Comparative study of Vegetation Indices for Machine Learning-Based Image Classification

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Abstract: Unmanned Aerial System (UAV), namely drone, is one of the aerial platforms, which used to monitor and mapping an agricultural sectors at large area. The platform equipped with some compact camera or sensors. The purpose of this research is some experiences related to analysis of multispectral data in case Botanical garden in Ulaanbaatar.

We use an unmanned aerial vehicle (UAV) with multispectral (visible, near infrared) sensors to determine the correlation of four agricultural land uses. Four vegetation indices the normalized difference vegetation index, NDVI; the Green normalized difference index, GNDI, and the soil-adjusted vegetation index, SAVI, chlorophyll red-edge index (CHL)) were applied to UAV imagery and a 3 m resolution to estimate vegetation indices through compare with three year frequency data. After that we use machine learning algorithms (K-Nearest Neighbor, Random Forest and Decision tree) to study the fusion of multispectral bands information and derived vegetation index for classification.

The results showed that: fusion of multispectral bands with vegetation indexes can improve machine learning-based classification accuracy if the vegetation indexes are properly selected.

Introduction

Soil is one of the dominant factors contributing towards the growth of agricultural crop. Different types of soil, such as clay, soft, silt, sandy and loam soils, have their own physical properties which structuring the nature of the soil [1]. The physical properties of soil such as moisture content, organic matter, color, and density, texture and pore space are different from each type of soil. Besides that, the physical properties of soil contribute to the crop healthiness covering the nutrients and water uptakes by the crops from the soil [2].

Currently, technology from remote sensing has been widely applied towards the management of crops around the world to monitor the growth and yield estimation. The energy that was absorbed and reflected by crop can be detected through the multispectral imagery which is transmitted through their spectral signature. UAV platform equipped with multispectral sensor is able to obtain the vegetation healthiness data at large area coverage in a shorter time [3]. Drone application can be one of the helpful technology for the planters to monitor the healthiness of their crops. On the other hands, orthophoto of spectral RGB and NIR images can be produce for the whole area of study. The orthophoto produced from RGB and NIR images can be uses to produce the Near Difference Vegetation Index (NDVI) to check the healthiness of the crop in the area. Based on the NDVI scale, the condition and healthiness of the crop can be detected and identified [4]. Multispectral imaging camera sensors on drones are widely used in agricultural as it provides fastest method for the planters to manage crops, soil, fertilizing, irrigation and many more [5]. Both visible and invisible images of crops and vegetation can be captured from multispectral camera remote sensing imaging technology, which provides the use of Green, Red, and Red-edge and Near-Infrared wavebands. An index of vegetation “greenness” can be identified by taking the ratio of red and near infrared bands from a remotely sensed image. Another way, NDVI is one of the methods to measure the health level of vegetation. NDVI for vegetation generally range from 0.3 to 0.8, with the larger values representing 'greener' surfaces. Bare soils range from about 0.2 - 0.3. When the value of NDVI is high, it is possible that is showing healthy vegetation, otherwise it is possibly showing of less or no vegetation.

While many studies used machine learning methods to build models based on spectral bands for ground classification [**5**], the nonlinear information contained in vegetation indexes has barely been fused into ground classification models. However, the unstructured information contained within vegetation indices may help with improving classification accuracy.

In this study, a UAV mounted with a five-band multispectral camera was used to measure an almond plantation. After the orthophoto was acquired, we first tested the classification of three surface types (tree, shadow, and soil) using different machine learning methods, namely KNN, Random forest, Decision Trees to determine which method obtained the best performance. Secondly, we developed a fusion pipeline incorporating both spectral bands and normalized vegetation indices into the machine learning process. Thirdly, we assessed the impact of fusing spectral bands and vegetation indexes on the performance of the machine learning models. Then, we comprehensively compared the results trained with vegetation indexes and determined the proper selection protocol for classification.

