Crop Field Classification using Data Fusion of Unmanned Aerial Vehicle (UAV) and Sentinel 2A satellite: Machine-learning algorithm –Random forest approach

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Abstract

Accurate crop classification using remote sensing based satellite imageries approach remains challenging due to mix in spectral signatures. Employing Unmanned Aerial Vehicle (UAV) together with satellite imageries is believed in improving crop classification at field. Accordingly, this study aims to evaluate the potential of UAV images by blending with Sentinel 2A satellite images for crop field classification in Ethiopian agricultural context. The main purpose of the blending is to upgrade and or improve the lower resolution of the data source that is the sentinel 2A data which was 10m resolution. In the study, UAV data was used and preprocessed. The preprocessing includes camera calibration, photo alignment, dense point cloud generation based on the estimated camera positioning of scouting crop types. Then, orthomosaic UAV image was generated from single dense point cloud. Then, the processed UAV data was fused with Sentinel 2A (medium resolution) satellite data using Gram Schmidt pan sharpening method.this method is the most approach that it can run large data sets of spatial resultions. For crop classification, the Random forest (RF) machine-learning algorithm and Maximum likelihood methods were applied. Apart from the UAV and S2A data, field data was collected for training the crop classification. The point field data was collected from Teff, Wheat, Faba bean, Barley and Sorghum crop fields The results show that RF classifier algorithm classifies the crop types with 94% overall accuracy whereas the Maximum likelihood classifier with 90% overall accuracy. This implies that fused image has a potential to be used for crop type classification together with relatively better classification technique with high accuracy level

Keywords: **UAV, Sentinel 2A, fusion, Random forest, maximum likelihood and crop type classification.**

Introduction

Remote sensing technology has a major role in data extraction of crop information and crop distribution mapping (Zhang Jiankang et al, 2012a). However, accurate crops classification remains difficult because of similar crop with different spectral signatures and different crops with same spectrum development within the field of agriculture. There are different approaches are employed to address the issue including use of UAV and blending of UAV with different satellite imageries.Nowadays, UAV are changing the game in application of remote sensing (RS) in the agricultural sector by making data capture more affordable and timely accessible for crop classification and crop monitoring. UAV role in agriculture are becoming important systems to collect data for precision agriculture and improve sustainability, efficiency and productivity of the agricultural practices. UAV help precision agriculture through helping variable rate mapping, and guide targeted farm management activities. As the future trend is to move to precision agriculture, cost, labor and time efficient technologies for the agriculturally data collection and analysis systems need to be in place. Apart from using only UAV images for crop classification, blending with satellite imageries are giving good performance for different agricultural application including crop classification. The results showed that the methods used in this study were fast and easy to implement and generated fused images with high integration quality color (the Gram-Schmidt method) and spatial detail. Yet, few studies exist on fusing Sentinel-2A data with UAV for finer crop classification. Rather than blindly selecting the highest spatial resolution, choosing appropriate flight parameters to obtain the optimal spatial resolution for crop identification classification will result in more accurate and efficient results.

Data and Methods

This study is conducted in Oda Dhawata area which is found in Arsi zone of Oromia Region, Ethiopia. The location is found at 8^0 1' 57.05" N and 39^0 10'39" E (figure 1). The area has wide altitudinal range from500 to 3000 masl. The area has bimodal rainfall and receiving an annual rainfall amount from 800mm to 1200mm. Temperature in the area ranges from 10^0c to 25 ^{0}c. Vertisols is the dominant soil type in the area and conducive to grow different type crops including Teff, Faba bean, barley, wheat and sorghum.

