area steeper than 15°. For the same reason the geology is very complex, with different kinds of rocks (by type and age) usually bordered with faults (Milevski 2015). As a result of topography, the climate of North

Macedonia is variable, especially with altitude. There is a mixture of the Mediterranean, continental, and mountain influences for which daily and seasonal temperature amplitudes are high (up to 20-30°C daily and up to 70°C annually). Most of the country is semi-arid, with 500-600 mm of annual precipitations unevenly distributed during the year (Milevski, et al., 2015). Therefore, short torrential rivers dominate the country with the Vardar River as the main drainage artery. There are also 15 reservoirs and three lakes (Ohrid, Prespa, and Dojran Lake), which represent most of the surface water area of the country. All of the previous factors result in diverse flora and fauna, with many relict and endemic species. Although small, North Macedonia is characterized by about 30 soil types or almost all soils found in Europe (Mitkova & Mitrikeski 2005). Most of the fertile soils cover the valley bottoms and plains, where most of the 2 million population is located and the highest agriculture production.

2.2. Materials and methods

Sentinel-1, the ESA's most recent SAR satellite, is an imaging radar spacecraft carrying a C-band sensor (5.405 GHz). It is a constellation of two satellites, Sentinel-1A launched in April 3rd, 2014, and Sentinel-1B launched on April 22nd, 2016. The C-SAR instruments may operate in dual-polarization: HH+HV and VV+VH. Sentinel satellites can be used for; Monitoring sea ice zones and the Arctic environment; Surveillance of the maritime environment; Mentoring land surface motion risks; Mapping of land surfaces: forest, water, and soil, agricultural; Mapping in support of humanitarian relief in disaster situations (Attema, et al., 2008: Torres, et al., 2012).

Sentinel-2, the first optical satellite, was launched in 2015, following the first radar satellite, Sentinel-1, in 2014. Sentinel-2 is a two-satellite imaging mission with middle spatial resolution (10-60 m) part of the European Copernicus program. Sentinel-2 Multispectral Instrument (MSI) is a follow-up mission to the SPOT and Landsat sensors, intending to provide continuity of remote sensing outputs. With 13 spectral bands in the visible, NIR, and SWIR wavelengths, Sentinel-2 has a higher spectral resolution than Landsat and SPOT. The three additional red-edge vegetation bands significantly advantage over comparable satellites.

In this study, we use Sentinel imagery integrated into GEE to investigate different datasets for land cover classification on a national scale over North Macedonia. GEE is a cloud computing platform designed to store and process huge data sets for analysis and ultimate decision-making (Kumar & Mutanga 2018). All the steps in the proposed methodology were processed in GEE.

