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Original Article

Land cover Classification using Spatial and Spectral Features from Remotely Sensed Data

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Abstract *- In Ethiopia, the agricultural sector relies on traditional methods like the GCES technique for estimating average crop yields. This method, based on crop-cutting experiments, faces significant limitations. It fails to provide timely information on critical aspects such as crop health, growth stages, acreages, and estimated yields for different crop types. Moreover, field surveys, which are often used for data collection, are prone to errors and require considerable time to analyze, leading to delayed and unreliable decision-making. This results in poor yield estimates, neglect of dynamic environmental conditions, and dependence on subjective expert judgments. To address these challenges, we proposed a crop classification and yield estimation algorithm utilizing hyperspectral image data. The study area was carefully selected to include diverse crop types, enabling effective classification and yield estimation. For classification, we employed machine learning algorithms, including Maximum Likelihood, Random Forest, and Support Vector Machines (SVM). Landsat images were acquired from the same study area three different times to monitor crop growth patterns. The proposed method achieved classification accuracies of 93%, 98%, and 97%, respectively. For yield estimation, high-resolution spectral image data were utilized, requiring a separate dataset. The results demonstrated that integrating remote sensing technology into Ethiopia's agricultural practices significantly improves production efficiency. It enables better crop growth management, land-use monitoring, real-time data analysis, and informed decision-making. These advancements highlight the transformative potential of remote sensing and machine learning in modernizing Ethiopia's agriculture sector and addressing its longstanding challenges.*

Keywords *- Yield prediction, Machine Learning, Remote Sensing, Crop Classification, Stacking method, Land use.*

1. Introduction

With a variety of ecological conditions, including forests, deserts, and mountains, Ethiopia is one of the largest countries in Africa. The main challenges of the Ethiopian agriculture sector are lack of advanced technology, lack of satellite and real-time data, and lack of information for farmers and stakeholders regarding current and historical data on crop yield, crop health, the proportion of land used for each crop, etc. [3][4]. The existing process of crop acreage started at the district level, and detailed data are obtained through complete inventory, whereas the average crop yield estimation on the specific area is obtained manually using the General Crop Estimation Survey (GCES). These techniques utilize randomly selected fields from the sampled villages to conduct the experiment. Since the approach is a manual system estimation procedure, it is highly prone to different errors and biased information due to many reasons: sample fields may not be representative, the procedure takes too much time to process the data, domain knowledge gaps in the interpretation of data due to personal judgement and dynamic environmental changes affect to make a real-time decision. The advent of remote sensing technology around the 1970s and its great potential in the fields of agriculture have opened new opportunities to improve the decision-making process of the agricultural sector by automating the existing manual trends [3][4]. Besides the advancement of technology in the domain area, the knowledge of spectral and spatial features about specific crops provides valuable information to identify the types of crops and factors affecting their growth and to plan priority for monitoring growth status. These challenges inherently motivate us to understand the spatial and spectral changes in crops and their impacts on the growth, land cover pattern and yield estimation process. According to [5], real-time information on agricultural production and yield estimation is essential to developing an agricultural strategic plan, conducting market analysis, formulating appropriate preventive action, normalizing agricultural product prices, and designing a proper policy to support the sector. Therefore, this research aimed to use a machine learning algorithm for performing crop classification and yield estimation based on remotely sensed image data. High concentration was given to the spectral [11] image data analysis for the study area, algorithm development, and representing and characterization of objects on the earth's surface to classify the objects on the basis of their spatial and spectral feature. The proposed model will be employed based on non-linear regression numerical algorithms to upgrade the prediction [10] accuracy and reliability of agricultural crop yield estimation and finally be deployed at various Ethiopian Agricultural agencies.

1.1. Background

The use of remote sensing technology in the area of agriculture to control and monitor crop health status and growth is not new. However, during the preliminary survey, we found that there are a lot of gaps in Ethiopia's case. Limited numbers of research are reported in the domain, and the main stakeholder is still using the manual system for crop classification and yield estimation; access to remotely sensed data is another big challenge due to the absence of the technology and farming trends are not pattern based in order to apply advanced technology easily. So this research work is mainly focused on utilizing machine learning methods [8] to perform two tasks: first, to identify the land cover by classifying the type of crop on the selected study area and second, to perform yield estimation tasks for every crop on the specified area. A review of related literature has been done, and different concerned organizations were communicated to assess their requirements in order to propose effective machine learning models that can handle the existing pitfalls in the selected study area. From the assessment, we found that the classification of crops based on the spectral and spatial features is a near real-time and continuous process that has an important role in planning, monitoring growth status, damage prevention, and designing strategies for different tasks in the sector.