Study Area

We performed the measurements in the park of the Botanical Institute of the Mongolian Academy of Sciences located in Ulaanbaatar, Mongolia. The garden is responsible for research, education, enlightenment, cognition, and recreation, and is a major research center that cultivates, introduces, and protects rare and endangered plants in its research area. We carried out mapping work on a total area of 22.9 ha, which is 4-5 ha of shrub land. The park is home to 70 species of plants and about 20 species of trees and shrubs that are included in the annex to Mongolia's natural plant protection law.

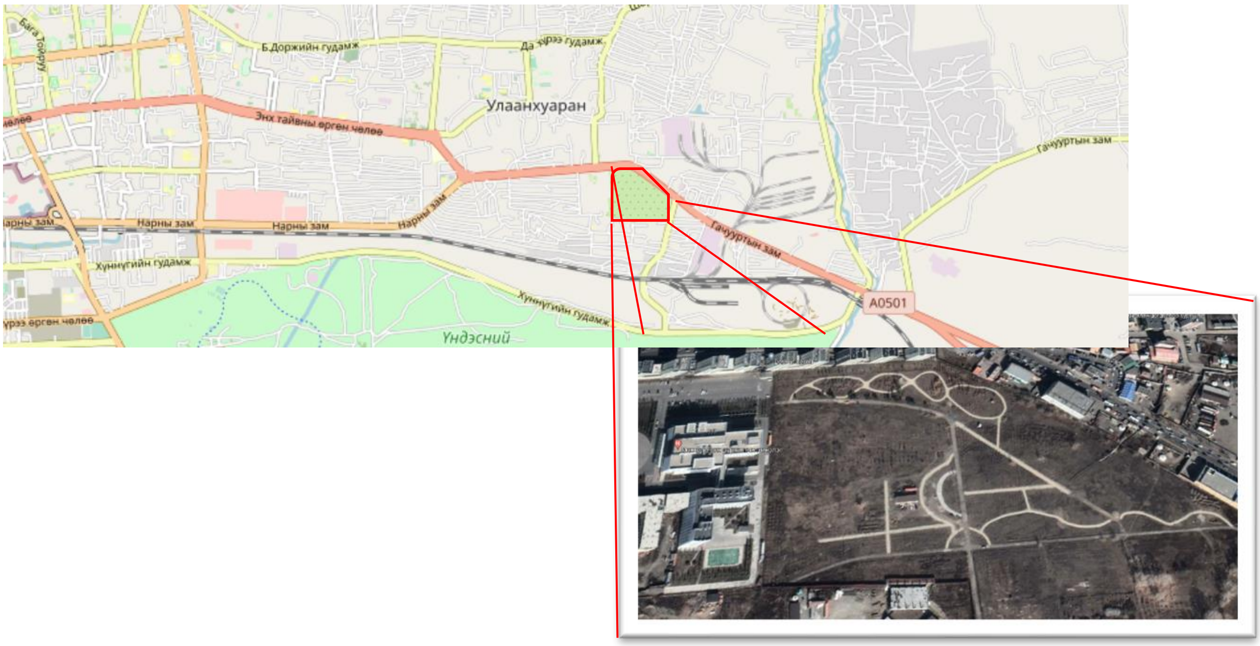


Figure 1. *Location of the study site in the Botanical garden*

Data collection

In this study, were compared 2020, 2021, 2022 years result within multispectral images were produced from the drone equipped with the multispectral imagery The multispectral data that collected from site were using DJI-Phantom 4 drone and Sentera multispectral double 4K sensor was used (Figure 2). The drone was flown at height 100m from the ground to cover all of the study area are in form of RedEdge, NIR and RGB images. A high side and forward overlap rate of 70% was adopted to assure high map quality. The experiment was carried out in mid-September.

