**Intercontinental Geoinformation Days**

igd.mersin.edu.tr

# Investigation of the effects of vegetation indices derived from UAV-based RGB imagery on land cover classification accuracy

**Muhammed Yusuf Öztürk*[1], İsmail Çölkesen[1]**

[1]*Gebze Technical University, Engineering Faculty, Department of Geomatics Engineering, Kocaeli, Turkey*

**Keywords**
LULC
UAV
Phantom 4 pro
RGB indices
Random forest

**ABSTRACT**

The production of land use / land cover (LULC) maps using UAV images obtained by RGB cameras that offer high spatial resolution has recently increased. Vegetation indexes (VIs) are one of the important tools used to increase the limited spectral information of the UAV image in pixel-based classification. The aim of this study is to examine the effect of RGB-based VIs, called green leaf index (GLI), red-green-blue vegetation index (RGBVI) and triangular greenness index (TGI) which are frequently used in the literature, on the accuracy of thematic maps produced from UAV images. For this purpose, five different combinations comprising of RGB bands and VIs were formed. It was observed that the use of vegetation indices together with RGB bands increases the overall accuracy (OA) of the produced thematic maps in all cases. Additionally, the highest OA value was calculated from the thematic map produced using Dataset-5. The classification result of Dataset-4 consisting of RGB band and TGI, showed superior performance compared to Dataset-2 and Dataset-3, and a 0.1% difference was calculated between Dataset-5. Thus, this study has shown that the TGI index is more effective compared to GLI and RGBVI for thematic maps produced from a three-band UAV image.

## 1. INTRODUCTION

Gathering accurate and reliable land use and land cover (LULC) information about the Earth's surface is a prerequisite for the success of a wide range of applications carried out at local, regional and global scales (Colkesen and Ertekin 2020). Recent developments in the field of unmanned aerial vehicle (UAV) technologies and imaging sensor systems have led to a renewed interest in extracting required information about surface objects from high spatial resolution UAV images (Yao et al. 2019). Image classification is one of the effective ways for extracting meaningful information from the remotely sensed imagery and the main output of the process is thematic maps depicting LULC types of a given study area widely-used as main data source for land related studies.

Supervised pixel-based image classification that one of the popular classification techniques to produce LULC maps in the literature (Huth et al. 2012; Tehrany et al. 2014; Goldblatt et al. 2018). Pixel-based image classification is generally based on the assignment of the image pixels into pre-defined LULC classes using their digital numbers. The RGB-UAV-based platform is an alternative and low-cost aerial platform technology ensuring the capturing surface images at very high spatial and temporal resolutions. Although the RGB cameras are able to provide high spatial information about the surface, their spectral resolutions are limited for distinguishing spectrally similar pixels (Yang et al. 2020). In order to overcome this limitation, the auxiliary data such as vegetation index, texture features and principal components have been widely used in image classification process. Combinations of various vegetation indexes (VIs) and RGB bands are frequently used in the literature to improve the classification performance of RGB-UAV images (Sumesh et al. 2021). Many vegetation indexes based on different sensor specifications been developed since the launch of the first remote sensing satellite, Landsat. They are widely used for quantitative and qualitative evaluations of vegetation information (Xue and Su 2017).

The main purpose of this study is to analyse the effect of the use of RGB based vegetation indices on the classification accuracy. For this purpose, three popular vegetation indexes, namely green leaf index (GLI), red-green-blue vegetation index (RGBVI) and triangular

* **Corresponding Author**

*(m.ozturk2020@gtu.edu.tr) ORCID ID 0000 – 0001 – 6459 – 9356
(icolkesen@gtu.edu.tr) ORCID ID 0000 – 0001 – 9670 – 3023

**Cite this study**

Ozturk M Y & Colkesen I (2021). Investigation of the effects of vegetation indices derived from UAV-based RGB imagery on land cover classification accuracy. 2nd Intercontinental Geoinformation Days (IGD), 135-138, Mersin, Turkey

greenness index (TGI) were utilized. Classification results were evaluated using overall accuracy (OA), Kappa coefficient and F-score measurements.