Also, the estimation of yield is important not only for farmers but also for providing an important insight into the country's current demand and supply variables. But the success of a computer-based crop classification system depends upon the careful selection of low-level features, the algorithm used for feature construction, integration of local heuristic knowledge and the dynamic factors like climate, soil and rain information, efficient use of spectral and spatial features obtained from remotely sensed data as well the algorithms used for classification and yield estimation. To get insights into this research area, our team has performed a literature survey of documents, journals, periodicals, books, and internet sites that have been reviewed. According to [2], it takes a larger number of crop-cutting experiments if the yield and health information are to be analyzed with a higher level of accuracy using the traditional techniques of crop estimation. The reason behind this is the fact that traditional crop estimation techniques are well suited for small area estimation, and survey-based techniques become more expensive and less reliable as the land cover size grows. On the other hand, the author has proposed a method for better estimation in small areas by providing a method to integrate the supplementary information with large-area remote sensing-based estimation techniques to compute the estimates for small areas correctly. The author suggests that better crop yield estimates can be produced by focusing on the property of spectral reflectance.

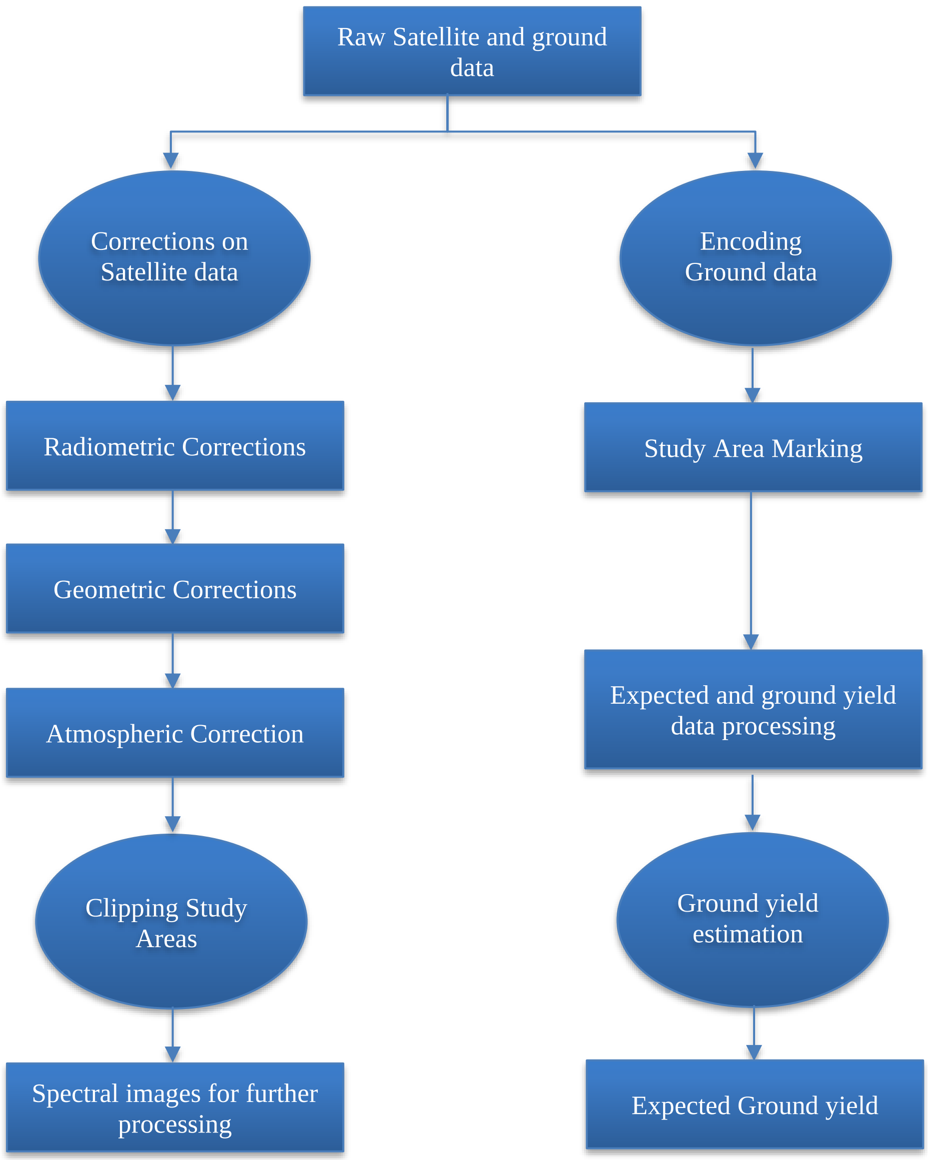
The location of experiments was selected using GPS, and the same were marked on NDVI and RVI images. To estimate crop yield, the following estimators were developed:

- ✓ Crop yield estimator for the district without using remote sensing data.
- ✓ Crop yield estimator for the district based on post stratification using satellite data in the form of NDVI and RVI for stratification.
- ✓ A direct estimator of crop yield at grid level.
- ✓ A synthetic estimator of crop yield at grid level.

2. Problem Statement

The major problem that the researchers identified during this research is that there is very limited research performed on the application of remotely sensed data in crop classification and yield estimation tasks in the context of Ethiopian farmlands. In fact, yearly estimates of the yield are directly performed on the basis of survey data. The agricultural survey of rural areas is a difficult task because sometimes it is not possible to access the rural areas due to connectivity, weather and other conditions. In that case, the surveying agency hardly gets any chance to draw exact conclusions about the type of crops sown and cultivated in particular land holdings. It has been observed that some farmers and private holdings prefer multiple crops in a field in order to minimize the risk.

In this case, the major problem of the Ethiopian agricultural agency is identifying significant chunks of each crop type, which directly affects the computation of the overall yield of that crop. This can be understood as a problem of automatic classification of crops with the help of some kind of Arial, satellite, drone or sensor-based imagery of the cultivated area. Once the crops are identified and their land cover area is computed, the next problem is to identify suitable spectral features if the infra-red and near-infra-red based images are used in computing the yield. Similarly, in order to predict yields precise, the spatial features of the crops are to be identified. These features shall help us identify dead and less productive croplands. Finally, the expected yield of the sampled chunks of land is to be computed based on the vegetation index of each sample, and the correlation of the estimated yield with the ground measurement has to be computed in order to come to confidence in the correctness of the proposed model.



Beyond these requirements, this research has identified that various agencies involved in agricultural institutions demand a platform that supports various operations of this pipeline on a desktop computer with the presence of the internet and with minimal training requirements for the staff.

3. Methodology

This research has followed an experimental, longitudinal research methodology where each experiment was designed on a sample of randomly selected chunks of cultivated land of unit area in size and located in an identified set of geographical coordinates. Those cultivated areas were selected for the research whose Arial images and ground yield estimates were available for the past several years so that our proposed model output can be compared against model estimates. Since the objective of this research is twofold in nature, therefore the first type of data collected was in the form of Arial and satellite images of the cultivated areas; this data was used for training the model for classification, while the second type of data was collected for subjective measure of ground yield so that the satellite data based yield can be compared with. The following figure shows the overall system architecture and how satellite images are acquired and processed to the required level.

3.1. Data Collection

The survey of agricultural fields in the above cities was performed with the necessary survey equipments, including GPS, Compass, scientific calculator, questionnaire, etc. The best time for belg season harvesting is from September to January in some highland areas; therefore, a subjective measure of ground yield has been computed for three months by physical measure while at the same time, the satellite data has been collected to perform crop classification and yield estimation using remote sensing techniques. The subjective estimate of ground yield was performed with the help of communication with farmers, agents and related agencies in the area. Therefore, in this subsection, we will discuss the overall data collection and processing in detail.

3.2. Study Area

For the purpose of this research, yarer Selassie in the Bishoftu Oromia Region of Ethiopia has been selected to acquire the satellite image. The area has been selected because of the availability of diverse crop communities.