Figure 2. Sentera Multispectral Double 4K additional camera

Table2. Sentera Multispectral Double 4K camera spectral bands width

Bands	**Width**
Blue	446nm x 60nm
Green	548nm x 45nm

Red	650nm x 70nm
Red edge	720nm x 40nm
Near Infrared (NIR)	840nm x 20nm

Methodology

The Normalized Difference Vegetation Index (NDVI) is a commonly used remote sensing technique that identifies vegetation and measures a plant's overall health. NDVI has been the standard for understanding plant health in the agriculture industry for many years. In the past, Near Infrared imagery has typically been captured by satellites or manned aircraft, but now drones are changing the game. Previously, it may have taken weeks or more to receive NDVI imagery from satellites. The most common in agriculture, characterizes the density of vegetation and allows farmers to assess germination, growth, the presence of weeds or diseases, as well as to predict the productivity of the fields. Index indicators are generated through satellite images of green mass, which absorbs electromagnetic waves in the visible red range and reflects them in the near infrared range [6]. The red region of the spectrum (0.62 - 0.75 μm) accounts for the maximum absorption of solar radiation by chlorophyll, and the near infrared zone (0.75 - 1.3 μm) has the maximum energy reflection by the leaf cell structure. That is, high photosynthetic activity leads to lower values of the reflection coefficients in the red region of the spectrum and large values in the near infrared region of the spectrum. The NDVI was calculated by using equation (1).

$$\text{NDVI}=\frac{NIR-Red}{NIR+Red} \qquad (1)$$

GNDVI is a modified version of the NDVI algorithm that combines Green and NIR light to better indicate the variation of chlorophyll content in the vegetation. It is similar to NDVI except that instead of the red spectrum it measures the green spectrum in the range from 0.54 to 0.57 microns [7]. This is an indicator of the photosynthetic activity of the vegetation cover; it is most often used in assessing the moisture content and nitrogen concentration in plant leaves according to multispectral data which do not have an extreme red channel. Compared to the NDVI index, it is more sensitive to chlorophyll concentration. It is used in assessing depressed and aged vegetation and calculated by equation (2).

$$\text{GNDVI}=\frac{NIR-Green}{NIR+Green} \qquad (2)$$

SAVI is used to correct Normalized Difference Vegetation Index (NDVI) for the influence of soil brightness in areas where vegetative cover is low [8]. Land Surface Reflectance-derived

SAVI is calculated as a ratio between the R and NIR values with a soil brightness correction factor (L) defined as 0.5 to accommodate most land cover types.

$$\text{SAVI}= \frac{NIR-Red}{NIR+Red+L}(1+L) \qquad (3)$$

L-correction factor (from 0.5 to 0.9)

In the NDVI, the difference between the near-infrared and red reflectances is divided by their sum. Data from vegetated areas will yield positive values for the NDVI due to high near-infrared and low red or visible reflectances. As the amount of green vegetation cover increases in pixels, NDVI increases in value up to nearly 1. In contrast, bare soil and rocks generally show similar reflectance in the near-infrared and red or visible, generating positive but lower NDVI values close to 0. The red or visible reflectance of clouds, shadows are larger than their near-infrared reflectance, so scenes containing these materials produce negative NDVIs.

K-NN is a type of instance-based learning, where the function is only approximated locally, and all computation is deferred until classification. A peculiarity of the K-NN algorithm is that it is sensitive to the local structure of the data. The best choice of k depends upon the data; generally, larger values of k reduces the effect of the noise on the classification, but make boundaries between classes less distinct. The special case where the type is predicted to be the class of the closest training sample is called the nearest neighbor algorithm.

Decision tree learning is a method commonly used in data mining. The goal is to create a model that predicts the value of a target variable based on several input variables.

Random forests or random decision forests are an ensemble learning method for classification, regression, and other tasks that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the types (classification) or mean prediction (regression) of the individual trees.

The idea of gradient boosting originated in Leo Breiman’s observation that boosting can be interpreted as an optimization algorithm on a suitable cost function. Jerome H. Friedman subsequently developed explicit regression gradient boosting algorithms.

