ASSESSING RICE HEALTH AND YIELD ESTIMATION BY USING REMOTE SENSING TECHNIQUES

CASE OF MBARALI HIGH LANDS ESTATE RICE FARM

BY

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A dissertation submitted in the Department of Geospatial Sciences and Technologies, in partial fulfillment of the requirements for the award of Bachelor of science degree, in Geographic Information Systems and Remote Sensing of Ardhi university

CERTIFICATION

The undersigned certify that they have proof read and hereby recommend for acceptance of a

Dissertation entitled «**ASSESSING RICE HEALTH AND YIELD ESTIMATION BY USING REMOTE SENSING TECHNIQUES**» in fulfillment of the requirements for the Bachelor of science degree in Geographic Information System and Remote Sensing.

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DECLARATION AND COPYRIGHT

I, Mbita, Pauline P. the undersigned, hereby declare that the content of this dissertation are the results of my own findings, obtained through studies and investigations. To the best of my knowledge, similar work has never been presented anywhere as the thesis for any award for diploma, degree or any other profession in higher learning institution.

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I would like to express my sincere gratitude Almighty God for blessing me with knowledge, good health and strength throughout the period of my studies, for which he gave me the strength to successfully complete my research.

"Not by might nor power, but my spirit, says the Lord Almighty' **Zechariah 4:6b.**

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DEDICATION

To my parents Flower and Plasdus Mbita, who have raised and educated me since I was a child to become the person I am today. I am grateful for everything you have done to me, your support, efforts, encouragement and love towards me, you have my undying love, gratitude and appreciation, I will never have enough words to express how much I love and value you.

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ABSTRACT

Rice yield to meet the country's rice demand has been a problem, as sometimes it leads to unexpected rice price of rice in the market, as farmers put much efforts compared to yield obtained. Low yield frequently results in insufficient production, this can put the national food security at risk. The country has enough of untapped land which can be used for large-scale farming performance for rice production, as it may be influenced by the government and investors, but among the challenges of performing large-scale farming can be lack of enough capital in terms of time and labor on the investment (as the bigger the farm, much resources will be required, and time and labor is among the important resources needed). Therefore, remote sensing technologies can be used to provide information and minimize the capital challenge in terms of labor and assessing time of rice throughout its growth. Two objectives were the used to accomplish the study; the use of indices and random forest classification algorithm, which showed how remote sensing can provide information about rice throughout its growth, and yield estimation. vegetation indices explain how indices can be used in assessing rice health throughout its growth. To accomplish this, three main indices were used, which are Normalized Difference Vegetation Index (NDVI), Modified Soil Adjusted Vegetation Index (MSAVI) and Normalized Difference Water Index (NDWI), this can assist farmers and other stakeholders in making informed decisions and improving rice yields through the obtained results, whereby for NDVI, NDWI and MSAVI -1 to 1 are the recommended results. Random forest classification algorithm being used to classify and obtain the area covered by rice on Mbarali highland estates rice farm, then by using the concept and knowledge of constant yield of production for every crop, which is 3700 per acre for rice which was obtained from Food and Agriculture Organization (FAO), the area covered with rice obtained after classification was multiplied by the constant yield of production which resulted in rice yield estimation per acre.The study ultimately came to conclusion that, vegetation indices can be clearly used in assessing rice health throughout, as indices tells condition of rice health in different stages, and it clearly shows how random forest algorithm can be used for yield estimation. The study finally recommended that the study is useful to assess health and yield as it produces sufficient information on health and yield of rice throughout its growth, also more studies should be carried out, to show how the method can be used in different other crops, also historical records should be well kept for use during researches and validation purposes.

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LIST OF ABBREVIATIONS

SHT	Southern Highlands of Tanzania
SAR	Synthetic Aperture Radar
FAO	Food and Agriculture Organization
GPS	Global Positioning System
GIS	Geographic Information System
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NDRE	Normalized Difference Red Edge Index
MSAVI	Modified Soil Adjustment Vegetation Index
USGS	United States Geological Survey
MOA	Ministry of Agriculture

CHAPTER ONE
INTRODUCTION

1.0 Background

Rice is among most important cereal crop in the developing world and is the staple food of over half the world's population. In Tanzania rice has been one of the important crops that contributed immensely to Tanzania's food and nutrition security, socioeconomic development, and country foreign exchange earnings. Rice is the most important food crop after maize, which is produced in 64 districts and widely consumed in the country (Nrds II, 2019). Rice needs a hot and humid climate. It is best suited to regions which have high humidity, prolonged sunshine and an assured supply of water (Nrds II, 2019).

About 30% of Rice in the country is consumed by farmers/producer at households, the remainder sold in the domestic and regional markets, with consumption being the highest in larger urban areas (Wilson & Lewis, 2015)In Tanzania, per capital consumption of rice is estimated to be 25kg, while 40kg in SSA (United States Social Security, with the highest reported in Madagascar 140kg (Nrds II, 2019), Rice is now being recognized as a strategic crop and a major component of food security and income for the region. Regional rice production meets only about 55% of demand, with the rest being met through imports, costing the region USD 5–6 billion annually, placing a considerable burden on the already struggling economies. In Tanzania, rain-fed areas, which constitute over 70% of rice areas, are not sufficiently exploited, and the country has plans to expand its irrigated areas.

The regional gap in demand for rice could significantly be narrowed with the largest untapped land and water resources and the enormous potential for increasing yields in Tanzania to at least match that being attained in Asia (Nrds II, 2019).There is an urgent need to enhance the yield as a key to promote food security from household to national and international levels (Rugumamu, 2014), this can be carried out through encouraging farmers and investors in performing large scale rice farming so as the supply can reach the demand and hence facilitate food security in the country. Among the complications on investing in large scale rice farming can be inadequate capital

(Ngailo, 2016) associated by large number of labor and time to be required in assessing and monitoring rice growth and maintenance, so as to achieve high yield production, this problem can be solved through the use of remote sensing techniques in both assessing rice health and yield estimation processes in large scale farming, this can be further a problem due to lack of much published studies, which shows how to use remote sensing techniques in assessing health and yield estimation of rice production.