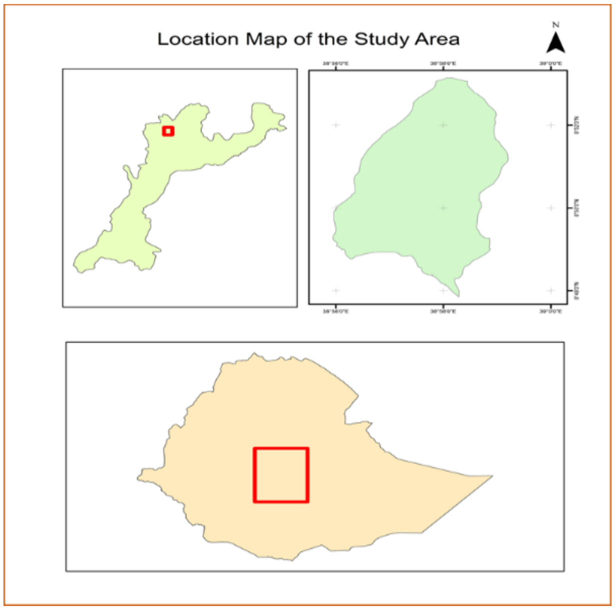


Fig. 1 Map of study area Bishoftu Yarer Selassie

3.3. Data Acquisition Process

Yarer Selassie is located at an altitude ranging from 1500 to 2000 m above sea level in Bishoftu, Oromia region. It is spread in East Showa Rift Valley and borders Dunga Bora, West Shewa, Akaki, Gimbichu and Lome. The highest point of Yarer selassie is Adaa and Misrek Shewa, which is located near the Akaki border. In order to carry out this study, three imageries (October 2018, November 2018, and December 2018) of the study area were acquired from the LANDSAT 8. Satellite images are useful in meteorology, oceanography, fishing, agriculture, etc. Although there are different imaging satellites, we acquire our image from the Landsat satellite.

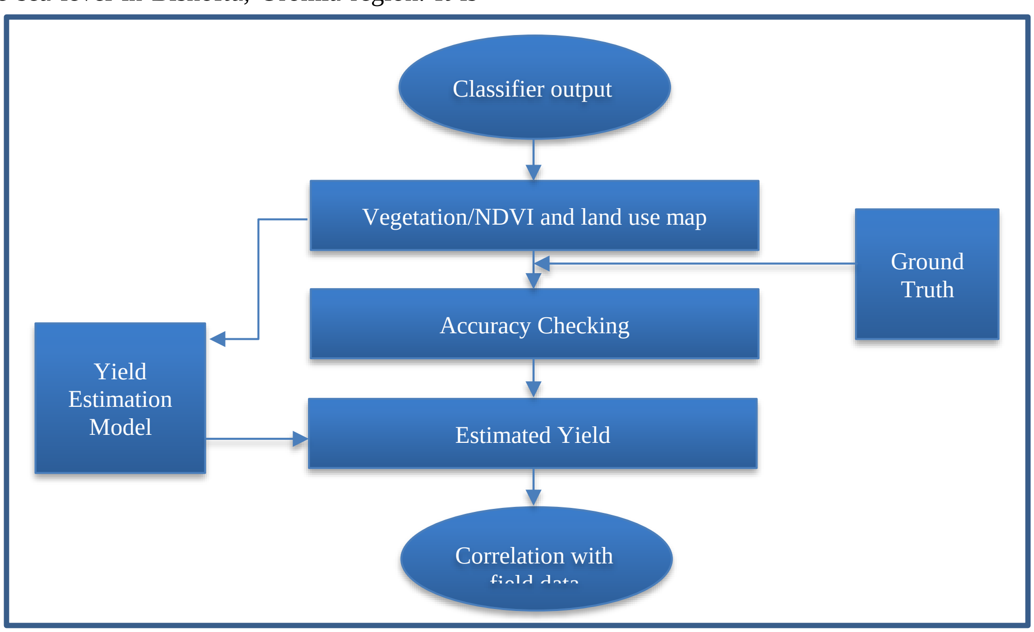
The Landsat images are freely available for researchers from different countries. We used seasonal coverage of landmass at the resolution of 30m provided by Landsat-8 using an operational-thermal infrared sensor; specifically, two sensors named OLI and TIRS are used for seasonal coverage in Landsat-8. The following table shows the spectral Landsat image in its respective resolution. For the purpose of this research, we used Band 1 to Band 5. Band selection mainly depends on the acquired resolution of the Landsat image.