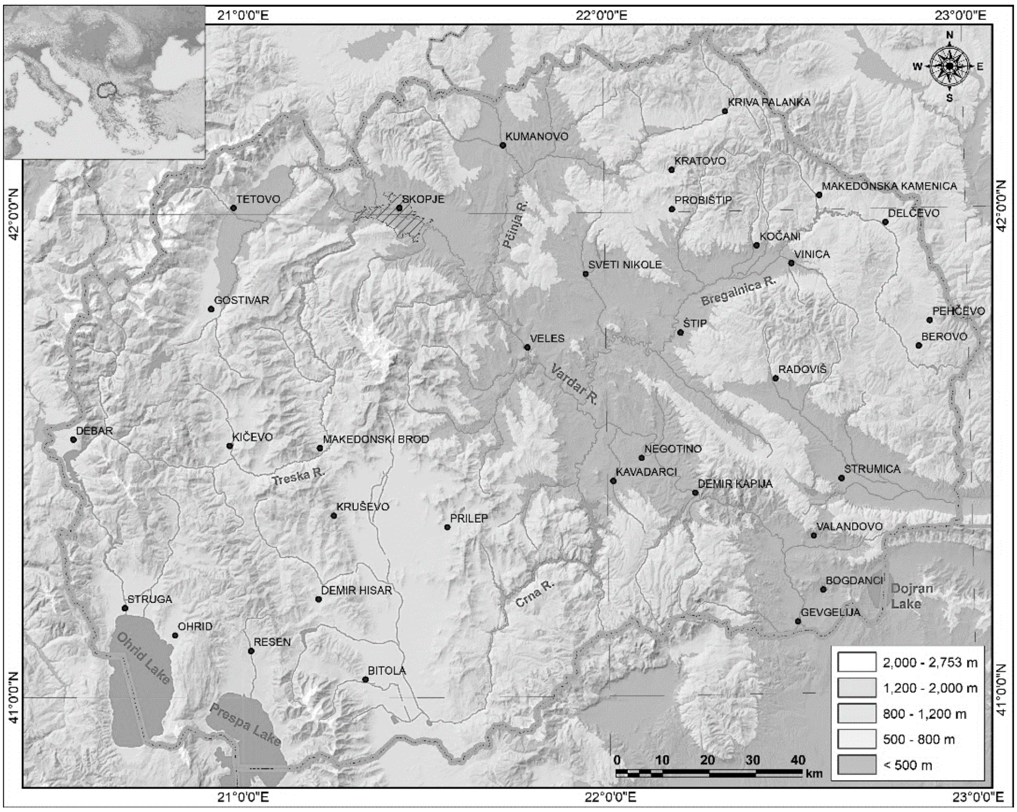

Figure 1. Study area, North Macedonia national borders and elevation data.

After the study area has been integrated as a shape file into GEE, the satellite imagery has been defined. Median values of image collections from different dates in 2020 have been used. A cloud filter has been set for the Sentinel – 2 image collection, where only images with less than 5% cloud cover have been selected. Four indices have been added to different datasets to see the influence of different indices. The first dataset consists of all of the Sentinel-2 bands in the summer period (June – September) when the vegetation cover over the study area is fully developed and the cloud cover is minimal.

Furthermore, Sentinel - 2 images from winter-spring (February – April) were used for classification, where there is no vegetation cover and there is snow cover on the high mountains. The optimal datasets have been investigated by adding different data such as Sentinel-1 bands from different dates indications, indices, Digital Elevation Model (DEM), and Slope. In this study, we use the latest version (3.1) of AW3D30 (Advanced Land Observing Satellite – ALOS World 3D - 30m) released in April 2020, as the most accurate available global DEM currently incorporated in GEE. The ALOSWorld3D 30 m DEM (AW3D30; version 3.1) was developed based on millions of images acquired by a panchromatic optical sensor (PRISM) onboard the Advanced Land Observing Satellite (ALOS) (Takaku, et al., 2020). Studies that have compared different DEM products have shown good accuracy for AW3D30 (Jain, et al., 2018; Courty, et al., 2019), which is outperformed by the newer 30-m Copernicus DEM (GLO-30) publicly available from 2021 (Purinton & Bookhagen 2021). However, since Copernicus DEM is not incorporated in GEE, it was not considered in this study. Also, four different indices have been included in the datasets (Table 1, namely, NDVI (Normalized difference vegetation index), NDWI (Normalized difference water index), UI (Urban index) and KBRI (Karst bare-rock index). Twelve different datasets have been investigated in this study to classify the land cover of North Macedonia. The details about the datasets are given in the results section.

Comparing the results of the datasets will indicate the influence of the radar data over the optical data in land cover classification. Also, the influence of the investigated data over every class will be discussed.

The classification was done over seven classes; anthropogenic, cropland, pastures, grassland, forest, barren land, and water. The division of the croplands to summer and winter croplands was necessary during the data collection as some of the croplands were vegetated, and some were bare. However, to have a single cropland class, the two cropland classes were considered a single cropland class. For every class, 100 training points were selected. The classification in GEE was done using the SVM (Support Vector Machine) classifier. After the classification, 100 points per class were used for validation. Overall accuracy and kappa were calculated for all classes, and producer and user accuracy were calculated for every class. The results were validated with Sentinel – 2 satellite imagery as reference data. Details about the methodology can be seen in Figure 2.

To further evaluate the results, we compare two of the most successful GEE outputs with the Corine Land Cover (CLC) dataset to reveal the correspondence between land cover categories of the CLC and the categories defined with our procedure. CLC datasets are widely used in land change monitoring and related applications (Feranec, et al., 2016). These datasets were distributed by the European Environment Agency and then by the Copernicus Land Monitoring Service (Leinenkugel, et al., 2019). We used the most up-to-date CLC2018 dataset based on 2017 and 2018 satellite images (mainly interpreted from Sentinel-2 images) over North Macedonia.

