Sentinel 2 Image Scene Classification: A Comparison Between Bands and Spectral Indices

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Abstract

Given the continuous increase in the global population, the food manufacturers are advocated to either intensify the use of cropland or expand the farmland, making land cover and land usage dynamics mapping vital in the area of remote sensing. In this regard, identifying and classifying a high-resolution satellite imagery scene is a prime challenge. Several approaches have been proposed either by using static rule-based thresholds (with limitation of diversity) or neural network (with data-dependent limitations). This paper adopts an inductive approach to build classifiers from spectral reflectances, comparing usefulness of the various spectral indices to raw bands information. More specifically, it considers Sentinel 2 data for six classes Scene Classification (Water, Shadow, Cirrus, Cloud, Snow and Other). The experimental results show that using raw bands performs equally well, claiming that raw bands information can be used as a replacement of the spectral indices.

1 Introduction

The integrated use of satellite and ground-based observations is widely recognized as the most feasible approach for the measurement and long-term monitoring of terrestrial variables needed by scientific investigators and decision-makers around the world. In particular, Earth observation applications are making use of the unique, synoptic capabilities of an ever-increasing number of satellite remote sensing imaging systems. A key challenge is to ensure that such measurements yield self-consistent and accurate geophysical and biophysical data over time and space, even though the measurements are made with a variety of different sensors under different observational conditions. In such Earth observations techniques, optical satellites play a major role, and one such satellite is Sentinel-2. Sentinel-2 is part of the Earth observation mission from the Copernicus Programme and systematically acquires optical imagery at a high spatial resolution over land and water bodies using 13 sensors (also known as bands). The band value (also known as surface reflectance) is defined as the fraction of incoming solar radiation reflected from Earth's surface for a specific incident or viewing case.

According to a study by the International Centre for Integrated Mountain Development (ICIMOD) [9], band ratios are used to remove undesirable effects on recorded radiances (e.g. variable illumination) since topographic slope and aspect, shadows or seasonal changes can cause differences in brightness values between identical surface materials. As a result, the interpreter's ability to correctly identify surface material in an image is hampered. The band ratio transformations can be used to mitigate these effects. Aside from that, the Spectral Indices can be used to model, predict, and track land change processes.

Between the last two decades (1999–2009 and 2009–2019), Polykretis *et al* [6] examined the impact of various spectral indices in detecting land cover changes on the Greek island of Crete. To do so, five index combinations were provided, resulting in a kappa index of 0.60–0.69 and overall accuracy of 0.86–0.96. According to Dixit *et al* [2], the visible, NIR, and SWIR bands are the most commonly used reflectance and absorptive properties for developing snow/ice cover mapping; based on these, they proposed the Snow Water Index (SWI) with an overall accuracy of 0.93 and kappa statistics of 0.94. Separately, according to Zhai *et al* [1], the majority of existing cloud/shadow detection methods are based on visible and infrared spectral band configurations with working mechanisms relatively complex and computationally complicated; as such, they proposed an unified cloud/shadow detection algorithm based on spectral indices with a cloud detection accuracy of 0.98 and a cloud shadow detection accuracy of 0.84.

Referring to all the previous work and approaches, this paper reports simulation study and encapsulating the below-mentioned contributions:

1. Focusing on the problem of optical satellite image scene classification;
2. Classification using property-specific spectral indexes and Sentinel-2 raw bands;
3. A comparison of results concerning the feature space and classification accuracy;
4. Claiming "raw bands do have impacts over overall classification" and can be used as a replacement to the spectral indices.

The rest of the document is structured as follows: Section 2 details the dataset acquisition and spectral indexes used for the study, Section 3 presents the experimental setup and obtained results and Section 4 summarises the findings and states future steps.

2 Materials

2.1 Dataset Acquisition

Raiyaini *et al* [7] published an extended database of manually labeled Sentinel-2 spectra with 13 bands values. The database consists of images acquired over the entire globe and comprises 6.6 million points (exactly 6,628,478 points) classified into one of the six classes (Water, Shadow, Cirrus, Cloud, Snow, Other). Table 1 describes the database.

Header	Description
Product ID	78 character string
Coordinates	Latitude and longitude
Bands/Features	Band 1 to 12 and 8A (13 values)
Scene	Class (Water, Shadow, Cirrus, Cloud, Snow, Other)

Table 1: Extended Sentinel-2 Database with Surface Reflectances [7].

Besides the dataset, 3 different classifier models were also published using Random Forest (RF), Extra Trees (ET) and Decision Trees (DT) (trained over default values) along with the corresponding training (50 products/images with 5,716,330 observations) and test sets (10 images with 912,148 observations). The micro-F1 [5] performance measured over the test set is presented in Table 2.