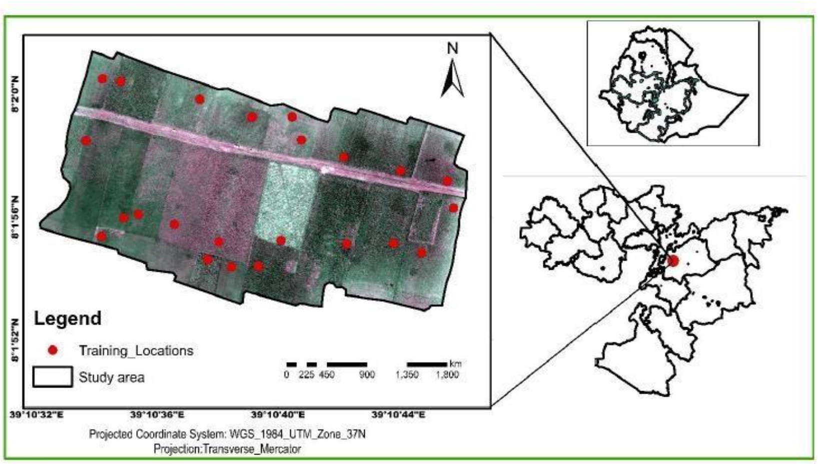

Figure 1 Study area

UAV data

Parrot blue grass it the drone which was employed to collected data in this study. It is multispectral sensors equipped with parrot sequoia that captures spectrally accurate high-resolution (fine grain) imagery in visible and near infrared part of electromagnetic spectrum, providing supplement to satellite and aircraft image. This small, light, multispectral camera four spectral bands in visible light and non-visible infrared light to analyze the health status or monitoring the crop status and crop type mapping. Sequoia has 16mp RGB camera and internal memory of capacity of 64GB. The screen of these instruments indicates about orientation of the multispectral sensor and the sunshine sensor, Irradiance screen also show the light intensity of each band and wavelengths (Green-550nm, Red-660, Red Edge-735 and near infrared-790).

UAV Data acquisition

Diversified crop types like teff, Faba bean, wheat, barley and sorghum have been captured in the cluster farmland of the study area .In this study, 1862 separate images acquired, at an altitude flight of 40m within four-flight mission time to cover an area of the field. Before starting the flight mission, the design of the flight path covering the area of interest was defined. The flight was done using pix4Dcapture –GRID for 2Dmaps. Captured images were orthomosaicked using pix4Dfield desktop (compatible with parrot, which is licensed for a year) and Agisoftware. Both Multispectral image and RGB image have been acquired in October 16/2020 and downloaded via server 192.168.42.2 of the drone in each flight mission in the field.

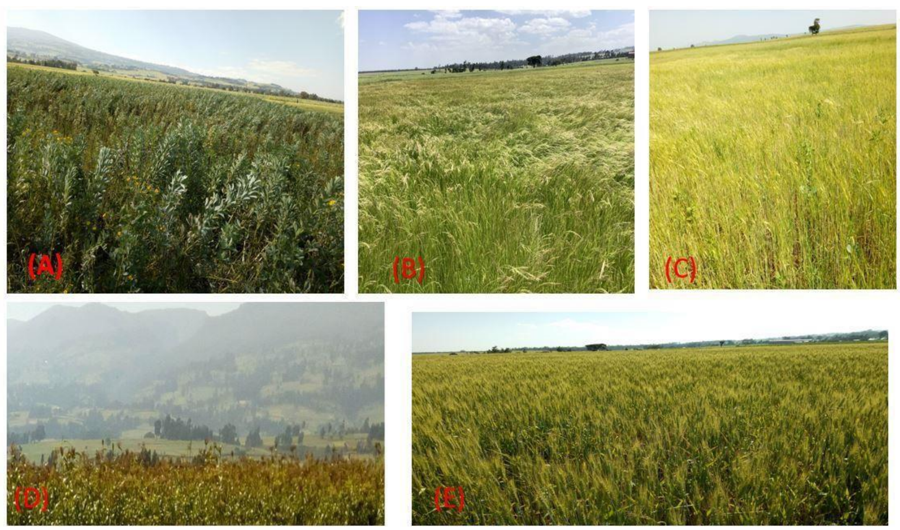

Figure 2 Crop types in cluster farmlands :(A)-Faba bean, (B)-Teff, (C)-Barley, (D)-Sorghum and (E) wheat

Sentinel 2A acquisition

In this study Sentinel 2A data were downloaded from https://glovis.usgs.gov.com website considering the time and space alignment with the UAV data. Then sentinel 2A product was then examined for cloud free coverage and applied all the necessary preprocessing steps on the image.