3. RESULTS

3.1. Classification results

The results of the statistical analyses are presented in Table 2 and 3. In Table 2 the overall accuracy and the kappa have been given, while in Table 3 the user and producer accuracy for every class have been presented.

The first dataset used in this study contains the all of the Sentinel-2 bands from the summer and the winter period (26 bands). The results of the second dataset were the higher in comparison with the first datasets. Sentinel – 2 satellite imagery performed with 83% OA, and 0.81 kappa. The first dataset gave best results in the Water and Forest classes, and lower results in the remaining classes. The class Barren land was the only class below 75% accuracy.

Table 1. Spectral indices used in the investigation.

	Index	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
4	KBRI	SWIR-1, NIR	B11, B8	B11-B8/20x sqrt(B11+B8)

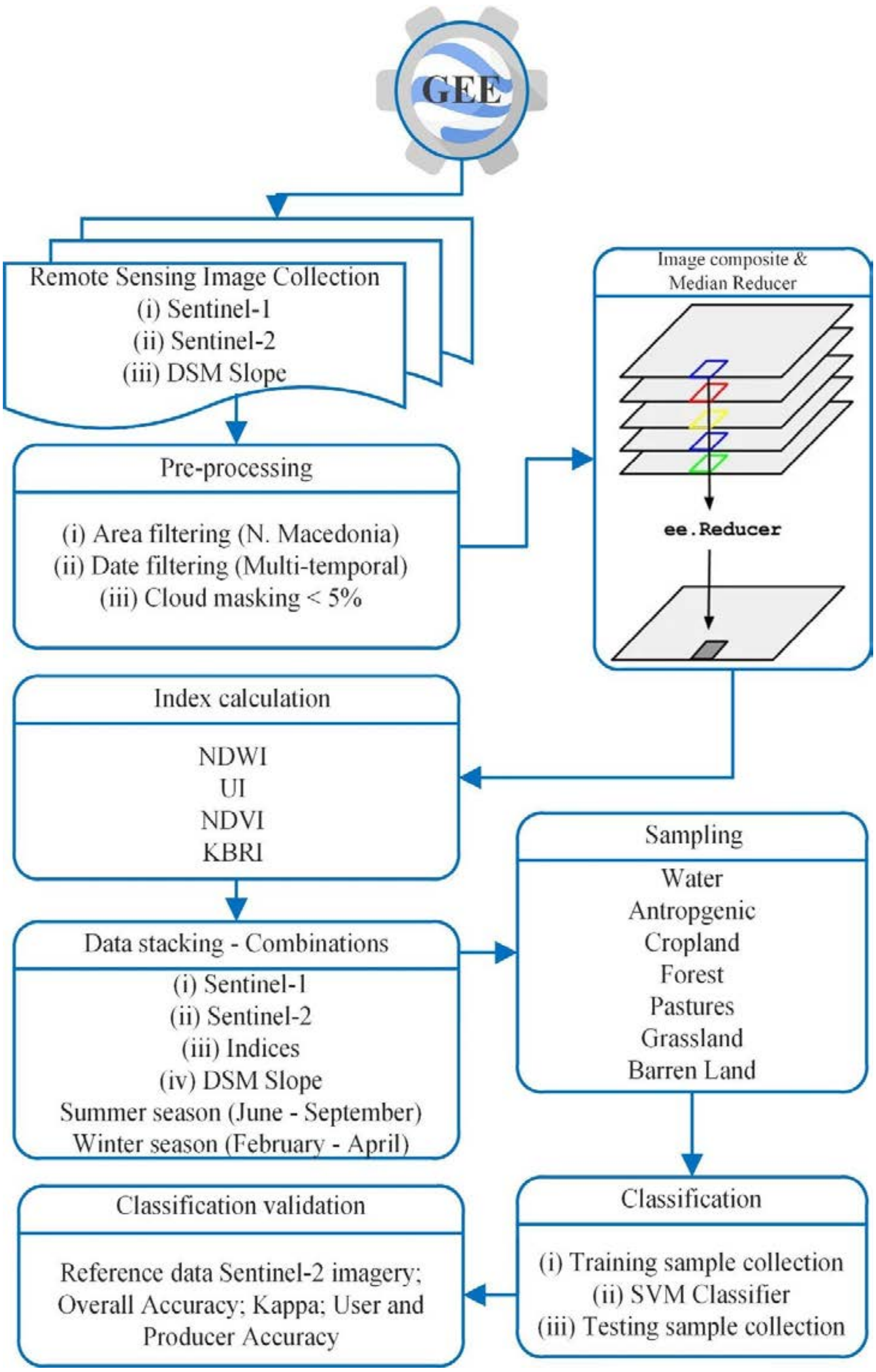

Figure 2. Flowchart of the used methodology.

