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LULC mapping accuracy enhancement through multispectral UAV imagery with nDSM integration

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Abstract

The requirement of land use and land cover (LULC) maps as a base in large variety of applications make necessary to improve low-cost and high accuracy production methods. Unmanned Aerial Vehicles (UAVs) present cost-effective alternatives for generating LULC maps when compared to traditional methods and stand out with advanced multispectral sensing technologies. This study aims to assess the multi-class LULC mapping performance of multispectral UAVs and enhance it through the integration of auxiliary data sources, in 11-classes study area. Specifically, high-accuracy normalized digital surface model (nDSM) was generated and incorporated into the classification process to enhance overall mapping accuracy. In addition, three different datasets were created with the various combinations of 68 features consisting of texture, spectral and geometric features of the segments. Object-based classification was performed with the Random Forest (RF) machine learning algorithm for all datasets, and dataset 3 (D3), consists of spectral bands + indexes + texture + geometry + nDSM, exhibited the most successful performance with an overall accuracy of 94.16%. The results clearly demonstrated that MS UAV data has high performance in LULC mapping, and NDSM increased the classification accuracy by 5%.

Introduction

Accurate land use and land cover (LULC) mapping is a pivotal first step in extracting information about many urban and environmental change-oriented studies [1-2]. Traditional space-borne and airborne sensing technologies face constraints in achieving high accuracy values for LULC map production, primarily attributed to their inherent limitations in spatial and temporal resolution. At this point, Unmanned Aerial Vehicle (UAV) is an alternative technology with providing periodic and high-resolution imagery from low flight altitudes [3-5]. In UAV-based LULC mapping approaches, two different cameras are preferable as red-green-blue (RGB) single band and multispectral (MS). RGB camera-equipped UAVs are insufficient for scientific studies such as the analyses of changes occurring in agricultural areas due to limited spectral ranges [6]. With the developments in MS UAV technologies, easier detection of spectral signatures reflected from objects has increased the performance in classification studies and encouraged research in this direction [7].

This study aims to investigate the performance of MS UAVs in LULC object-based classification using random forest machine learning algorithm, to produce and integrate auxiliary data to improve this performance. In this context, high quality nDSM, having same grid interval with classified MS orthomosaic, was generated and integrated into the classification processes. In addition, different indices, texture, and geometry were added as other auxiliary data to determine their effects on the classification accuracy. Accordingly, three datasets were created by using different combinations of the auxiliary data and their contributions were analyzed by statistical and visual approaches.

Study Area and Materials

The study area is located in the northern part of Gebze Technical University Campus in the Gebze district of Kocaeli province of Türkiye (Figure 1). The study area, which stands out with its many natural and man-made structures, has a very rich class diversity for LULC mapping. In the context of LULC mapping, the study delineates 11 different classes, encompassing red roof, concrete roof, road, bicycle path, dense vegetation, low vegetation, thorn trees, broad-leaved trees, soil, water, and shadowed areas. Aerial photos were collected by using DJI Phantom 4 MS UAV equipped with FC6360 camera includes six imaging bands as RGB composite, blue, green, red, red edge, near-infrared. This UAV is equipped with a real-time kinematic (RTK) GNSS receiver, but for the purpose of analyzing the positional accuracy of the study, eight polycarbonate ground control points (GCPs) were installed homogeneously in the study area. The 3D coordinate measurements of all GCPs were conducted using the CHC i80 GNSS receiver. In addition, the MAPIR reflectance panel V2 was used for spectral calibration with the aim of achieving maximum radiometric accuracy.