1.1 Statement of the research problem

Most farmers in Tanzania hesitate in engaging themselves into large-scale rice farming due to having inadequate capital in terms of time and labor and insufficient knowledge on how they can estimate yield before harvest for different purposes, such as to prepare cost of rice on the market. This is due to lack of information on the expected yield for a particular year and on the means which can help them to easily assess health throughout its growth. Hence, this calls for a need to employ remote sensing technologies in large scale rice farming so as to provide the required information and to support decision making so that to enhance productivity in agricultural sectors to ensure adequate food security in both country and regional level.

1.2 Research objectives

1.2.1 Main objectives

To estimate the rice yield and health information, so that to support farmers in decision making for enhanced rice productivity to ensure food security.

1.2.2 Specific objectives

i. Assessing rice health through its growth using vegetation indices (NDVI, NDWI, MSAVI) for three consecutive years.

ii. To carry out classification by using random forest algorithm.

1.3 Significance of the research

The aim of this research is to support decision making in relation to rice productivity in Tanzania, through providing information on how remote sensing technologies can be used in minimizing cost required mainly in terms of time and labor, as the study shows how remote sensing can be used in assessing rice health and yield estimation, specifically in large scale farming, this is so that to reduce the problem of failure of farmers and investors to perform large-scale farming, due to lack of adequate capital in terms of labor and intensive assessing time.

1.4 Beneficiaries of the research

This study aims at providing information on how remote sensing technologies can assist in agricultural sector mainly at large scale rice farming, the following the users who cab benefit from the study.

1.4.1 Farmers

The outcome of this research will help farmers in easy implementing large-scale farming, it shows how farmers can overcome the problem of inadequate capital in terms of labor and intensive assessing time, as the research explains how farmers can use remote sensing techniques in assessing rice health during its growth, whereby farmers can use this information in understanding the trend of rice growth.

1.4.2 Decision makers

The outcome of the research can be use usefully on decision makers as, the research explains how to predict rice yield by using remote sensing techniques, and therefore, decision makers can use this information on making decisions on the rice market, in matters concerning salary and how to save the yields for future use.

1.4.3 Researchers

The outcome of this study, can be used in the future researches, as researchers can use this study as the starting point of their own research's, resulting in improved methodologies or better strategies for generating better research outputs.

1.5 Scope and limitation

This research focuses at Mbarali district in Mbeya region in Southern Highlands of Tanzania (SHT), mainly at Mbarali highland estates rice farm, located between latitude -8.63°S and -8.68°S and longitude 34.23°E and 34.03°E, at 36°S zone, the research aims at assessing rice health and yield estimation on large scale farming, as remote sensing techniques appears to be more efficient and effective method to be used on large-scale farming compared to small scale farming, since it is cost effective and less time consuming when used on large scale.

1.6 Software used

The study mainly was carried out through the use of software, which were used from data processing, data analyzing to output generation processes.

1.6.1 Quantum geographical information system (QGIS)

The software was mainly used in data pre-processing, processing, carrying different kind of analyses of different methods used in obtaining the results, and in displaying the results mainly through map making processes.

1.6.2 Google earth pro

The software was mainly used during reconnaissance stage and data collection processes, it helped in gaining the better understanding of the study area, as it gives a better view of the appearance of the farm (Mbarali highland estates rice farm).

1.6.3 Google Earth Engine

The platform was mainly used during carrying out the methodology, as it was the main platform where the research was carried on, mainly on the calculation of indices.

1.7 Description of the study area

This research is carried out in Mbarali district in Mbeya region mainly focusing on Mbarali highland estates rice farm, located between latitude -8.63°S and -8.68°S and longitude 34.23°E and 34.03°E, at 36°S zone, it has an area of about 14,439 Km², and it is among the famous district in paddy (rice) production, in Mbeya region, in the SHT. The district has the population of about 300,517 people (https://www.citypopulation.de). Rice is one of key crops in the farming system of the district and serves a dual purpose as a major source of households' income and food security (Ngailo, 2016). Figure 1.1 shows the location of the study area, and how the study area appears on satellite images. The total area under rice production in the district is about 20,453 ha and the acreage is on the increase each year. Climate condition is; rainfall <650 mm and average annual temperature of 22-27 ℃ in Mbarali districts (Ngailo, 2016).