## 2. STUDY AREA and DATASET

The study area covers the north-eastern part of Gebze technical University located in Gebze district of Kocaeli province. Within the boundaries of the study area, there are faculty buildings, other man-made structures, green vegetation and bare soil areas as shown in Figure 1. Study area consists of six main LULC classes: concrete including gray stone floor, road, gray and white roofs, forest class including deciduous trees, coniferous trees and grass, parkour including bicycle road, basketball and tennis court, shadow, soil and tile roof.

In this study, UAV-based high-resolution remote images were acquired by Phantom 4 Pro V2.0 drone equipped with a 20 MP RGB camera on 24 September 2020. "Pix4Dmapper" application was preferred for flight planning. The images collected from 80 m flight altitude with 80% forward overlap and %70 side overlap, resulting in ground sampling distance 2.3 cm. Agisoft PhotoScan software was used to process the obtained images and as a result, an 8-bit ortho-mosaic with a spatial resolution of 5 cm was produced.

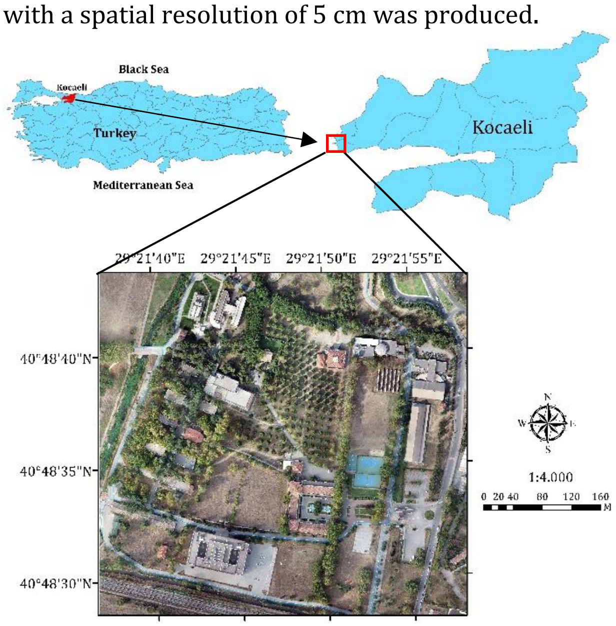


**Figure 1.** Study area

## 3. METHODOLOGY

In this study, the effect of the use of RGB based GLI, RGBVI and TGI vegetation indexes on the accuracy of thematic maps produced from UAV image were analyzed. For this purpose, training and validation pixels for each LULC classes were collected over UAV images. Random forest, one of the fast and robust ensemble learning algorithm, was utilized to construct classification model using training samples. Then, the data sets consisting of the combinations of UAV images and vegetation indexes were classified with the constructed classification model and thematic maps were produced. In order to conduct the accuracy assessment, OA, kappa coefficient and F-scores were calculated.

### 3.1. Random Forest (RF)

The RF algorithm, proposed by (Breiman 2001), is popular ensemble learning algorithm for produce thematic maps derived from pixel-based image classification procedure due to its robust and efficient performance (Nitze et al. 2015; Fu et al. 2017). RF utilizes multiple decision trees in that each tree trained using bootstrapped samples of input dataset for construct classification model and majority voting rule is applied to make the final prediction and simple majority rule is applied for final prediction (Colkesen and Kavzoglu 2017). Based on bootstrapping strategy, decision trees are trained using two thirds of input dataset and the remaining one-third of input dataset is utilized to evaluate the classification error (Tonbul et al. 2020). The results of each tree are aggregated, and final model output is composed.

### 3.2. Vegetation Indexes (VIs)

VIs are obtained from the mathematical equations applied to two or more spectral bands to emphasize the vegetation characteristics. Various VIs based on RGB bands have been developed. In this study, GLI, RGBVI and TGI indexes, frequently used in various studies in the literature, were evaluated.