Data Processing results

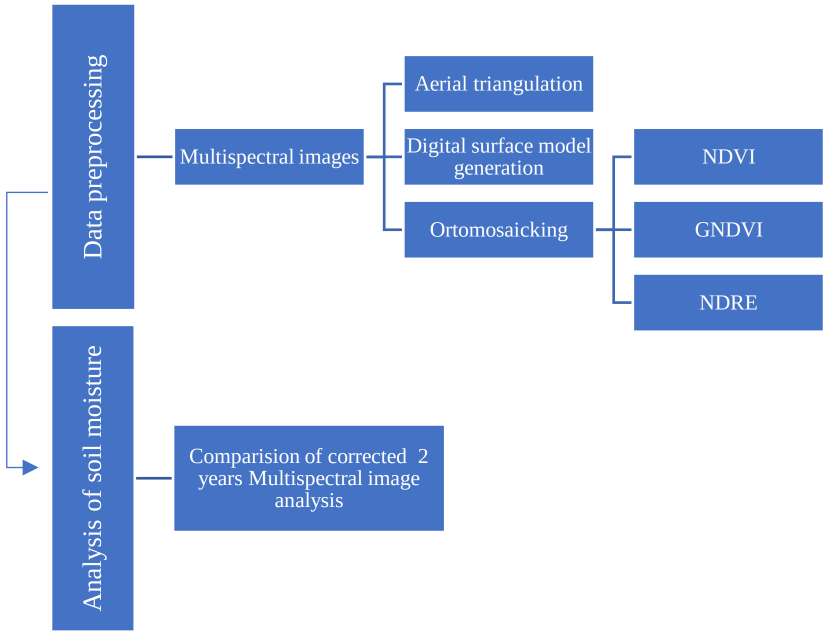


Figure 3. Flowchart of soil moisture evaluation steps.

To cover the entire study area, 177 images were captured for each of the five spectral bands in a first camera (GSD of 6.8 cm pixel−1). An RGB camera mounted in the UAV in a second camera allowed us to capture 177 images in the visible spectrum (24,144 × 23,700 pixels, and 0.017 m of GSD) with some overlap, which allowed us to elaborate a mosaic of orthorectified images resulting from the preprocessing operations (involving homographic corrections and stitching) upon the acquired images. The photogrammetric processing was performed using proprietary Agisoft photoScan professional software. The process follows three steps: (1) aerial triangulation; (2) digital surface model generation, and (3) orthomosaicking. The resulting orthomosaicked images have high resolutions and are accurate throughout consecutive images. Thus, they guarantee optimal performance of the subsequent classification analysis. After that, the data from the two flights were joined to manage, transform, and export the images (five different images, one for each channel) to a TIFF format. 177 images were calibrated and geolocated using 24,489 matches per calibrated image. In this way, the quality of the image content was evaluated to test its influence on the outcomes of the photogrammetric processing and vegetation indices.

Figure 4 shows Image overlap and camera location.

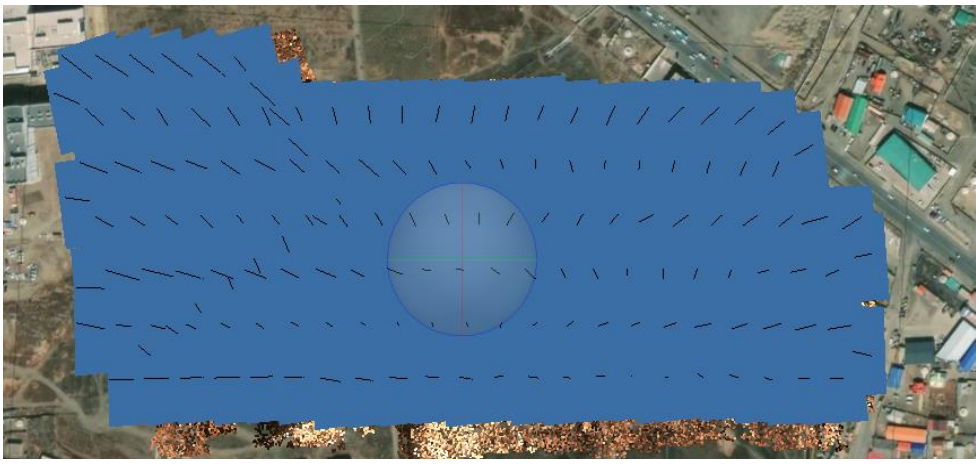


Figure 4. Preprocessing steps with Agisoft PhotoScan professional software for 239 RGB images: image overlap and camera location.