3.4. Data Analysis

Analyzing data in this project ranges from simple Geo-processing techniques to complex spatial models. The study involves two major processes. The spatial model used in this research involves Geometric modeling functions (conversion of digital numbers into Reflectance and Topographic Correction. The analyses performed in this research study have been described below:

4. Modelling and Corrections

The following model is developed during this research, which performs the task of classification, atmospheric correction and yield estimation from the satellite data in a pipeline.



In the next sections, we describe the basis of various types of corrections applied to the images. Subsequently, we provide details of classification models and algorithms used in this research. The yield was estimated on classified crop areas and validated against the ground truth.

4.1. OLI Top of Atmosphere Reflectance

To estimate from the Landsat-8 OLI/TIRS TIR band, the DN of sensors were converted to spectral radiance. TOA reflectance can be computed from 16-bit integer values in the L1 product by using the following equation:
Level 1 DN values to TOA reflectance: $\rho\lambda' = M\rho * Qcal + A\rho$
Where
$\rho\lambda'$ = TOA-PSR*
* No correction for solar angle is performed
$M\rho$ = RMSF for the band
RMSF *= Reflectance multiplicative scaling factor
*REFLECTANCEW_MULT_BAND_n is taken from the metadata.
PSR= Planetary Spectral Reflectance
Qcal = is the L1 value of the pixel in DN
$A\rho$ = RASF
RASF=Reflectance additive scaling factor for the band
*(REFLECTANCE_ADD_BAND_N taken from the metadata).
The value of $\rho\lambda''$ does not represent a true TOA Reflectance due to the absence of solar elevation angle corrections. This correction is done on specific user requests on L1 scaling, depending on the choice of users to perform the operation on the small number of pixels under consideration or on the whole area.
Where:
$\rho\lambda$ = Reflectance
$\rho'\lambda$ = Planetary Reflectance i.e. TOA
$\sin(\theta)$ = Solar Elevation Angle, it can be computed or taken from metadata

Erdas software was used for performing various steps in the research pre-processing, analysis, quality enhancement, and enhancing the readability of features.

The preprocessing step is composed of applying various corrections to the image data for errors in the transmission, scanning, and recording of the data. To improve the radiometric and geometric properties of the image, the following steps were performed based on the literature review:

4.2. Radiometric Correction and Topographic Correction

The azimuth and elevation of the sun and other atmospheric conditions, like the existence of aerosols, delay in sensor response, etc., cause radiometric effects, such as the electromagnetic energy observed at the sensor not matching the energy emitted by the object. These radiometric distortions must be corrected in order to get the actual reflectance data. The following architecture depicts the procedure of data correction to the required output.

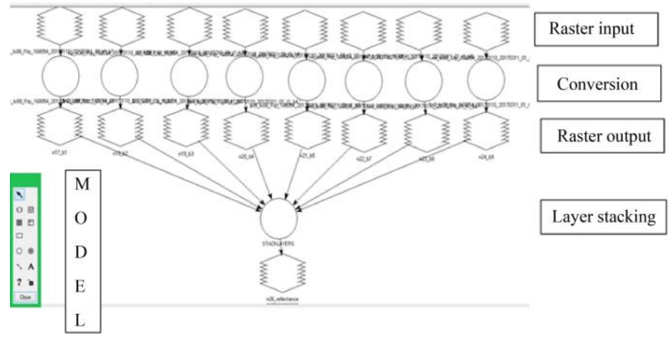


Fig. 2 Procedure for applying corrections

In our study area, we used landsat8 images. All these satellite images are already geometrically corrected. So, we haven't gone further with the process of geometric correction.

Table 1 NDVI values range for different features.

4.3. Atmospheric Correction

Atmospheric correction is to eliminate unwanted noise inserted during the transmission and recording processes. This correction is done mainly if there is cloud coverage of the atmosphere during acquisition. All the Landsat images are acquired in the winter season. According to the Ethiopian context, winter is the time where no rain and it is very dry. We have selected this season to eliminate cloud coverage during acquisition. So, we haven't done any process for removing the cloud.