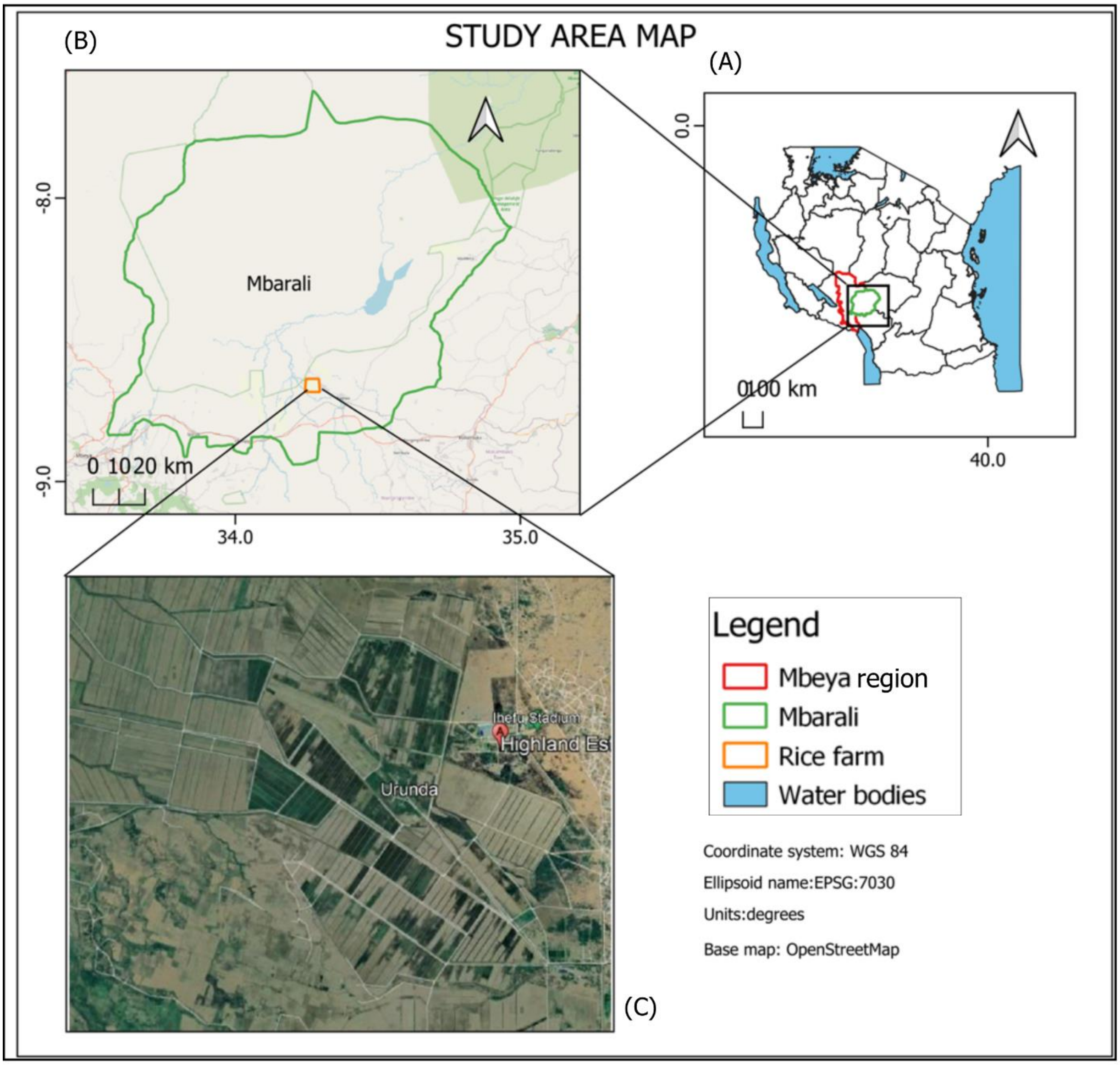

Figure 1.1: Study area location map

CHAPTER TWO
LITERATURE REVIEW

2.0 Overview

This chapter reviews different literature relating to rice crop yield production, food security and hunger, it also explains some indices which can be used in assessing rice health as they explain some factors which are potential in affecting rice during its growth.

2.1 Normalized difference vegetation index

NDVI is one of the most commonly used vegetation indices in ecological studies (Pettorelli et al., 2003).. It is calculated based on near-infrared (NIR) and red (RED) light reflectance assessments as shown in equation 2.1

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED}) / (\mathrm{NIR} + \mathrm{RED}) \qquad \ldots\ldots\ldots\ldots\ldots\ldots 2.1$$

Where NIR and RED are the amounts of light reflected by growing vegetation and registered by satellite sensor (Jackson and Huete 1991). Green vegetation has high visible light absorption and high near infrared reflectance, which results in high, positive NDVI values. Senescence or dry vegetation, snow, water, clouds and soil absorb considerably more of NIR leading to lower NDVI values (Myneni et al., (1995)). Theoretically, NDVI values are represented as a ratio ranging in value from -1 to 1 but in practice extreme negative values represent water, values around zero represents bare land, soil and values over 6 represents dense green vegetation (Roderick et al., 1996)

Normalized difference vegetation index (NDVI), is useful for estimating crop yields because it is relatively low cost and globally scalable. NDVI is a common vegetation index that has been in use since the 1970s for monitoring crop biomass and has been used in many agricultural applications including crop yield estimation, crop yield monitoring, and index-based crop insurance (Benami et al., 2021)

2.2 Normalized difference water index

The Normalized Difference Water Index (NDWI) is a remote sensing derived index estimating the leaf water content at canopy level. Is a satellite-derived index from the Near-Infrared (NIR) and Short-Wave Infrared (SWIR) channels. The SWIR reflectance reflects changes in both the vegetation water content and the spongy mesophyll structure in vegetation canopies, while the NIR reflectance is affected by leaf internal structure and leaf dry matter content but not by water content. The combination of the NIR with the SWIR removes variations induced by leaf internal structure and leaf dry matter content, improving the accuracy in retrieving the vegetation water content (Ceccato et al. 2001).

The NDWI product is dimensionless and varies between -1 to +1, depending on the leaf water content but also on the vegetation type and cover. High values of NDWI in blue correspond to high vegetation water content and to high vegetation fraction cover. Low NDWI values (in red) correspond to low vegetation water content and low vegetation fraction cover. In period of water stress, NDWI will decrease (Ceccato et al. 2001).

2.3 Modified soil adjusted vegetation index

Modified soil adjusted vegetation index (MSAVI) is a modified version of soil adjusted vegetation index (SAVI), is an index designed to substitute NDVI and NDRE (normalized difference red edge index) where they fail to provide accurate data due to low vegetation or a lack of chlorophyll in the plants (https://eos.com). Soil background condition exert considerable influence on partial canopy spectral and the calculated Vis, in order to reduce the soil background effect, it was proposed to use soil adjustment factor, L, to account for first order vegetation soil background backscattering, and soil variation, and obtained a soil adjusted vegetation index (SAVI).