The second dataset used in this study contains the all of the Sentinel-2 bands from the summer period. The results of the first dataset were the lowest in comparison with the other datasets with 85% OA, and 0.82 kappa. The second dataset slightly improved the results of all classes. The addition of VV band from Sentinel-1 from the summer period (third dataset) significantly improved the results of the Barren Land class. On the other hand, VH band was slightly effective then VV in the Urban, Pastures, and Barren Land classes. With addition of the both Sentinel-1 bands, VV and VH (fifth dataset), the results did not improve from the third dataset. Changing the date of the image collection from Sentinel-1 from summer to winter-spring period (sixth dataset), improved the accuracy of the Anthropogenic class. However, combining both Sentinel-1 and Sentinel-2 summer and winter images (30 bands) did not improve the classification, but the results of the Barren class were significantly lower.

Table 2. Overall accuracy and kappa statistics of the investigated datasets.

	DataSet	OA	Observed Kappa	Lower Limit	Upper Limit
1	S2s	0.83	0.81	0.77	0.85
2	S2s + S2w	0.85	0.82	0.79	0.86
3	S2s + S2w + S1(VV)s	0.85	0.83	0.78	0.87
4	S2s + S2w + S1(VH)s	0.86	0.84	0.81	0.88
5	S2s + S2w + S1(VH + VV)s	0.85	0.83	0.8	0.87
6	S2s + S2w + S1(VH + VV)w	0.86	0.83	0.8	0.87
7	S2s + S2w + S1(VH + VV)w + S1(VH + VV)s	0.85	0.83	0.8	0.87
8	S2s + S2w + S1(VH + VV)w + NDVIs	0.84	0.8	0.76	0.84
9	S2s + S2w + S1(VH + VV)w + NDVIs + NDWIs + Uis + KBRIs	0.86	0.83	0.79	0.88
10	S2s + S2w + S1(VH + VV)w + KBRIs	0.86	0.83	0.79	0.88
11	**S2s + S2w + S1(VH + VV)w + DSM**	**0.87**	0.86	0.82	0.89
12	**S2s + S2w + S1(VH + VV)w + DSM + slope**	**0.87**	**0.87**	**0.84**	**0.89**

* kappa with Linear Weighting
* Values were significant at an alpha of 0.05.
* Standard Error for all datasets was 0.02.
* + does not represent mathematical expression, but addition of data, s stands for summer, while w for winter data.

Table 3. User and producer accuracy for the individual classes using the investigated datasets.

Class	Water	Urban	Forest	Grassland	Pastures	Croplands	Bare Land
Dataset	UA/PA						
1	100/96	73/82	94/93	91/78	76/85	75/73	44/58
2	100/96	75/88	94/96	96/92	78/66	77/89	56/49
3	100/96	75/93	94/96	96/92	77/65	77/89	66/50
4	100/97	78/93	94/96	96/92	77/76	77/78	66/51
5	100/96	74/93	94/96	96/92	78/77	77/78	66/50
6	100/97	78/92	94/96	96/92	78/77	78/78	63/53
7	100/97	78/93	94/93	96/92	78/77	78/74	53/52
8	100/97	71/85	94/96	96/92	80/77	78/73	35/37
9	100/97	78/88	94/96	96/92	78/77	78/78	56/51
10	100/97	77/89	94/96	96/92	78/77	78/78	56/50
11	100/97	78/90	**97/98**	**98/98**	**82/74**	**80/80**	**60/60**
12	**100/98**	**79/92**	**97/98**	**98/98**	81/74	**80/80**	60/56

Having concluded that the best results of the combination of Sentinel-1 and Sentinel-2 can be produced with summer Sentinel-2 and summer and winter Sentinel-1 data, we decided to continue and try to improve the results from the six dataset different data, starting with the NDVI. While the results of separate classes all except Barren Land were the highest compared to the previously investigated data, the Barren Land showed the lowest results within this dataset (35/37%, UA/PA). Adding all of the considered indices (ninth dataset) improved the accuracy of the Barren Land class over 50%. The overall accuracy of this dataset is 86% with 0.83 kappa value. Wanting to investigate the influence of the KBRI over the Barren Land class, the tenth dataset has been constructed by adding KBRI to the sixth dataset, however, the results were not significantly changed in comparison with the previous dataset where all four the indices were added, but were higher than the dataset with the use of only one index, the NDVI.