4.4. Classification Models

After the Landsat data preprocessing task was completed and once the required staked image was obtained, the research team started to implement the classification task. The crop classification is possible with multispectral[f] and spatial features. Therefore, this research tries to integrate the spectral and spatial features so that the classification accuracy is improved. The proposed model of Spatial Crop Profile for each cropland is defined as a set of spatial crop attributes to clearly identify each cropland's color, shape, size, and boundary.

In this research, we proposed different classification algorithms such as Maximum likelihood, Random Forest, and Support Vector Machine Learning Models. The proposed models are selected on the basis of their classification capability to handle hyperspectral data. For our experiment, we have used three satellite images captured in different time periods from the study area. So, our main target is to apply our model to all image datasets and evaluate the proposed model's classification performance.

4.5. Yield Estimation

The Normalized Difference Vegetation Index (NDVI) is defined as a measure of vegetation and the identified land cover area. If the vegetation is good enough, it is clearly shown in the image and can be differentiated from poor vegetation areas. NDVI can also be used to identify water and ice, but we have used it here to compute the vegetation of the selected area. It measures the difference in the reflectance computed from the obtained wavelength ranges. The values of NDVI lie between -1 and 1, while the NDVI value of 0.5 represents dense vegetation, and values less than zero represent no vegetation in the area.

Cover type	Red	NIR	NDVI
Dense	0.1	0.5	0.7
Dry, bare soil	0.690	0.285	0.025
Cloud	0.227	0.228	0.002
water	0.022	0.013	-0.257

4.6. Data Preparation for Experiments

As it is mentioned in the data collection section, the input image was collected during 2018-10-12, 2018-11-12 and 2018-12-12. According to the domain expert, this period is critical to following the growth and health status of crop cover. At the same time, we can obtain good-quality satellite images since the size and volume of clouds and fog are highly reduced in this period. From the above output, we can clearly observe the pattern of land cover. The result shows that during the last month of 2018-12-12, most of the crops were harvested, which is why the majority of the land is bare land.

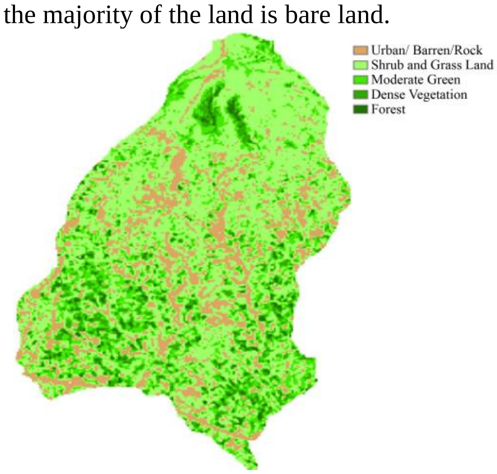


Fig. 3 NDVI of 2018-10-12 on study area

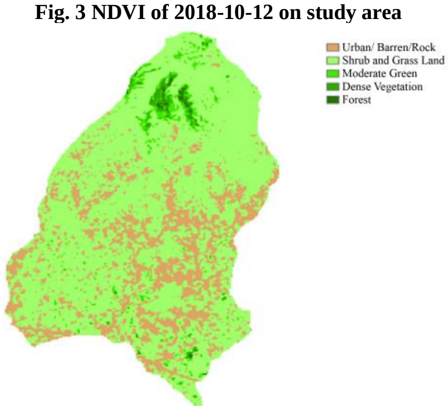


Fig. 4 NDVI of 2018-11-12 on study area

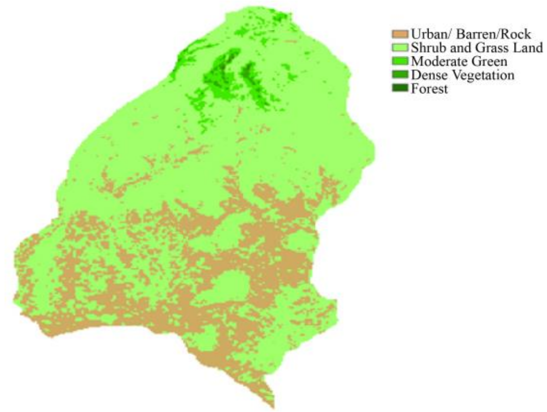


Fig. 5 NDVI of 2018-11-12 on study area

Table. 1 Land uses and their description

Class	Description
Built up	All residential, commercial, and industrial development.
Waterbody	Water refers to oceans, rivers, streams, canals, seas and lakes
Bare land	Bare land, bare earth or soil.
Dense vegetation	An area dominated by plantation
Sparse vegetation	vegetation dominated by shrubs.