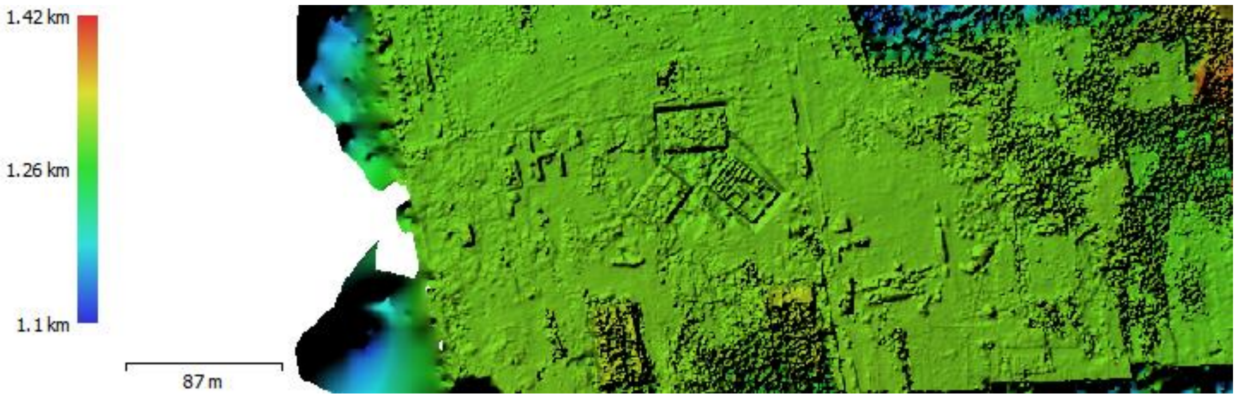


Figure 5. Sparse digital surface model (DSM) before densification obtained in the reprocessing process

Figure 5 shows the sparse digital surface model (DSM) before densification obtained in the previous process. Vegetation indices results The vegetation indices used to create vigour maps and to verify uniform growth of the crops were calculated using the raster calculator tool of ENVI 4.8, which was also used to build the maps. The reflectance images were obtained from their respective band indices which were procured from the preprocessing (orthorectification) performed with the Agisoft Photoscan professional software, as mentioned before. Each resulting image has a spatial resolution of 0.06839 m and shows pixels with reflectance value and other pixels with no data. As seen from the calculated NDVI but the GNDVI result shows more sensitive for vegetation covers in general. The SAVI result has confirmed the adequacy of SAVI vegetation index over the more popular NDVI in arid. The methodology adopted in this study shows quantitatively that at our study both SAVI and NDVI have comparable performance to detect vegetation cover. Additionally, the in-situ evaluation is required for the VI's results and need to investigate the correlation between other biophysical parameters such as biomass, soil or vegetal moisture etc.