Data fusion approach

In this study the Gram Schmidt transformation method was applied for fusion of UAV and Sentinel images. The reason for choosing the Gram Schmidt approach is the criteria-based algorithm is extremely fortunate to keep the color content and offers satisfactory spatial detail enhancement compared to different algorithms.

Table 1 the comparison of band wavelengths (nm) of parrot sequoia and sentinel 2A (10m)

Sensor	Blue	Green	Red	Red edge	NIR
Parrot sequoia	-	550	660	735	790
Sentinel 2A (10m)	492.4	559.8	664.6		864.7

Training data from field

Data was collected in Oda Dhawata cluster farmland in16 October 2020. Garmin Oregon 650 GPS was used to collect training data of the cluster cropland. These points were used to train (70%) and evaluate (30%) data for classification.

Overall the area of study extents 7.55ha after fusion within sentinel 2A .Before that the area of UAV data captured was 5.3ha .Thus concluded that the fusion technique enhances the smaller area from UAV data .Then machine learning algorithm –Random forest classification was done, this is because of it run huge amount of data .

Methodology

To evaluate the both UAV and Sentinel 2A crop classification performance, a small subset of area of interest (AOI) will be tested and performed. For both data products, the same step-by step approach will be used and tested within multispectral cameras. Crop classification, orthomosaic of both multispectral and RGB, and accuracy assessment of MS have been done. First, UAV data, sentinel 2A and Training location had already acquired. These all data was preprocessed (camera 35 calibration, photo alignment, dense point cloud generation – this based on the estimated camera positioning of scouting crop types. Then, it is to calculate the depth information for each camera to be combined by Ties and into single dense point cloud, which provides to generate orthomosaic. For crop classification, Random forest (RF)approach, used in machine learning algorithm on R software by exploring different packages of machine learning and also UAV spatial resolution impact on crop classification explored. The general workflow of UAV data and Sentinel -2A for crop classification approach is described.