GLI was developed for determinate wheat cover areas using 8-bit RGB camera. GLI values take values between -1 and +1. Negative values correspond to soil and lifeless features, whereas positive values correspond to green vegetation (Louhaichi et al. 2001).

$$GLI = \frac{2 \times Green - Red - Blue}{2 \times Green + Red + Blue} \tag{1}$$

RGBVI was developed for biomass estimation. It can be described as the normalized difference of the squared green spectral band and the product of blue×red bands (Bendig et al. 2015).

$$RGBVI = \frac{Green^2 - Blue \times Red}{Green^2 + Blue \times Red} \tag{2}$$

TGI, based on red, green and blue spectral bands, is sensitive to chlorophyll content at leaf and canopy (Hunt et al. 2011). Since this index uses the bands in the visible region, chlorophyll content can be estimated with TGI on images acquired from UAVs equipped with an RGB camera.

$$TGI = Green - 0.39 \times Red - 0.61 \times Blue \tag{3}$$

### 3.3. Accuracy Assessment

In this study, OA and kappa coefficient calculated from confusion matrix were utilized to evaluate the accuracy of the thematic maps produced. Additionally, F-score values were calculated using harmonic mean of the user's accuracy and the producer's accuracy for analysis class-based measurements.

## 4. RESULTS

In this study, the effect of VIs on pixel based LULC classification of RGB image acquired by UAV was investigated. To achieve this purpose, three VIs (i.e., GLI, RGBVI and TGI) were calculated using equation given in section 3.2 and stretched to 0-255 pixel values. In order to construct classification model and evaluate accuracies of thematic maps, 5,000 pixels as training and 1,000 pixels as validation for each LULC class were selected on UAV image. Five datasets were created using RGB bands and different combination of VIs for evaluate classification results: Dataset-1 includes only RGB band, Dataset-2 consists of RGB bands and GLI, Dataset-3 consists of RGB bands and RGBVI, Dataset-4 consists of RGB bands and TGI and Dataset-5 corresponds to combination of RGB bands and all Vis considered. All datasets were classified with RF classifier and thematic maps were produced. Accuracy assessment results of each thematic map were given in Table 1. It should be noted that all classification process was done in R software.

**Table 1.** Accuracy assessment of thematic maps

| LULC Class | F-scores | | | | |
|---|---|---|---|---|---|
| | Dat-1 | Dat-2 | Dat-3 | Dat-4 | Dat-5 |
| Concrete | 91.3 | 91.8 | 92.4 | 92.4 | 94.6 |
| Forest | 97.5 | 97.0 | 96.9 | 97.2 | 96.7 |
| Parkour | 98.5 | 99.4 | 99.5 | 99.7 | 99.2 |
| Shadow | 89.2 | 90.4 | 90.0 | 90.5 | 89.9 |
| Soil | 79.5 | 81.2 | 79.5 | 80.0 | 80.0 |
| Tile roof | 84.5 | 85.8 | 85.9 | 87.2 | 87.3 |
| OA | 90.0 | 90.8 | 90.6 | 91.1 | 91.2 |
| Kappa | 0.88 | 0.89 | 0.89 | 0.89 | 0.89 |

As could be seen from table, the use of datasets consisting of VIs with UAV image increased the OA values in all case compared to use of only Dataset-1. In other words, the highest OA value was estimated as 91.2% (Kappa value of 0.89) from Dataset-5, whereas the lowest OA value was observed as 90.0% (Kappa value of 0.89) from Dataset-1. On the other hand, the OA value calculated from Dataset-4 was very close to the OA value of Dataset-5 (i.e., OA value of %91.1 and Kappa value of 0.89). Additionally, Dataset-2 and Dataset-3 were produced similar result with respect to the estimated OA values. These results showed that the TGI index performed more effectively in improving the classification results compared to other indexes. The results of class-based measurements (i.e., F-score) indicated that, when the highest F-score values were estimated for parkour class, the worst F-score values calculated for soil class. The reason why the class-level accuracy of the soil class is lowest may be that various substances that are mixed into the soil and have similar spectral properties with other LULC classes can be easily distinguished in the images obtained with the UAV. On the other hand, the addition of the aforementioned VIs to RGB bands increased the class-based accuracy of concrete and tile roof about 3%. Moreover, in thematic maps produced by classifying the data sets consisting of vegetation indexes and UAV images, the F-score values of forest class decreased.

