Contribution of Sentinel 2 images spectral bands for mapping forest land cover: Application to Tbeynia site, Jendouba, Tunisia

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1 Abstract

Many previous researches have already shown the advantages of Sentinel2 (S2) optical images for land-cover classification especially in agriculture. This work focuses on the contribution of a single data Sentinel2 multispectral image in classifying forest crops. The potential of S2 spectral bands, especially the red edge bands will be assessed deriving 33 vegetation indexes dedicated to S2 images.
A manual feature selection results are compared to an automatic feature selection based on iterative backward feature elimination approach using random forest classifier. Both combinations were used with a maximum likelihood classifier.
This study presents a first experience in Tunisia, on Tbeinya Forest Site in the West Northern of Tunisia. The overall accuracy based on solely spectral information reached about 80.95% while the incorporation of red edge information increased the classification accuracy to 91.5% (+10.55%).

Keywords

Pixel-based classification, Sentinel 2A, Forestry, Land cover mapping, Feature selection.

2 Introduction

During the last years, an increasing number of earth observation satellites have been set in orbit with ever increasing spatial, temporal, spectral, and radiometric resolutions. Since 2015, the European Space Agency (ESA) is spending notable effort to put in operation a new generation of advanced Earth-observation satellites, the Sentinel constellation. In particular, the Sentinel-2 a Multispectral Instrument (MSI) imaging sensor with 13 spectral bands and provides high frequency acquisition every 5 days. In literature various works assessed the importance of S2 images for forest areas mapping [7,11] or forest change detection [13] but these works didn't assess the importance of dedicated S2 vegetation indexes to land cover mapping. Other previous works assessed the importance of derived indices for forestry but on rapideye [9] or Pleiades images[1].
In this research, Seven land cover classes were considered: Coniferous forest, Hardwood forest, Shrubland, Urban, Bare area, Water, and Agriculture. Our objective is to evaluate the potential of the new S2 spectral bands around the red-edge domain in vegetation discrimination and land cover production using feature selection methods.

3 Data and study area

3.1 Data and processing

A Sentinel-2A MSI image (processing level 1C) acquired on 13 February 2017 was downloaded from the ESA Sentinels Scientific Data Hub. The processing level 1C includes radiometric and geometric corrections with sub-pixel accuracy [5]. It covers the VNIR/SWIR spectral region in 13 bands (Fig. 1) and incorporates three new spectral bands in the red-edge (RE) domain which are centered at 705, 740 and 783 nm [8].

3.2 Study area

The study area is located in the North-Western Tunisia forest area of Tbeinya, Jendouba, located between 36º43.81'N on bottom, 36º43.81'N on top, and 8º42.33'E on left, 8º53.92'E on right, it has a total area of 123km^2 (Fig. 2). The North-West of Tunisia, known as the Kroumirie eco-region, is characterized by its unique forests and mountains landscape where elevation ranges between 250 m and 950 m above sea. The climate of the study area is mostly humid and is characterized by high rainfall ranges from 1200 to 1300 mm/year. The soil is in general very acidic and developed on Oligocene ferruginous. Land covers present in this area are mainly divided into three strata: tree stratum (Cork oak, maritime pines, pinyon pines, Zeen oak), shrub stratum (lentisk, myrtle, rosemary, narrow-leaved mock privet, tree heath, the Strawberry Tree), herbaceous stratum (white clover, starwort, plantain).

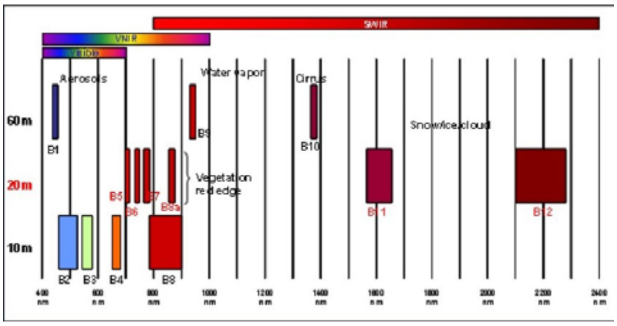

Fig. 1: Sentinel-2 spectral bands [10]

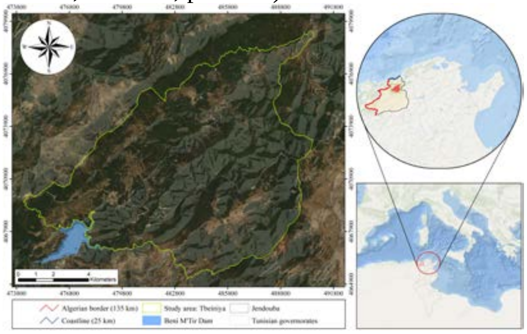

Fig. 2: Location of study area [6]

4 Methodology

Figure 3 illustrates the proposed methodology.