Class	RF	ET	DT	Support
Water	0.90	0.90	0.83	117010
Shadow	0.80	0.81	0.67	155715
Cloud	0.82	0.81	0.72	134315
Cirrus	0.71	0.73	0.59	175988
Snow	0.88	0.88	0.82	154751
Other	0.80	0.83	0.71	174369
micro-F1	0.81	0.82	0.72	912148

Table 2: micro-F1 performance using Sentinel-2 13 Bands values.

2.2 Spectral Indices

Spectral indices are combinations of the pixel values from two or more spectral bands in a multispectral image. Spectral indices are designed to highlight pixels showing the relative abundance or lack of a land-cover type of interest in an image. From the indexes available in the literature, a subset was chosen specifically to identify each of the specific six classes. These are enlisted in Table 3.

Class	Spectral Indices	Reference
Water	Normalized Difference Water Index (NDWI) Sentinel-2 Water Index (SWI)	[3]
Shadow	Shadow Enhancement Index (SEI) Saturation Value Different Index (SVDI)	[8]
Cloud	Cloud Index (CI) Brightness Index (BI)	[1] [4]
Cirrus	Band 10	Sentinel-2
Snow	Normalized Difference Snow Index (NDSI) Normalized Difference Snow Ice Index (NDSII) S3 Snow Water Index (SWI)	[2]
Other	Bare Soil Index (BSI)	[6]

Table 3: Classes and Spectral Indices.

3 Experimental setup & Results

All the 3 classifiers RF, ET, and DT were trained using the default algorithm parameters parameters. The evaluation of these models (using the information from Table 3, namely 11 Indexes plus Band 10) was done using micro-F1 (F1) score [5].

Table 4 presents the results using only the spectral indices and them along with the 13 bands information. All the 3 models give similar results, having higher F1 values for Water (90%) and lower F1 values for Shadow (75%). Adding the 13 bands values to the spectral indexes does not seem to improve the results. Moreover, by comparing the results obtained using the Bands (Table 2) and the Spectral Indices (Table 4) it is possible to conclude that the use of indexes does not improve the classifier.

	Spectral Indices			13 Bands + Spectral Indices		
Class	**RF**	**ET**	**DT**	**RF**	**ET**	**DT**
Water	0.90	0.90	0.82	0.89	0.89	0.81
Shadow	0.75	0.75	0.62	0.76	0.76	0.66
Cloud	0.81	0.82	0.70	0.80	0.81	0.71
Cirrus	0.78	0.79	0.63	0.74	0.76	0.62
Snow	0.87	0.87	0.81	0.88	0.87	0.83
Other	0.79	0.80	0.66	0.81	0.81	0.71
micro-F1	0.81	0.82	0.70	0.81	0.81	0.72

Table 4: micro-F1 with Spectral Indices and 13 Bands.

By analyzing the indexes presented in Table 3, one notices that the Spectral indices models only use information from 10 bands (not included bands - 6/7/8A) of the available 13 bands of Sentinel-2. Having this in mind, classifiers were built using raw information from those 10 bands only. The obtained results are presented in Table 5 and show that there is no significant difference on classifiers performance (1% more for Random Forest and Extra Tress). Thus, we can definitively conclude that there is no need to calculate and use spectral indices instead of raw bands for Sentinel 2 Image Scene Classification (at least for studied six classes: Water, Shadow, Cirrus, Cloud, Snow and Other.)

Class	RF	ET	DT
Water	0.89	0.89	0.81
Shadow	0.76	0.76	0.66
Cloud	0.80	0.81	0.71
Cirrus	0.74	0.76	0.62
Snow	0.88	0.87	0.83
Other	0.81	0.81	0.71
micro-F1	0.81	0.81	0.72

Table 5: micro-F1 using 10 Bands (not included bands - 6/7/8A).

To further investigate, models were built using raw data only from the 10 bands used by the 12 spectral indices referred in Table 3. The obtained results, presented in Table 5, show that the performance is not decreased when compared to the models that use all 13 bands. Furthermore, looking at individual F1 values, one can see that the maximum difference of model performance over any two classes is 15%, 13%, and 21% for RF, ET, and DT respectively. (For example, with RF, Cirrus has a "worst" micro-F1 of 0.74% and Water has a "best" micro-F1 of 0.89%, generating the maximum model performance difference of 15%). Comparing to Table 4 (Spectral Indices) results, where the maximum difference is 15%, 15%, and 20% for RF, ET, and DT respectively. Apart from this, for a single class (Water and Cirrus), both the approaches (raw bands and Spectral Indices) have the maximum F1-score around 89%-90% with minimum value around 62%-63%; showcasing an equivalent performance.

4 Conclusion

Through our experiments, we were able to provide a study that proves that raw bands of Sentinel-2 can be used as features instead of using different Spectral Indices. This can be verified from the results presented on Tables 4 and 5. Moreover, when bands and spectral indices are used together no improvement is verified (Table 4).

As future work, the authors of the paper would like to incorporate radar information from Sentinel 1 and verify their impact over Water, Shadow, Cirrus, Cloud, and Snow detection.

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