As the study area is complex, DEM and Slope data have been considered to the datasets. Although the addition of DSM did significantly improve the overall classification results, this was not the case for the Barren Land class (60%). The addition of the slope data was slightly effective in the Water and Anthropogenic class. The results have been visually presented in Figures 3 and 4.

As the randomly added points do not represent the whole area, visual comparison was made in addition to the statistical analysis. It was noticed than in the results, some of the classes were misclassified to other land cover classes. For example, the mountains with no vegetation rocks were generally misclassified as urban areas. Also, shrubs were classified as forest. This is due to the class's limitation. The seven appointed classes are main classes of the land cover in the study area, North Macedonia, while classes such as rocks and shrubs are minor classes, and adding them as a separate class may give less accurate results.

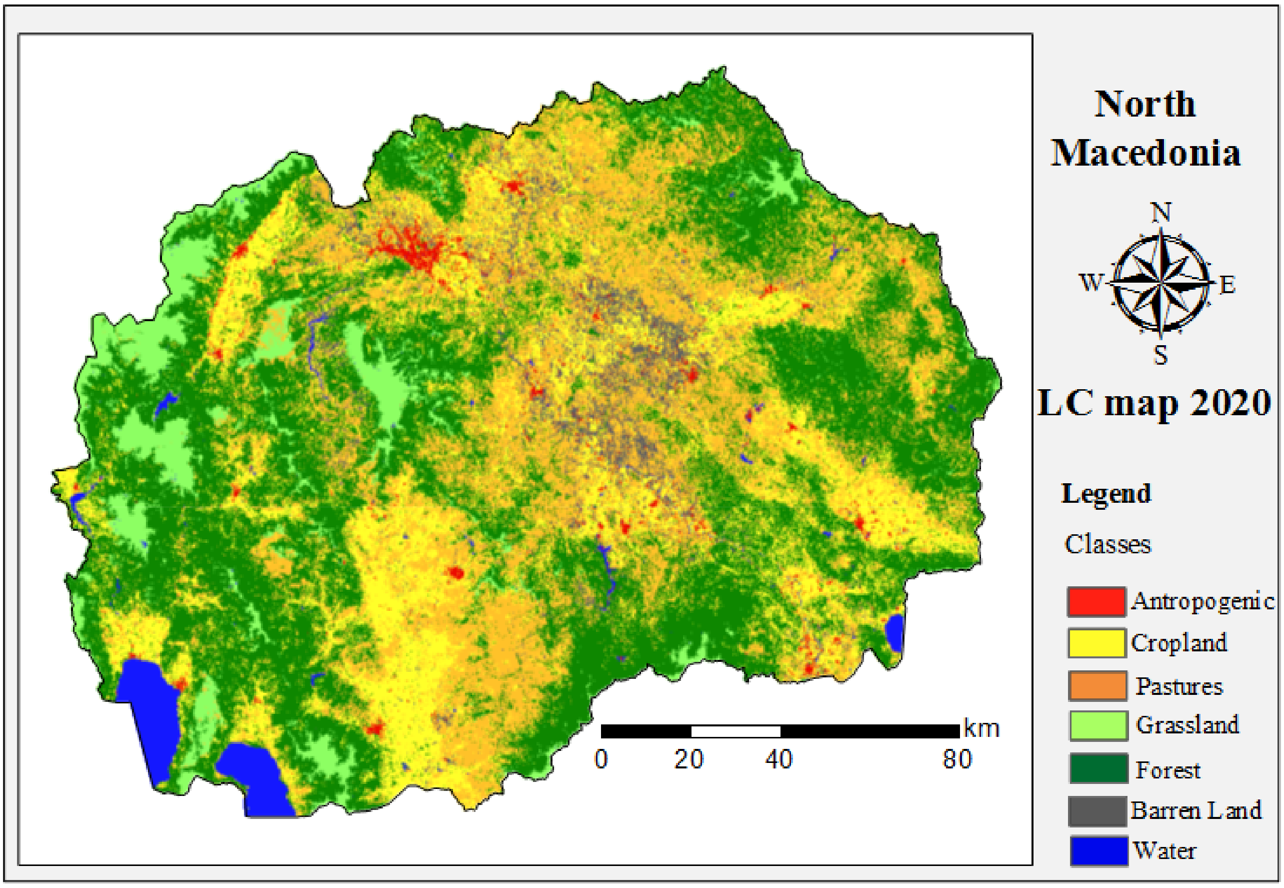

Figure 3. Classification results using dataset #12.

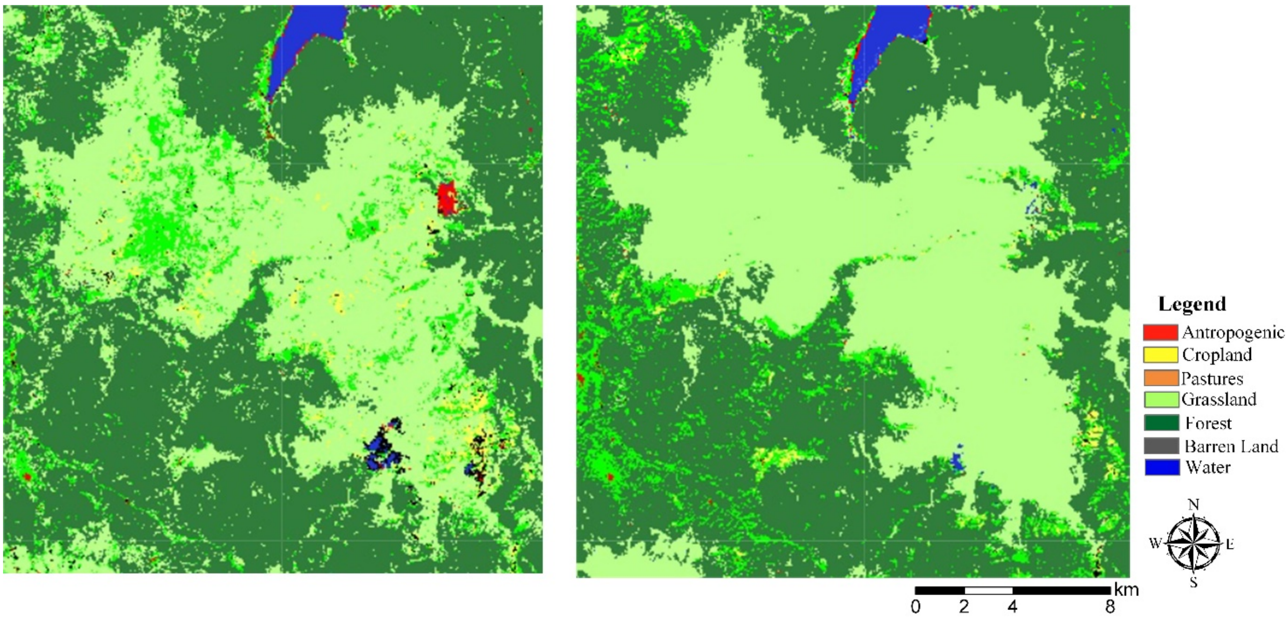

Figure 4. Improvement in the Grassland class. Result comparison between dataset 1 (left), and dataset 5 (right).

3.2. CLC comparison

For the proper comparisons, CLC-2018 Level 2 classification was grouped into the investigated classes, and the results are shown in Table 4. First, Transitional woodland and shrub class was not considered in the comparison as the structure of the class is mixed and complex, containing different kinds of vegetation. Aside of that, there is high correspondence of the CLC categories with the results obtained in GEE, especially in regard to artificial areas, croplands, grasslands, and water bodies area (in %

Table 4. Comparison of the obtained results (GEE) with CLC2018 as the % of the total country area including the reclassified categories of the transitional woodland and shrubs (CLC2018b).