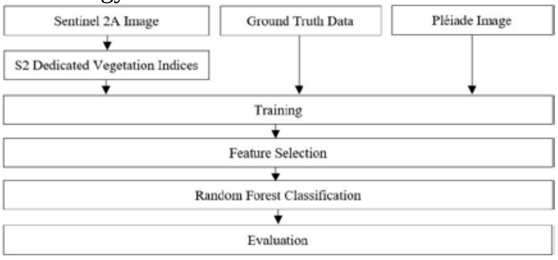

Fig. 3: Flowchart for image classification using pixel-based approach.

The overall bands spatial resolutions were set to 10 m using the nearest neighbour resampling. Thirty-three spectral indices were computed. Table 1 includes the spectral indices based on the VIS-NIR domain, while Table 2 includes the spectral indices based on the RE channel.

Table 1: Reference spectral indices

NDVI	Normalized Difference Vegetation Index
NDVI-GREEN	Normalized Difference Vegetation Index - Green
GRVI1	Green-red Vegetation Index
GNDVI	Green Normalized Difference Vegetation Index
EVI	Enhanced Vegetation Index
EVI2	Enhanced Vegetation Index 2
DVI	Difference Vegetation Index
PSSR	Pigment Specific Simple Ratio
NDII	Normalized Difference 819/1649
CRI1	Carotenoid Reflectance Index 1
PSRI-NIR	Plant Senescence Reflectance Index - Near Infra-red
SAVI	Soil Adjusted Vegetation Index
MSAVI2	Second Modified Soil Adjusted Vegetation Index
LAI-SAVI	Leaf Area Index - Soil Adjusted Vegetation Index
NDBI	Derived Built-up Land Image
MNDWI	Modified Normalized Difference Water Index
NDWI	Normalized Difference Water Index

Table 2: Red-edge spectral indices

NDre1	Normalized Difference red-edge 1
NDre2	Normalized Difference red-edge 2
NDVIre1	Normalized Difference Vegetation Index red-edge 1
NDVIre1n	Normalized Difference Vegetation Index red-edge 1 narrow
NDVIre2	Normalized Difference Vegetation Index red-edge 2
NDVIre2n	Normalized Difference Vegetation Index red-edge 2 narrow
NDVIre3	Normalized Difference Vegetation Index red-edge 3
NDVIre3n	Normalized Difference Vegetation Index red-edge 3 narrow
IRECI	Inverted Red-Edge Chlorophyll Index
CIre	Chlorophyll Index red-edge
MSRre	Modified Simple Ratio red-edge
MSRren	Modified Simple Ratio red-edge narrow
NDI45	Normalized Difference Infrared Index
CRI2	Carotenoid Reflectance Index 2
PSRI	Plant Senescence Reflectance Index
RE-NDWI	Red Edge - Normalized Difference Water Index

Data for training and validation were collected respectively from forest inventory data and visual interpretation of very high spatial resolution images Pléiade.

The maximum likelihood technique was used for supervised classification. As for feature selection, two approaches were tested: a manual and an automatic iterative backward elimination selection by Random Forests [12].

5 Results and discussion

5.1 Manual band selection

Different band combinations are manually selected and used in the classification to investigate if the use of Red-edge spectral indices improves the classification accuracy (Table 3).