5. Classification Models and Experimental Results

Three different classification models were used to classify the images of the study area for land use, and three different crops were identified to estimate the yield of each area.

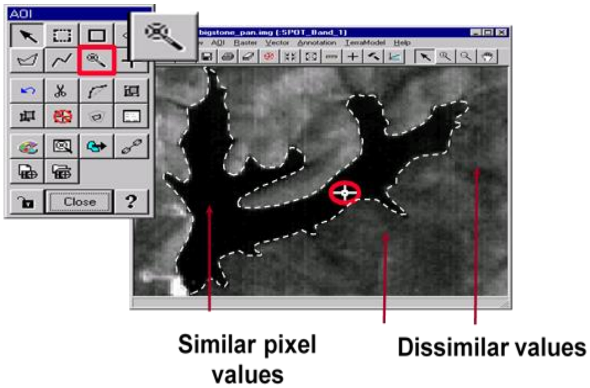
The models were selected based on past research, and the point of the research was to investigate the performance and accuracy of selected models in case of difficult terrine and other conditions of the study area with and without the application of various types of corrections on the image data.

The performance of the model was studied by using specially designed spectral and special features from the crop images. In the next section, we describe each classification algorithm used in this research.

5.1. Maximum Likelihood Algorithm

This algorithm is based on an estimate of the probability that a pixel belonging to a particular class can be computed from the sample of the pixels.

It can be further stated in terms of estimating the parameters that maximize the likelihood of class given a data point. The assumption is that the probabilities of each pixel are equal for all classes, and every pixel is placed into a class based on probability.



Erdas Imagine and ArcGIS tools have been used by the Maximum Likelihood algorithm to classify the image pixel based on the given parameters. The features used to label image classes have already been discussed during the class description section.

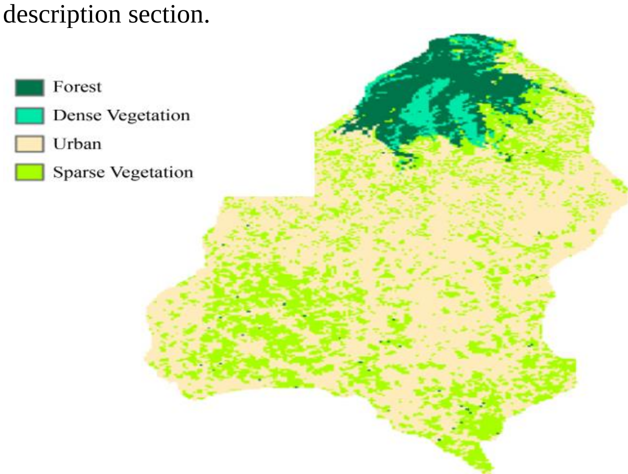


Fig. 6 Maximum Likelihood classified Image of 2018-10-12

Table 2. MLE estimates for an image of 2018-10-12

F ID	Class	Area (Km^2)
1	Forest	1.4598
2	Dense Vegetation	0.6903
3	Sparse Vegetation	12.2598
4	Urban	44.4501

5.2. Random Forest Image Classification

The machine learning community has a number of solutions for nonlinear classification problems, and Random Forests are considered to be one of the representative algorithms in this area.

RF and its variants have been successfully used in the past on satellite and aerial image classification for land cover and biomass estimation.

Based on the accuracy, recall and precision of RF variants we have employed these models in our research for classifying the selected study area.

Fig. 7 RF classified image of 2018-10-12

RF was used to classify the area of study for different classes trained first based on the semiautomatic method of training. Subsequently, the trained model was used to classify the study area, as shown in Figure 7. The overall accuracy of the RF model was as follows.