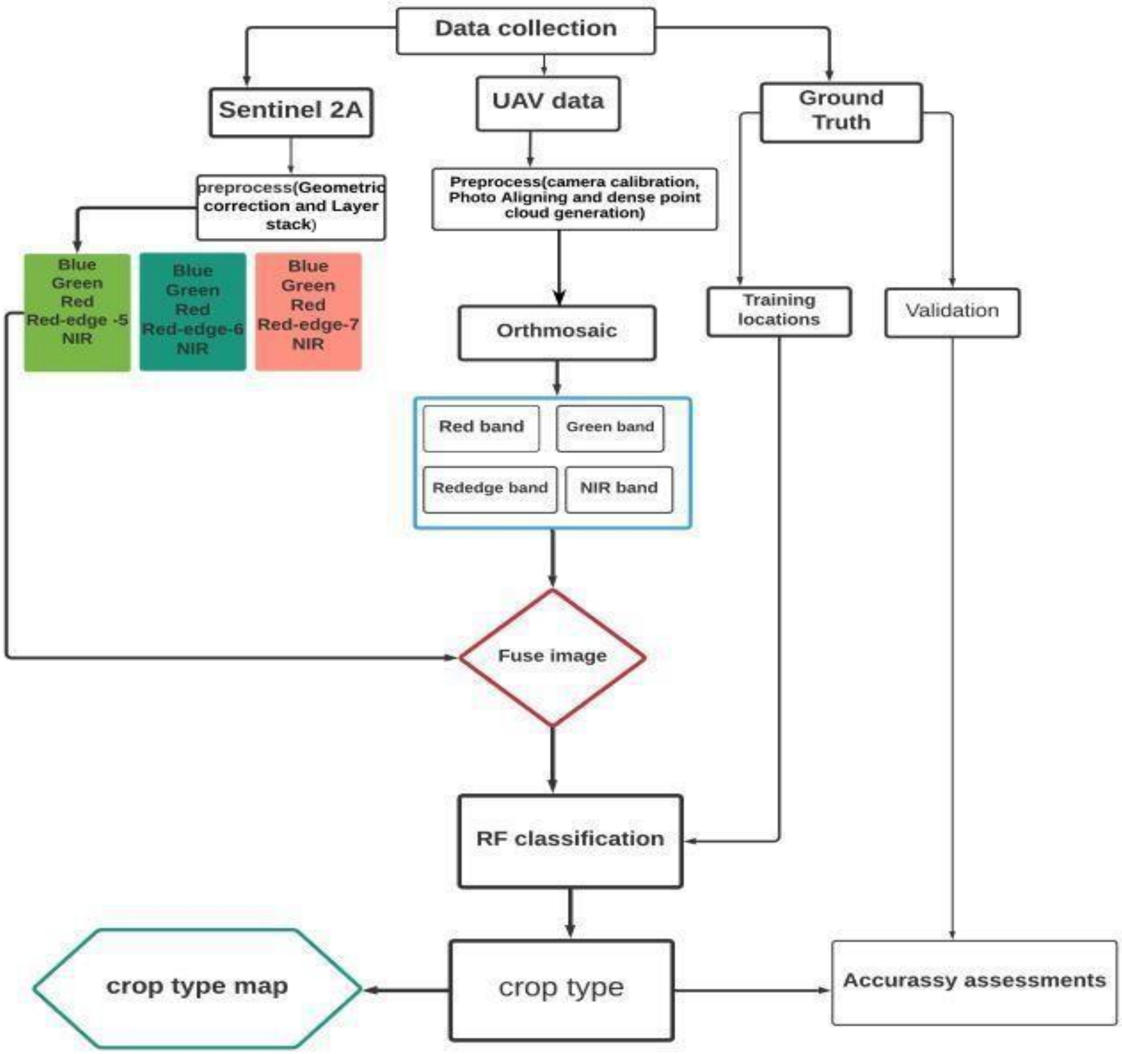

Figure 4 general work flow chart of the Research

Results

Image fusion

The UAV and Sentinel data fusion was conducted using the Gram-Schmidt pan sharpening technique. During fusion the high spatial resolution represents the information content of the images much more in detail and provides synthetic image close to reality when enhancing the resolution. This provides a radical improvement of the lower resolution of sentinel 2A and helps for crop classification. This is very essential and useful to get accurate information of each crop types. Figure x shows the sentinel 2A image, UAV data and the fused one.