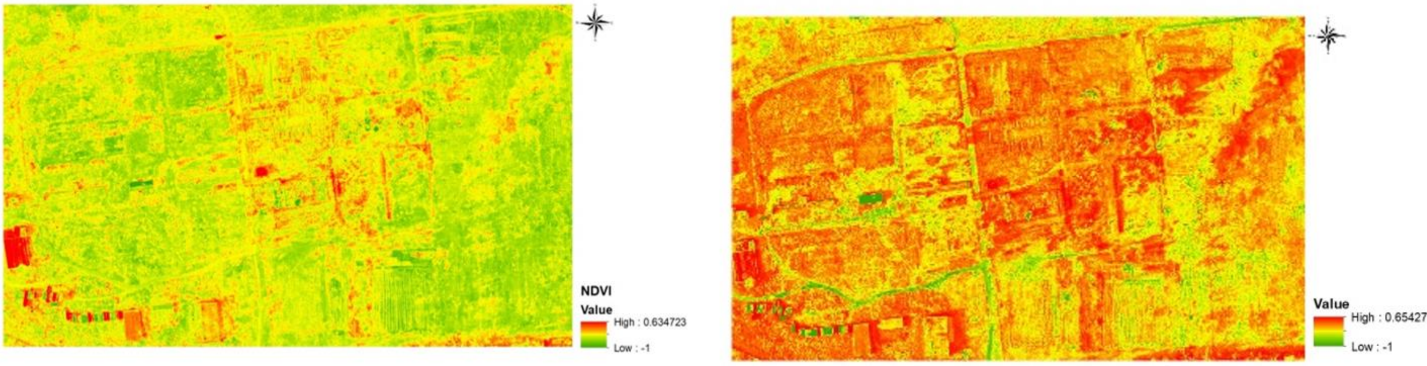
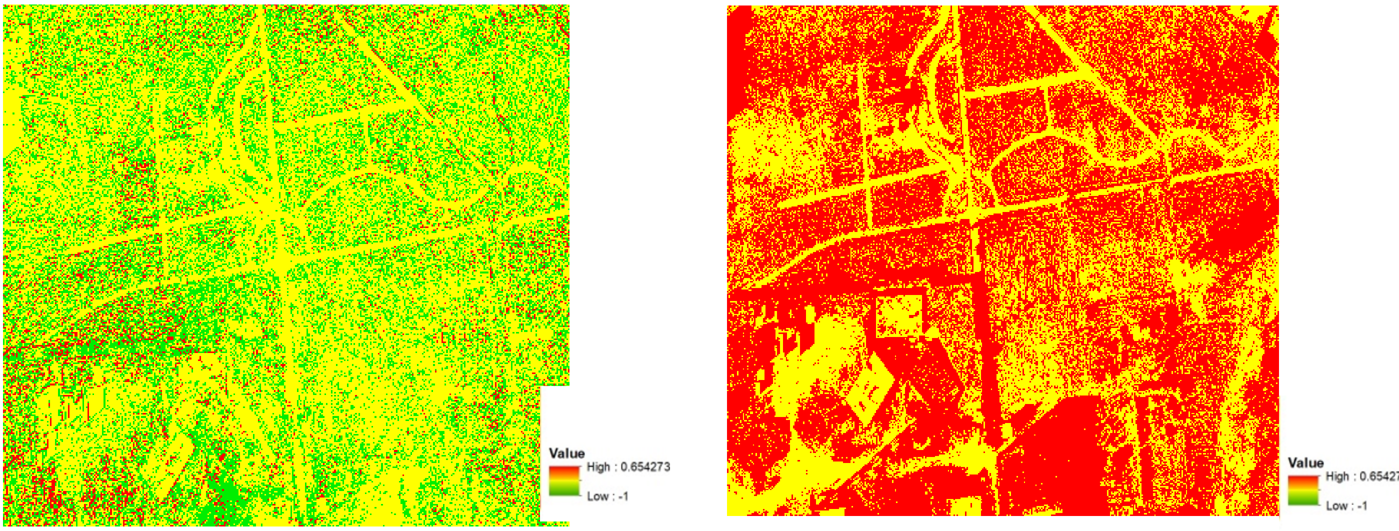


Figure 6. *Images of vegetation indices*

NDVI and GNDVI result in 2020.