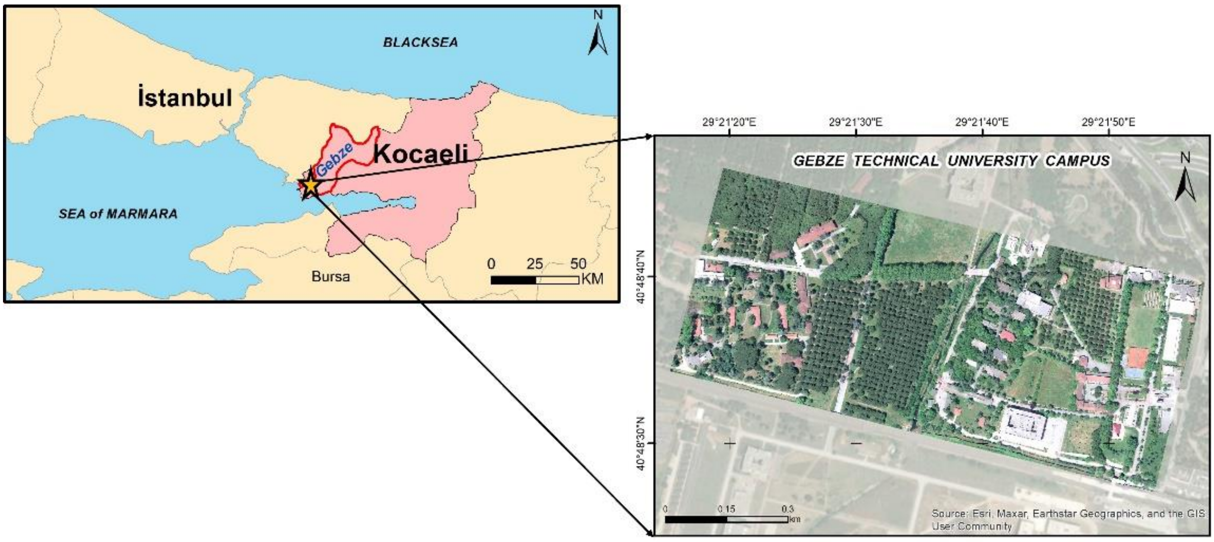

Figure 1. The northern part of Gebze Technical University campus

Methodology

This research encompasses a comprehensive methodology, starting with on-site field reconnaissance, establishing GCPs, acquiring aerial images, generating precise photogrammetric products, conducting LULC mapping, and culminating accuracy analysis of the final outputs. Considering the surface area and safe flight altitude of the study district, images were taken from a flight altitude of 110 m with a ground sampling distance (GSD) of 5.5 cm. To optimize the sensitivity of reflection detection during data collection, a 90° camera angle was chosen, and polygonal flight was performed. Furthermore, data acquisition was carried out during midday hours, leveraging ideal illumination conditions to attain the utmost radiometric accuracy in our detection processes. Subsequent to image acquisition, radiometrically calibrated high accuracy orthomosaic, digital surface model (DSM), and digital terrain model (DTM) production was generated and nDSM production was completed by taking the differential of DSM and DTM [8]. Prior to integrating for classification, the nDSM and orthomosaic data, a 10 cm co-resolution was used in the production to achieve maximum coherence, especially at the roof edges.

The multiresolution segmentation method was employed to generate the necessary segments for subsequent feature extraction. The Estimation of Scale Parameter 2 plug-in was then utilized to determine the optimal scale parameter for the segmentation process. The object-based classification approach was realized using random forest classification algorithm which is a tree-based ensemble machine learning algorithm. It is worth noting that the random forest algorithm is widely used in accurate LULC mapping purposes [9]. Optimal parameter determination (number of estimators, maximum depth, and minimum sample split) of the random forest algorithm was carried out with the GridSearchCV optimization algorithm. To train the model, representative samples were collected for each class within the study area, and subsequently, object-based classification was conducted on three distinct datasets listed in Table 1.

Table 1. Datasets used for classification

Dataset	Features
D1	Spectral bands + Indices
D2	Spectral bands + Indices + Texture + Geometry
D3	Spectral bands + Indices + Texture + Geometry + nDSM

Results and Conclusion

As a result of the classification process, accuracy assessment analysis of LULC maps produced with D1, D2 and D3 datasets yielded overall accuracy of 89.10%, 89.49% and 94.16%, respectively. In this context, it has been discerned that texture and geometric features exert minimal influence on the classification results. While the classification with D1 and D2 datasets showed very similar results, the classification with D3, involving nDSM contributions, demonstrated the highest success. It has been determined that the advantage of high-accuracy elevation data provided by nDSM facilitates the distinction between concrete roofed structures and road class, and the F1 score of road class increases by 8.3% with the D3 dataset (Table 2). The used orthomosaic image and its LULC map produced with D3 dataset are given in Figure 2.

Table 2. Class-based F1 score (%) for three different datasets

Datasets	Concrete roof	Road	Shadow	Water	Bicycle path	Dense vegetation	Soil	Low vegetation	Broad leaved	Thorn tree	Red roof
D1	82.6	88.7	90.4	95.6	93.3	90.7	83.7	78.3	93.2	91.5	98.0
D2	82.6	**89.5**	89.7	95.9	93.6	91.5	82.9	79.3	93.6	92.1	98.0
D3	95.3	**97.8**	90.7	96.3	93.1	93.0	85.3	79.5	95.6	93.3	98.1

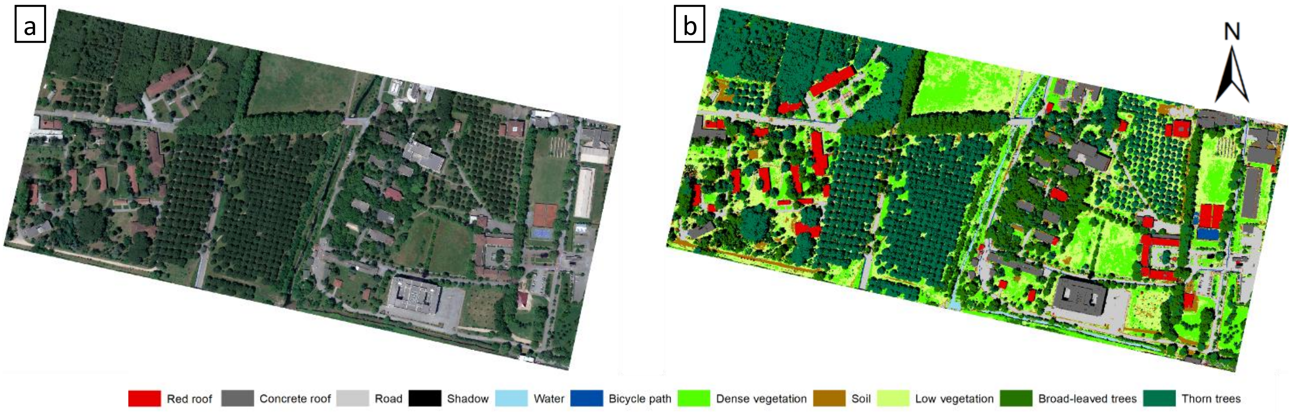

Figure 2. Radiometrically calibrated orthomosaic (a) and LULC thematic map (b)

The approach proposed in this study provided very satisfactory results and proved to be suitable for high-resolution data. Following through statistical and visual analyses, it has been conclusively established that UAVs equipped with MS sensors have yielded successful outcomes in the realm of LULC mapping.

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