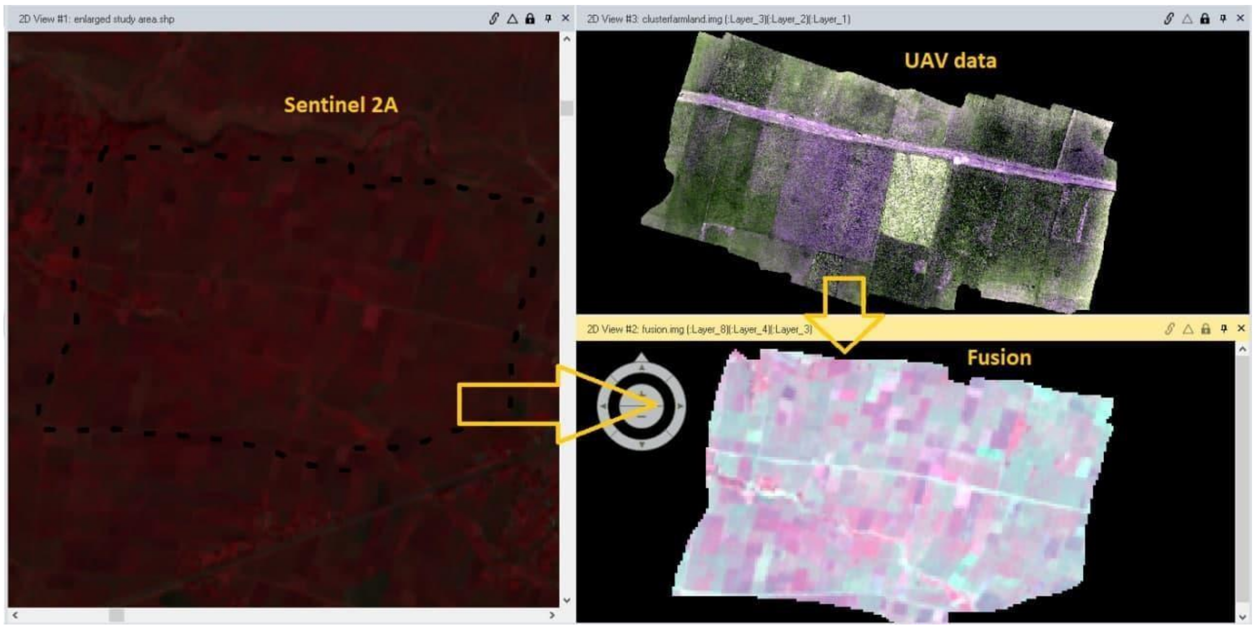

Figure 5. Fusion of UAV and Sentinel 2A

Crop classification

In this study two classification techniques were employed to classify crops types using the fused images. The methods are the random forest image classification techniques and the maximum likelihood classifier. For both classifications, the point data collected from field were used for training and validation. Five crop types were identified in the training data and used by the classification techniques. The identified crop types are Teff, wheat, Faba Bean, Barley and Sorghum. Accordingly the RF classification technique was applied and the crop type's maps are produced. For comparison purposes, the maximum likelihood classier was also applied on the fused image (figure).

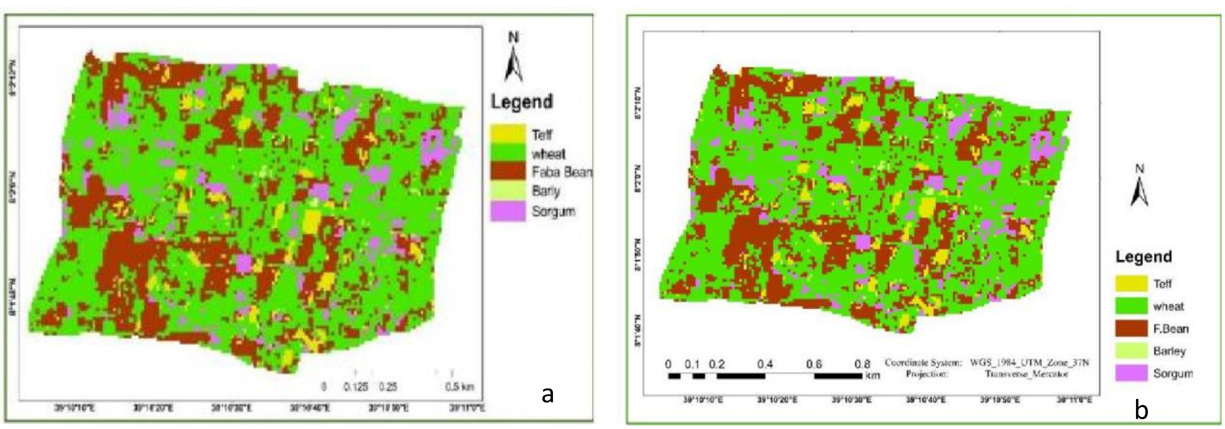

Figure 6 Crop type classification map using Random forest (a) and maximum likelihood classifiers
(b)

Accuracy Assessments

Accuracy assessment was done to validate the classified map of crop types based on fuse image in both classification techniques. In the assessment overall accuracy, user's accuracy and producer accuracy were used to measure the performance. Accordingly, the overall accuracy for RF algorithm is 94% and the maximum likelihood classifier is 90%. This implies the classification techniques and the data used for classification is quite important to obtain a better classified map. The statistical accuracy assessments of both classifications were shown in (Table 8 and 9).