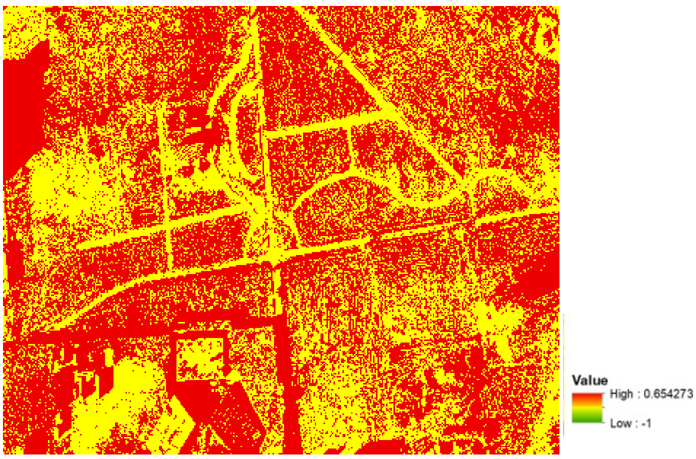


Figure 7. *Images of vegetation indices*

a) *NDVI, b) GNDVI, c) SAVI (L=0.5) result in 2021..*

Conclusions

In this paper, we report a study involving the use of UAVs in precision agriculture based on the comparison of vegetation indices calculated from multispectral images of high spatial resolution (6.8 cm pixel−1). These high-resolution data allow for a fairly detailed characterization of the biophysical variables of the crops. After comparing vegetation index maps incorporating the red edge band, the use of NDRE instead of the traditional NDVI can be recommended to identify possible heterogeneities in the vegetation cover, even when the vegetation does not fully cover the ground and patches of bare soil with varying degrees of roughness are the norms. NDVI values lower than 0.2 indicate no vegetation, just soil. Negative values are either water or urban areas. The higher the NDVI values the denser the healthy-vegetation. NDVI start saturating after the value of 0.7, while SAVI at this point is only 0.3. This means SAVI can be better used in dense vegetation, that the L parameter needs to be adjusted when having more dense vegetation cover.

High spatial resolution hyperspectral data often used in precision farming applications are not available from current satellite sensors, and difficult or expensive to acquire from standard aircraft. Alternatively, in precision landcover and land use mapping,

Referenses

[1] Das B M and Sobhan K *Principles of Geotechnical Engineering, 9th Edition* (USA: Cengage), 2018

[2] Bartholomew D P, Paull R E and Rohrbach K G the *Pineapple Botany, Production and Uses* 1st ed. (Honolulu: CABI Publishing), 2003

[3] Adão T, Hruška J, Pádua L, Bessa J, Peres E, Morais R and Sousa J Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry *Remote Sensing* **9**(11) 1110, 2017

[4] Corrigan F *Multispectral Imaging Camera Drones In Farming Yield Big Benefits* retrieve on 2019 from https://www.dronezon.com/learn-about-drones-adcopters/multispectralsensor-drones-in-farming-yield-big-benefits/, 2019

[5] Misra, A.; Vojinovic, Z.; Ramakrishnan, B.; Luijendijk, A.; Ranasinghe, R. Shallow water bathymetry mapping using Support Vector Machine (SVM) technique and multispectral imagery. *Int. J. Remote Sens.* **2018**, *39*, 4431–4450. [Google Scholar] [CrossRef]

[6] Hassan-Esfahani L, Torres-Rua A, Ticlavilca A M, Jensen A and McKee M Topsoil moisture estimation for precision agriculture using unmmaned aerial vehicle multispectral imagery *2014 IEEE Geoscience and Remote Sensing Symposium (Quebac, Canada)* (Institute of Electrical and Electronics Engineers (IEEE)) pp 3263-3266, 2014

[7] https://www.soft.farm/en/blog/vegetation-indices-ndvi-evi-gndvi-cvi-true-color-140

[8] Gitelson, A.A., Kaufman, Y.J., & Merzlyak, M.N. Use of a green channel in remote sensing of global vegetation from EOS-MODIS. Remote Sensor Environment, 58(3), 289–298. doi:10.1016/S0034- 4257(96)00072-7, 1996

Huete, A. R. A Soil Adjusted Vegetation Index (SAVI). Remote Sensing of Environment. Vol. 25, pp. 295–309, 1988