Several modifications were made in SAVI’s equation, which some lead in obtaining modified soil adjusted vegetation index (MSAVI) which will be used as one of the factors to be considered in assessing rice health during its growth. MSAVI values range from -1 to 1, where: -1 to 0.2 indicate bare soil. 0.2 to 0.4 is the seed germination stage. 0.4 to 0.6 is the leaf development stage (https://eos.com)

Modified soil adjusted vegetation index (MSAVI) works where other vegetation indices do not example during seed germination and leaf development stages. It can be used on crop monitoring to monitor seedlings when there is a lot of bare soil in the field. Seed development is threatened by a number of risks such as; uneven growth, cold stress & heat stress, abnormal precipitation, elevation differences, etc. MSAVI can be used in remote sensing to detect uneven seed growth. It can be compared to weather data on the graph revealing the correlation between extreme weather and crop health. This knowledge at the early stages of plant development will allow the farmer to readjust their field management practices and get more yields (https://eos.com).

2.4 Classification

Is the process of categorizing all pixels in an image or raw remotely sensed satellite data to obtain a given set of labels or land cover themes, or is the process of categorizing and labeling pixels or groups of pixels in satellite or aerial images based on their spectral values (Fassnacht et al., 1997). Image classification plays a critical role in GIS and remote sensing, as it helps in extracting valuable information from the remotely sensed data (https://mapscaping.com). This information can be utilized for various purposes, such as land use and land cover mapping, urban planning, agriculture monitoring, natural resource management, and environmental studies, among others. By categorizing the pixels into different classes, image classification simplifies the data and makes it easier for users to analyze and understand spatial patterns, trends, and relationships (Fassnacht et al., 1997). Classification can be supervised or unsupervised (Fassnacht et al., 1997).

2.4.1 Unsupervised classification

Is the process by which each image in a dataset is identified to be a member of one of the inherent categories present in the collection without the use of labelled training samples, unsupervised categorization of images relies on unsupervised machine learning algorithms for its implementation (Olaode et al., 2014)

2.4.2 Supervised classification

Is the procedure most often used for quantitative analysis of remote sensing image data. It rests upon using suitable algorithms to label the pixels in an image as representing particular ground cover types or classes (Richards, (1986). a variety of algorithms is available for this, ranging from those based upon probability distribution models to those which the multispectral space is partitioned into class specific regions (Richards, (1986) is created using what's called a training dataset. The model is trained using many different examples of various inputs and outputs, and thus learns how to classify any new input data it receives in the future. This is how algorithms are used to predict future outcomes. In this study supervised classification is used based on random forest classification algorithm (Amaratunga, 2008).

2.5 Random Forest classification

Is a powerful and versatile supervised machine learning algorithm that grows and combines multiple decision trees another type of algorithm used to classify data (Cutler et al., 2012) Is a simple non-parametric machine learning technique that's used to solve regression and classification problems It grows multiple decision trees which are merged together for a more accurate prediction, combines the output of multiple decision trees to reach a single result (Amaratunga, 2008).

The random forest algorithm establishes the outcome based on the predictions of the decision trees. It predicts by taking the average or mean of the output from various trees. Increasing the number of trees increases the precision of the outcome. A random forest produces good predictions that can be understood easily. It can handle large datasets efficiently. The random forest algorithm provides a higher level of accuracy in predicting outcomes over the decision tree algorithm (Amaratunga, 2008).

Random Forest was found highly capable of predicting crop yields and outperformed Multi Linear Regression benchmarks in all performance statistics that were compared (Jeong et al., 2016) Random Forest is an effective and versatile machine-learning method for crop yield predictions at regional and global scales for its high accuracy and precision, ease of use, and utility in data analysis (Jeong et al., 2016).

2.6 Accuracy assessment

Accuracy assessment or validation is a key component of any project employing spatial data. There are a number of reasons why this assessment is so important including: The need to know how well you are doing and to learn from your mistakes, the ability to quantitatively compare methods and the ability to use the informa tion resulting from your spatial data analysis in some decision-making process (Russell, 2001). It is used to assess how well a classification worked and to understand how to interpret the usefulness of someone else’s classification (Congalton, 1999). Accuracy assessment should be done by using ground truthing data which was collected on the field. Also, accuracy assessment includes user accuracy, producer accuracy and overall accuracy (Congalton, 1999). The accuracy assessment can be obtained as shown on equation 2.2 (https://www.nateko.lu.se/sites)

(Total correct reference/total true reference) x 100……………………. 2.2

2.7 Rice yield estimation

Timely, objective and quantitative information regarding to paddy-rice yield can provide important information for government agencies and producers that can be used for planning harvest, storage and marketing activities. Therefore, paddy-rice-yield prediction is important for the food security of the country (Huang et al., 2013). In this research model used to estimate yield is by area of crop obtained from classification times constant of production as shown on equation 2.3

Area of Crop x Constant of Production………………2.3

2.8 Constant of production per unit acre

The term constant of production per unit acre is not commonly used or well-defined concept in agriculture of crop science field, as it is a combination of multiple terms (FAO Statistical yearbook, 2022). Crop constant is referred to a fixed value used to estimate crop yield or growth based on certain factors such as weather conditions, soil fertility or management practices. The specific value of the crop constant would depend on the crop as shown on Table 2.1 and the specific model or calculation being used (Kimutai et al.,2022). Unit acre is a unit of area commonly used in agriculture to measure land area, the unit acre is used to quantify the size or extent of agricultural fields or land area dedicated to crop cultivation (Kimutai et al.,2022)

Table 2. 1: Constant of production per acre for some crops (source: Geospatial solutions to food security (Kimutai et al., 2022))

CROP	CONSTANT PROCUCTION PER ACRE
Maize	1800
Coffee	200
Bananas	16500
Lettuce	4400
Beans	70
Cabbages	20000
Capsicum	30000
Dania	3700

CHAPTER THREE

METHODOLOGY

3.0 Overview

This chapter describes overall workflow ranging from data collection to methods used. It includes the data collection, data processing and data analyses that were used to obtain the results. the research is mainly carried out by using Google Earth Engine platform with the use of sentinel 2 data, where all the indices used in assessing rice health growth and classification to be used as a model of prediction of rice yield will be carried out.