Spectral Reflectance curves of Different crop types

The spectral reflectance curves are created the average value of surface reflectance of spectral bands. This proceeded after UAV and Sentinel images was atmospherically corrected to get true reflectance value of each crop type image. The spectral response of each band is calculated by considering the average response of all pixel values in each crop type in the study area. It has been observed .The spectral response of each crops is more distinguishable after band four to last bands range. It is known that NIR (Near-infrared) and or Band4 wave length is useful in vegetation and also in Crop identification soil/crop and land/water contrast.so that the below figure proves this science. Thus, the reflectance of each crop type was increased starting from NIR wavelength.

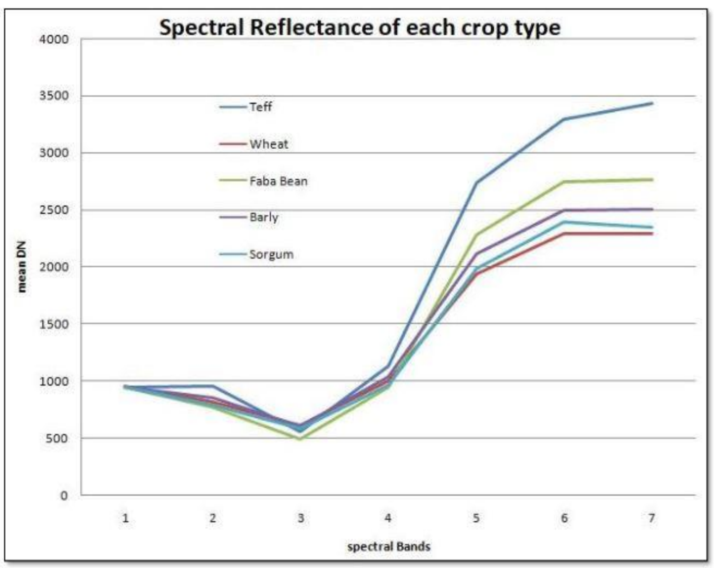

Figure 7 Spectral response curve of each crop type.

In general, the Random forest algorithm produced very good results and the accuracy assessment was very good. Firstly, the main emphasize of this project was to know the potential of Blending of UAV ad Sentinel 2A for crop type mapping. The fused image, the pixel size of UAV improves the sentinel 2A (the low resolution) data. Classifying at high spatial resolution produces the very highest accuracy for crop type mapping and both sensors (UAV and S2A). Most of the literature states that very similar results can be obtained from both classification approaches when a noncomplex scene is being used, however if the scene is complex then RFs are superior. Maximum likelihood has been around for a long time and has been research extensively. It can offer satisfactory results and is easy to perform. Random forests are newer in comparison and offer a power full approach for remote sensing classification approach. Random forest classification uses a large number of decision trees to get the result. Each tree is created using random sample selection. A random subset of input predictors is used at every tree to split it making new node. The results gathered from the majority vote created by all the trees in the process.

Overall, it was concluded that the fusion of UAV and S2A approach performs better than separate sensors in discriminating crop type classes and co-existing crop type classes in heterogeneous landscapes because of its high spectral and spatial resolution (Taona, 2019)

Conclusion

In this study Sentinel 2A and UAV has been fused together using Gram Schmidt (GS) technique for crop type mapping using Random forest algorithm and Maximum likelihood classification method. The accuracy assessment evaluated for each classification approach to determine the best method, bands, and sensor to use when classifying crop type in heterogeneous landscape of the cluster farmland. From the fused approach, the Random forest classification algorithm obtained high classification accuracy 94%, the maximum likelihood classification accuracy was 90 % and from UAV data 84% using Random forest. This is showing that Random forest classification in fusion approach have high capability of the moderate spatial and spectral resolution of the data in accurately identifying and distinguishing the diversified crop type mapping. Regarding the performance of the classifier, it was observed that RF algorithm produced high classification accuracy and it was for field-based crop classification using multispectral data. The study emphasized that RF is effective and accurate means for agricultural crop identification and mapping. Generally, it is found that both classifications were good enough to categorize crop types with fair accuracy level. Comparing the performance of the two methods the Random forest approach classified at higher accuracy level than the maximum likelihood classier. This implies that the potential of using fused image with better classification technique to classify crop field in the Ethiopian agricultural context.

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