Thematic maps produced by the RF classifier for each dataset were given in the Figure 2. According to visual analysis results, similar thematic maps were produced for each dataset. It is seen that the soil class is mixed with shadow and concrete classes. This visual result is consistent with the F-score values of the soil class. In addition, it is seen that the noise generated in the concrete class is reduced in the thematic map produced using Dataset-5 compared to other thematic maps.

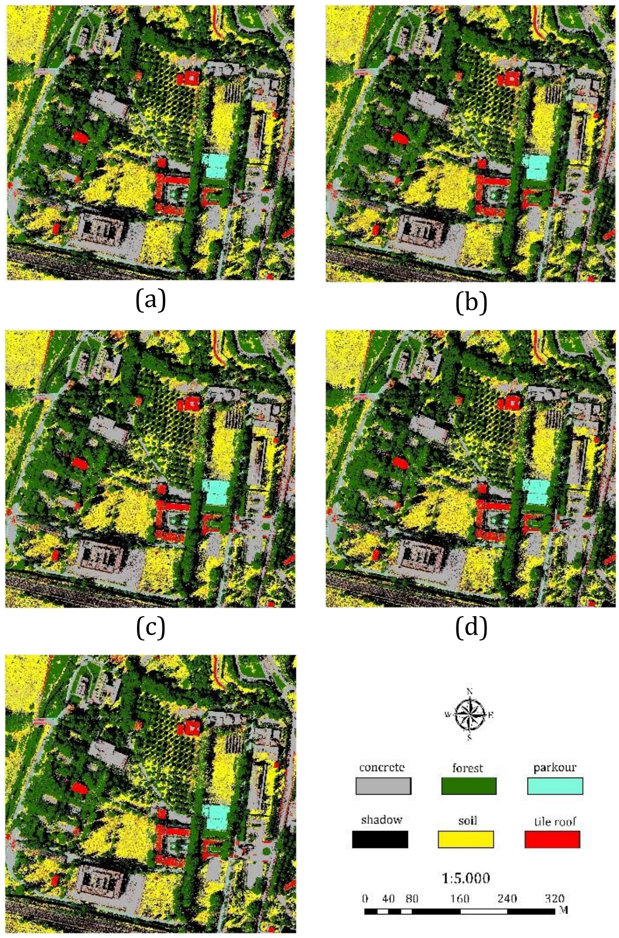


**Figure 2.** Thematic maps of (a) dataset-1, (b) dataset-2, (c) dataset-3, (d) dataset-4, (e) dataset-5

## 5. DISCUSSION AND CONCLUSION

In recent years, there has been an increasing interest in the production of thematic maps with UAV images using machine learning algorithms. Vegetation indices used to highlight the features of the Earth's provide a great advantage in increasing the spectral information in the pixel-based classification of RGB images. In this context, the effects of GLI, RGBVI and TGI indices used in various studies in the literature, on the thematic maps produced using UAV image with limited band number were evaluated. For this purpose, five datasets containing different combination of VI and UAV image was created and thematic maps of each dataset were produced by random forest classifier.

The following conclusions can be made by analyzing the classification results obtained. The accuracy of the thematic maps produced using VIs and RGB bands were increased about 1% compared to the thematic map accuracy derived from the classification of visible spectral bands only. This could be probably results of the increase in spectral information by means of vegetation indices usage. On the other hand, the estimated OA value in the dataset using the TGI index (i.e., Dataset-4) outperformed the results calculated from datasets using other indices (i.e., Dataset-2 and Dataset-3). Moreover, there is only 0.1% difference in OA between Dataset-4 and Dataset-5. According to these results, it can be said that TGI is the most effective index in classifying three-band UAV images for considered dataset used in this study.