3.1 Workflow

The following section describes the detailed description of each of these methods, as shown on Figure 3.1, it shows a brief description of the methods and procedures carried out to achieve the research results prior to the objectives of the research.

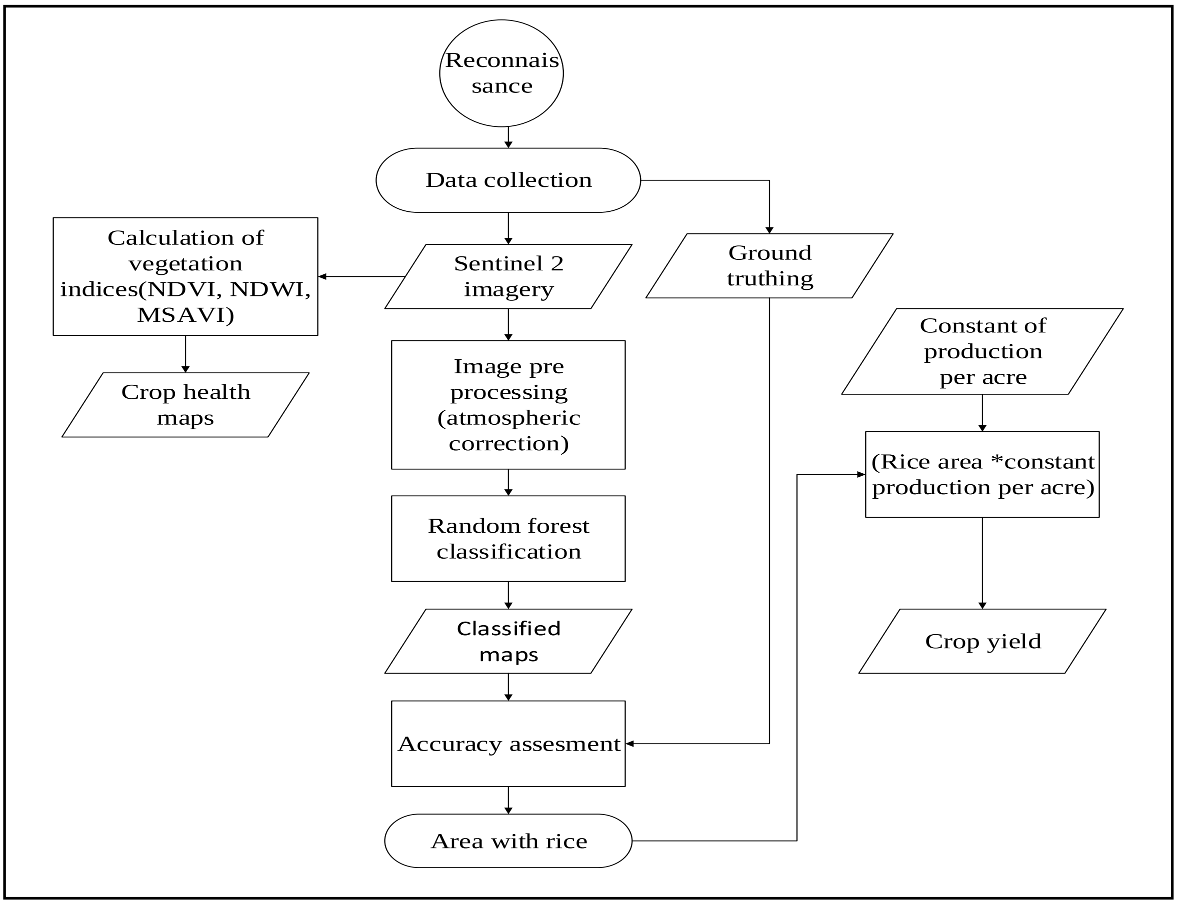

Figure 3. 2: Methodology workflow

3.3 Reconnaissance

Reconnaissance involved a comprehensive literature review, data collection, field observation and data analysis by using GIS and RS techniques. It involved both field and office observation, through visiting site, and through the use of software. The goal was to gain a better understanding of the study area.

3.4 Data collection

On doing this research, sentinel 2A satellite images of 2020, 2021, 2022 of different stages during rice growth will be used to calculate different indices (NDVI, NDWI and MSAVI) on google earth engine, then the results will be exported for analysis, the data will be used for assessing rice health during its growth.

In rice yield estimation, three different sentinel 2A images, of three different years (2020, 2021, 2022) were downloaded from USGS (United States Geological Survey) platform. Also, ground truth data of Mbarali highland estates rice farm were obtained through the use of hand-held GPS, it involved five classes (crop(rice), vegetation, water, built up and bare land).

3.5 Assessing rice health

In this study, rice health is being assessed by the use of vegetation indices, which are normalized difference vegetation index, normalized difference water index and modified soil adjusted vegetation index. These indices help in explaining the favorable conditions for rice growth throughout its growth.