RF Overall accuracy result:
147 samples, 3 predictor, 4 classes: '1', '2', '3', '4'
No pre-processing
Resampling: Bootstrapped (25 reps)
Summary of sample sizes: 147, 147, 147, 147, 147, 147...
Resampling results across tuning parameters:

Accuracy	Kappa
0.9819653	0.9745824
0.9811111	0.9734910

5.3. Support Vector Machine (SVM) Classification

SVM is another machine learning model that we have employed for classification in our study area, as they are able to handle nonlinearity in data and can be used in classification and regression settings. Land-cover classification of a 2,3,4,5 -band Landsat8 image taken in 2018 that has been processed to surface reflectance, as shown previously.

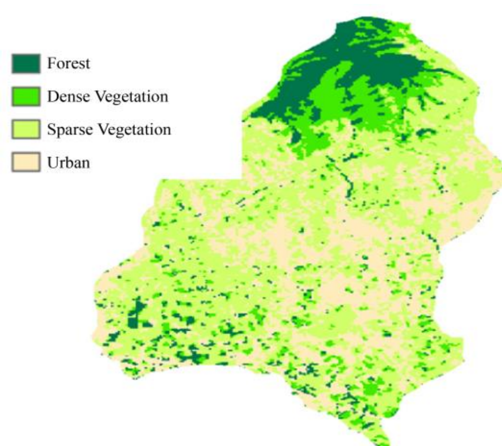


Fig. 8 SVM classified image of 2018-10-12

To evaluate the classification accuracy of the SVM model, a Google Earth image of the time frame has been used. Accordingly, the classifier obtained higher accuracy performance for each spectral image dataset. The above result is obtained using the SVM linear kernel function. However, the SVM model is powerful enough to integrate with many other kernel functions so that it is possible to determine the best one that fits the problem.

In this research, our last target was to perform yield estimation based on the special and spectral features of the classified crops. The main requirement to accomplish the task is to get high-resolution satellite image datasets. Our spectral image's resolution is more than 30 higher, so it is difficult to use this image to perform the required task. Therefore, Arial images of the individual crops were used to identify the crops and estimates of their areas. Finally, the NDVI of each area for each crop was computed and validated against the ground truth. The accuracy of the yield estimates was found to be highly correlated with the accuracy of the classifier output as well as the identification of the crop type for each area.

5.4. Yield Estimation Results

The yield of identified cropland was estimated after obtaining the area of each type of cropland using visible light images due to the absence of high-resolution satellite images of the mixed crop fields. The yield of each sample crop area was estimated by NDVI using the following formula.

$$NDVI = \frac{(BAND4 - BAND3)}{(BAND4 + BAND3)}$$

Based on this analysis, the following was the estimated yield of the sample area:

Parameter	Lebel	Crop Types	Yield Estimation Procedure
Number of heads/pods per square meter	A	Wheat	250
Average number of grains per head/pod	B		58
Number of grains per square metre = AxB	C		= 250 x 58 = 14500
Yield per square meter = C/100 x 3.4gms	D		= 14500/100 x 3.4 = 493.00gms
Yield in t/ha = D/100			= 493/100 = 4.93t/ha (44.72 quintal)

6. Evaluation of Results

As per the evaluation of classification results and corresponding NDVI value and subsequently estimated yield for three different crops in the study area, it was found that the best results were obtained from the SVM classification algorithm, while the random forest algorithm was able to perform satisfactorily as compared to the MLE estimate of land usage.

This can be explained in terms of the power of SVM to classify the land use areas with nonlinear boundaries easily as compared to RF and MLE based models. The estimated yield of the sample area computed from the NDVI measure was found to be consistent with the expert and historical data.

The validation of the actual output of the selected field was performed. Based on the framer's expert advice, our estimate was found to be significant and satisfactory, which showed less than 10% variation from the actual output.

7. Conclusion and Recommendations

The purpose of this research was to develop an effective method to compute the yield from land use and land cover data after doing a model-based classification of the study area. The images were transformed using various corrections, and the classification task was successfully performed. The scripts for doing correction, preprocessing and classifications were developed and can be employed by agriculture agencies in Ethiopia.

The major problem faced with this research was the unavailability of high-resolution satellite data of the study area in order to differentiate crops among themselves, the unavailability of aerial photographs of the study area, and the unavailability of yield data for the specific area under study. The outcome of this research can be used to identify the areas of good crop production in various regions of Ethiopia, and estimates of NDVI can be used to compute the crop yield by simply putting NDVI to yield transform.

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