**REFERENCES**

Bendig J, Yu K, Aasen H, Bolten A, Bennertz S, Broscheit, J, Gnyp M L & Bareth G (2015). Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley. International Journal of Applied Earth Observation and Geoinformation, 39, 79–87.

Breiman L (2001). Random Forests. In Machine Learning. 5–32, Chapman and Hall/CRC. https://doi.org/10.1023/A:1010933404324

Colkesen I & Ertekin O H (2020). Performance analysis of advanced decision forest algorithms in hyperspectral image classification. Photogrammetric Engineering & Remote Sensing, 86(9), 571–580.

Colkesen Ismail & Kavzoglu T (2017). The use of logistic model tree (LMT) for pixel- and object-based classifications using high-resolution WorldView-2 imagery. Geocarto International, 32(1), 71–86. https://doi.org/10.1080/10106049.2015.1128486

Fu B, Wang Y, Campbell A, Li Y, Zhang B, Yin S, Xing Z & Jin X (2017). Comparison of object-based and pixel-based Random Forest algorithm for wetland vegetation mapping using high spatial resolution GF-1 and SAR data. Ecological Indicators, 73, 105–117. https://doi.org/10.1016/j.ecolind.2016.09.029

Goldblatt R, Stuhlmacher M F, Tellman B, Clinton N, Hanson G, Georgescu M, Wang C, Serrano-Candela F, Khandelwal A K, Cheng W H & Balling R C (2018). Using Landsat and nighttime lights for supervised pixel-based image classification of urban land cover. Remote Sensing of Environment, 205(February 2017), 253–275.

Hunt E R, Daughtry C S T, Eitel J U H & Long D S (2011). Remote sensing leaf chlorophyll content using a visible band index. Agronomy Journal, 103(4), 1090–1099. https://doi.org/10.2134/agronj2010.0395

Huth J, Kuenzer C, Wehrmann T, Gebhardt S, Tuan V Q & Dech S (2012). Land cover and land use classification with TWOPAC: Towards automated processing for pixel- and object-based image classification. Remote Sensing, 4(9), 2530–2553. https://doi.org/10.3390/rs4092530

Louhaichi M, Borman M M & Johnson D E (2001). Spatially located platform and aerial photography for documentation of grazing impacts on wheat. Geocarto International, 16(1), 65–70.

Nitze I, Barrett B & Cawkwell F (2015). Temporal optimisation of image acquisition for land cover classification with Random Forest and MODIS time-series. International Journal of Applied Earth Observation and Geoinformation, 34(1), 136–146. https://doi.org/10.1016/j.jag.2014.08.001

Sumesh K C, Ninsawat S & Som-ard J (2021). Integration of RGB-based vegetation index, crop surface model and object-based image analysis approach for sugarcane yield estimation using unmanned aerial vehicle. Computers and Electronics in Agriculture, 180(July 2020), 105903.

Tehrany M S, Pradhan B & Jebuv M N (2014). A comparative assessment between object and pixel-based classification approaches for land use/land cover mapping using SPOT 5 imagery. Geocarto International, 29(4), 351–369.

Tonbul H, Colkesen I & Kavzoglu T (2020). Classification of poplar trees with object-based ensemble learning algorithms using Sentinel-2A imagery. Journal of Geodetic Science, 10(1), 14–22. https://doi.org/10.1515/jogs-2020-0003

Xue J & Su B (2017). Significant remote sensing vegetation indices: A review of developments and applications. Journal of Sensors, 2017, 1–17. https://doi.org/10.1155/2017/1353691

Yao H, Qin R & Chen X (2019). Unmanned aerial vehicle for remote sensing applications—A review. Remote Sensing, 11(12), 1443.

Jang G, Kim J, Yu J K, Kim H J, Kim Y, Kim D W & Chung Y S (2020). Cost-effective unmanned aerial vehicle (UAV) platform for field plant breeding application. Remote Sensing, 12(6), 998.