Category	CLC2018	Tran*.%	CLC2018b	GEE	Diff. %	Diff.%
Artificial	1.80	0.01	**1.82**	**1.60**	0.20	0.22
Croplands	20.95	1.74	**22.69**	**21.57**	-0.62	1.12
Pastures	16.56	**6.61**	**23.17**	24.41	-7.85	-1.24
Grassl	7.87	4.23	12.11	**6.43**	1.44	**5.68**
Forest	32.13	**4.97**	**37.10**	40.38	-8.25	**-3.28**
Water	2.20	0.00	**2.20**	**2.16**	0.04	0.04
Bareland	0.79	0.11	0.91	3.44	-2.65	**-2.54**
Total	82.32*	17.68	100.00	100.00		

from the total country area). Significant differences in GEE classes are find for the category of pastures and forests (-7.85% and -8.25% respectively). This is mainly because the CLC category of transitional woodland and shrub (with area of 17.68% from the total). However, further analysis of the transitional woodland and shrub category, shows that most of this class represents pastures and forests in comparison with the GEE classes, and with reclassification, a better final corresponding is obtained. Considering that the CLC-2018 is based on the satellite images from 2017-2018, and the limited accuracy (Aune-Lundberg & Strand 2021) of the CLC dataset, the corresponding results are fairly good

4. DISCUSSION

Mapping and monitoring large areas, such as national land covers, is challenging in remote sensing. Motivated by this challenge and the need for timely update of national data, we examine different remote sensing datasets within the GEE platform in this study. Different datasets gave different results over different classes, as shown in other studies (Kaplan & Avdan 2019). Overall, two datasets consisting of multitemporal satellite data (both summer and winter) and the addition of radar data from winter, with a combination of DEM and slope, resulted in the highest overall accuracy. Both datasets gave similar results. However, the addition of the data slopes slightly improved the overall classification.

The water class`s accuracy was not affected by any of the datasets, and it gave the best results among all classes. The water class was followed by the grassland class, where the accuracy was significantly improved by adding multitemporal data from winter period. This is due to the fact that in winter, the high grasslands are covered with snow, and their spectral characteristics are easy to be separated from the other classes (Fig. 4). From Figure 4, it can be seen that the Pastures class was only affected by the elevation and slope data, which slightly improved the results in comparison with the other datasets.

The other classes were affected by the low accuracy of the barren land class. Pastures, Croplands, and Anthropogenic classes were misclassified as barren land. The barren land class was strongly positively affected by the Sentinel-1 data. However, the addition of vegetation indices negatively affected the accuracy.

The studies on mapping national land cover using satellite imagery are limited. In order to determine the land cover changes on the national level, most countries develop a national land cover database using middle-spatial-resolution satellite imagery (Yang, et al., 2018). Similar studies have been conducted for Buthan (Gilani, et al., 2015), United States (Xian, et al., 2009, Jin, et al., 2019), Jordan (Jawarneh and Biradar 2017). The overall accuracy of similar studies ranges 83% – 89%, which is similar to the results in this study. However, none of the mentioned studies have been made within GEE. A land cover of Iran (Ghorbanian, et al., 2020) has been made in GEE. However, the number of classes is different from the one used in this paper, as Iran's area and characterization is different from the study area in this paper. Also, one of the main objectives of this paper was to investigate the optimal dataset for the main classes over North Macedonia.

5. CONCLUSION

In this study, different datasets have been investigated for a national land cover map using middle-resolution satellite imagery (Sentinel) within the GEE platform. The medium resolution of the used images offers essential data for national land cover classification. The results of the investigated sets showed that adding different data, especially multitemporal satellite data, can have a significant positive effect on both overall and single class accuracy. The results are significant as the paper investigates a large-scale study area. The results can be useful in supporting national and sub-national decision-making for natural resource management planning, combining the data with population statistics, and other relevant data. Also, one of the main objectives of this paper was to investigate the optimal dataset for the main classes over the Republic of North Macedonia. For future studies, the number of the classes can be increased. For example, the Forest class can be re-classified to deciduous and evergreen, water to water bodies and wetlands, anthropogenic areas, urban, industrial, etc.

Funding information: N/A

Software: All the analyzes and classifications were made in GEE. After the classification, the results were exported in tiff file, and the maps were produced in ArcMap.

Data Availability Statement: The data that support the findings of this study are available on request from the corresponding author.

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