3.5.1 Normalized difference vegetation index

The NDVI index detects and quantifies the presence of live green vegetation, using this reflected light in the visible and near-infrared bands. But simply, NDVI is an indicator of the vegetation greenness, the density and health of each pixel in a satellite image. It is calculated as shown in equation 3.1 (https://www.usgs.gov)

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED}) / (\mathrm{NIR} + \mathrm{RED}) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \; 3.1$$

Whereby; Red = B4, NIR = B8

The sentinel images are of three different years (2020, 2021, 2022), whereby for each year, NDVI images of three different months during rice growth which are of January, March and May were exported from google earth engine platform as shown on figure 3.2.

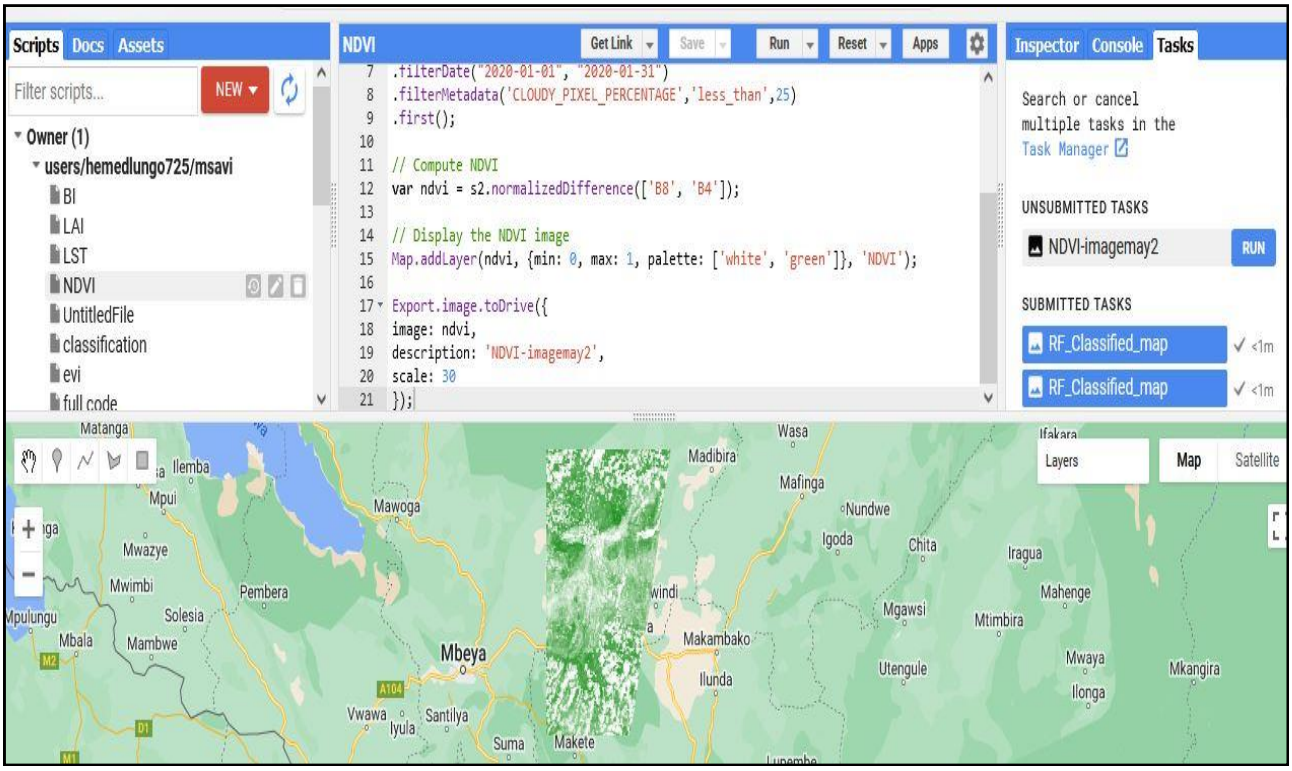

Figure 3. 2: Processing and exporting NDVI from Google earth platform

3.5.2 Normalized difference water index

The NDWI is a remote sensing-based indicator sensitive to the change in the water content of leaves (Gao, 1996). In this study, NDWI is used to detect and monitor the moisture condition of rice canopies on large scale farming, as rice crop needs enough water content for its growth. It is calculated as shown in equation 3.2 (https://foodsecurity);

$$\text{NDWI} = (\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.2$$

Whereby; NIR = band 8, SWIR = band 12

The sentinel images are of three different years (2020, 2021, 2022), whereby for each year, NDWI images of three different months during rice growth which are of January, March and May were exported from google earth engine platform as shown on figure 3.3.