Table 3: Best manual band combinations

Combinations	Sentinel bands	Ref spectral indices	Red edge spectral indices	overall accuracy	kappa
8 bands S2	×			80.95%	0.77
GRVI1	×	×		87.30%	0.85
GRVI1 NDVIre2 MSRre	×	×	×	91.53%	0.9

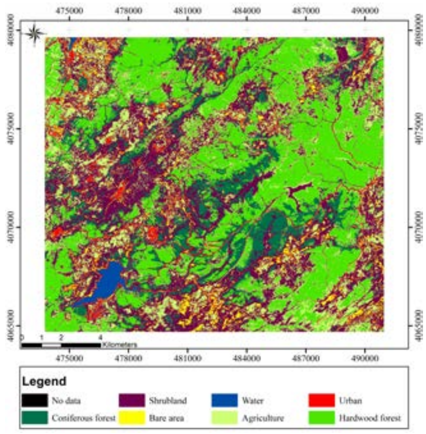

Fig. 4: Forest land cover map of Tbeynia.

The overall accuracy of the classification produced by the pixel-based method using only spectral information was 80.95%, with Kappa statistic of 0.77, whereas the overall accuracy and Kappa statistic of the classification produced by the pixel-based method using red edge information were 91.53% and 0.90, respectively (Table 3), confirming the contribution of red-edge channels.

5.2 Automatic band selection

Random Forest (RF) is a tree-based ensemble classifier that uses the bagging technique to create new training sets. RF employs recursive partitioning to divide the data into many homogenous subsets called regression trees (ntree) and then averages the results of all trees. One additional feature of Random Forest is its ability to evaluate the importance of each input feature by the internal OOB (Out-Of-Bag) estimates [2]. In the present work, band selection was processed by a wrapper approach based on iterative backward elimination of features using random Forests[12](Package *varSelRF* in R)

The authors showed its robustness to noise and redundant features. It was than successfully used in remote sensing on urban areas [3,4].
The feature subset with the highest accuracy is selected.

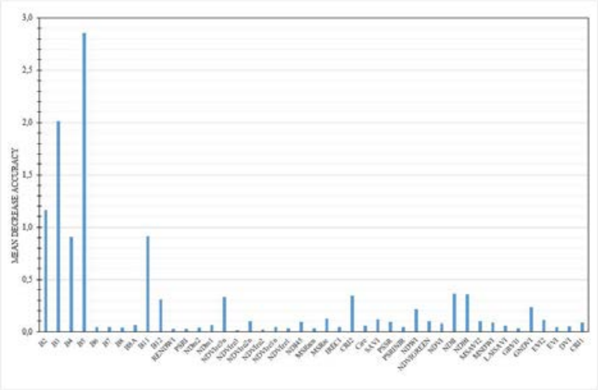

Fig. 5: Variable importance by mean decrease accuracy for the first *VarSelRF* iteration.

Table 4: Selected bands using random Forests (varSelRF).

S2 Bands	B11, B12, B2, B3, B4, B5, B6, B8, B8A.
Reference spectral indices	CRI1, DVI, EVI, EVI2, GNDVI, MSAVI2, NDVI, NDVIGREEN, NDWI, PSRINIR, PSSR, SAVI.
Red edge spectral indices	CRI2, IRECI, MSRre, MSRren, NDI45, NDre1, NDre2, NDVIre1n, NDVIre2n.

To select the most relevant features, Random Forests is iteratively fit. Aside from classification, Random Forests provide measures of variable importance based on the permutation importance measure which was shown to be a reliable indicator (Fig. 5) [4]. At each iteration, a fraction of the least important features is eliminated and a new forest is built. By default, the fraction is fixed to 0.3. A combination was formed with 30 selected bands (Table 5). The accuracy of Random Forest is 89.95 % with Kappa statistic of 0.88. Comparing to the previous results (Table 3), the combined set has reached higher accuracy (+9%) with Random Forest than using only spectral information.

Conclusion

Due to the significant spectral heterogeneity and spectral confusion with other land cover classes at 10 m resolution, the forest land cover extraction using spectral data from sentinel 2A series data alone is a challenging task.
This paper proposes a method that combines Red-edge spectral indices and reference spectral indices in forest land cover classification (Fig. 4). The experimental results indicated that the inclusion of the Red-edge spectral indices outperformed the use of spectral data alone. In particular, the combination of GRVI1, NDVIre2 and MSRre with Sentinel-2 bands increases in the kappa coefficient from 0.77 to 0.90 compared to all other data combinations. The methodology will be applied to another Tunisian forest area called Sidi Zid in Zaghouane Region to confirm these first conclusions.

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