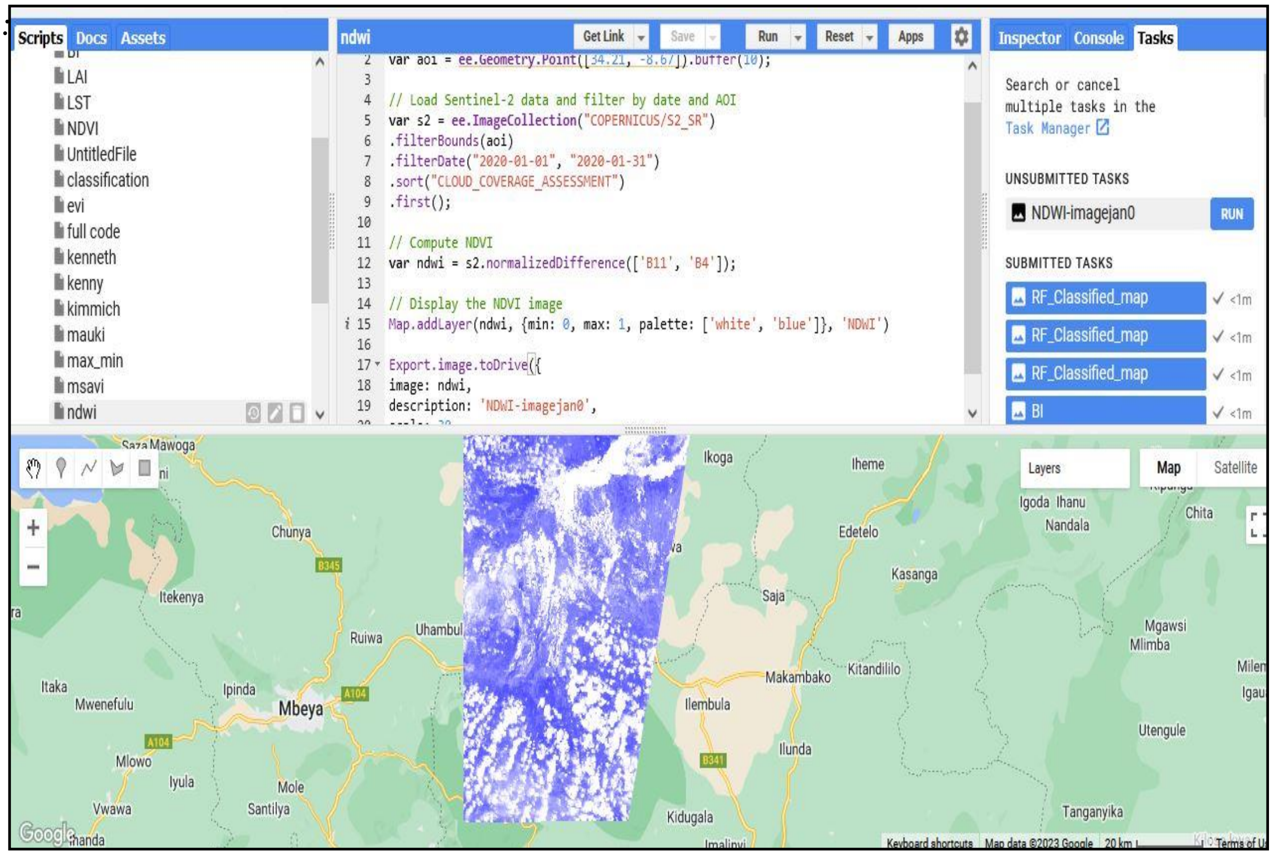

Figure 3. 3: Processing and exporting NDWI from Google earth platform

3.5.3 Modified soil adjusted vegetation index

It is calculated as a ratio between the R and NIR values with an inductive L function applied to maximize reduction of soil effects on the vegetation signal. It is calculated as shown in equation 3.3 (https://www.usgs.gov)

$$\text{MSAVI} = (2 * \text{Band 4} + 1 - \text{sqrt}((2 * \text{Band 4} + 1)2 - 8 * (\text{Band 4} - \text{Band 8}))) / 2 \qquad \ldots 3.3$$

Whereby; band 4 = red band, band 8 = NIR

The sentinel images are of three different years (2020, 2021, 2022), whereby for each year, MSAVI images of three different months during rice growth which are of January, March and May were exported from google earth engine platform as shown on figure 3.4.

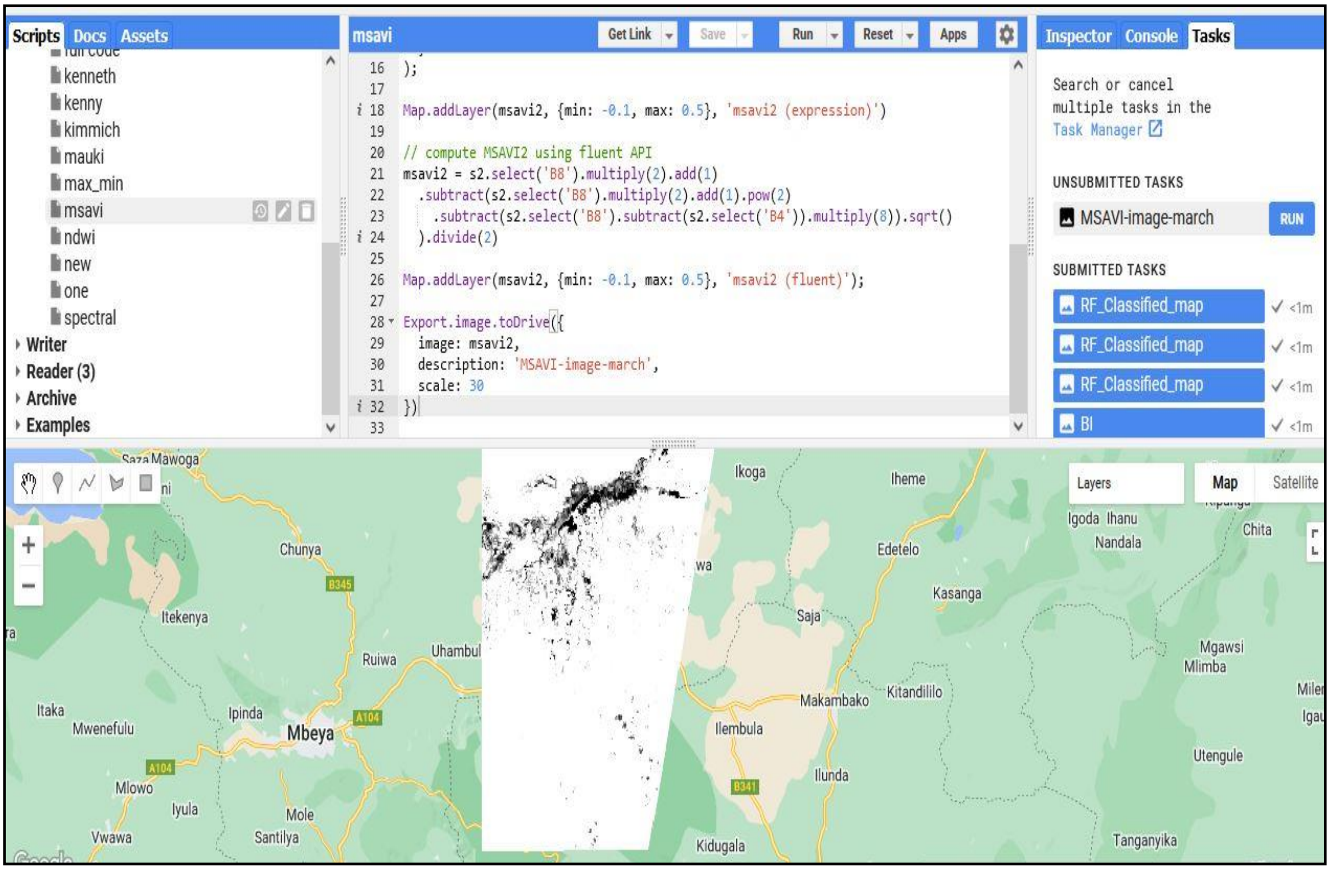

Figure 3. 4: Processing and exporting MSAVI from Google earth engine platform

3.6 Classification

In this study, classification of three different sentinel images (of three consecutive years 2020, 2021 and 2022) is done through random forest algorithm in order to achieve the research objectives

3.6.1 Data preparation

After the process of data collection, data were pre-processed through various stages which are layer stacking, re-projection, mosaic and image subset.

3.6.1.1 Layer stacking

Process of combining multiple separate bands in order to produce a new multi-band image. The layer stacking done was for sentinel 2A images for years 2020, 2021 and 2022 which consists of band 2,3,4 and 8 as Blue, green, red and NIR bands with the resolution of 10meter.

3.6.1.2 Re-projection

A process of changing band from one coordinate system to another system. Sentinel 2A images of 2020, 2021 and 2022 were re-projected from WGS 84 to Arc 1960 UTM Zone 36S system in order to match the ground coordinates with image coordinates.

3.6.1.3 Mosaic

A process of merging or combining two or more images of the same scene into the larger image. Three images were correctly merged in order to get one full image representing the area of interest the process was done for images of all three different years.

3.6.1.4 Subset

A process of defining a portion of an image from a mosaicked image. After mosaicking the images, the image obtained (mosaicked image), the study area was obtained (Mbarali highland estates rice farm) through the subset process, where further classification processes take place.

3.6.2 Image processing

Random forest classification; is the supervised machine-learning classifier based on constructing a multitude of decision trees, choosing random subsets of variable for each tree and using the most frequent tree output as the overall classification. The classification was achieved with five training samples which are Rice, Built up, Bare land, Vegetation and Water.

3.6.3 Training samples generation

The acquired images were already geo rectified, there was no need to do any geometric corrections, training samples generation preceded after the atmospheric correction was done. In this part training samples were selected in the images for all the classes with regard to the ground data that was gathered during field reconnaissance, so as to make the algorithm aware of the reflectance of the classes used, that will enable it to do classification for all images.

3.6.4 Supervised classification

The classification was not based on the computer, but supervisor based. The algorithm used in this procedure was machine learning algorithm, random classification algorithm.

The images of 2020, 2021, and 2022 were classified, using the random classifier, basing on the training samples generated during training step, hence the samples for each class were used so as the algorithm to classify.

3.6.5 Accuracy assessment

The classified images of 2020, 2021, and 2022 were then assessed to see if there were accurate. It was done using Semi-Automatic Classification Plugin, in which Reference data was prepared to match land cover classes then through accuracy assessment tool within the plugin Reference data was compared to classified map to generate confusion matrix in which it shows number of pixels classified correctly or incorrectly, basing on this Accuracy metric was generated which contain accuracy obtained for all images was above 80%.

3.6.6 Rice yield estimation

After the classification process, the area of with rice was obtained through raster unique value reports, then from the knowledge of constant of production from FAO (food and agriculture organization), which explains that every crop has its constant of production per acre, whereby for rice the constant of production is 3700 per acre (Kimutai et al.,2022). Therefore, by multiplying area with rice times constant of production (3700) as shown on equation 3.4, rice yield estimation was obtained for each year.

$$\text{Rice area} * \text{constant production per acre} \qquad \ldots\ldots.3.4$$

CHAPTER FOUR
RESULTS, ANALYSIS AND DISCUSSION

4.0 Overview

The results and analysis and discussion clarify a path to achieving the research objectives, thus the outputs for the entire study are described in this chapter. The chapter provides a detailed review of the research findings and results mainly through the use of maps.

4.1 Results of data collection

After data collection process through the use of hand help GPS with coordinate reference system of WGS 84, A total of 122 coordinates needed for ground truthing were collected, which generalized things such as vegetation, water bodies, rice, built ups and bare land, the final results obtained were into two classes; area with rice and area with no rice.

4.2 Assessing rice health

After calculation and extraction of indices (Normalized difference vegetation index, Normalized difference water index and Modifies soil adjusted vegetation index) from Google Earth Engine, three outputs of three different years (2020, 2021, 2022) were obtained for each index as shown and explained below;

4.2.1 Normalized difference vegetation index

After the calculation of NDVI in google earth engine, the results obtained were maps which shows difference in greenness (which symbolizes vegetation) in different stages of rice growth, with its values ranging from 0.07 to 0.5, where 0.07 represents unhealthy vegetation while 0.5 representing healthy vegetation, as shown in Figure 4.1, 4.2 and 4.3.

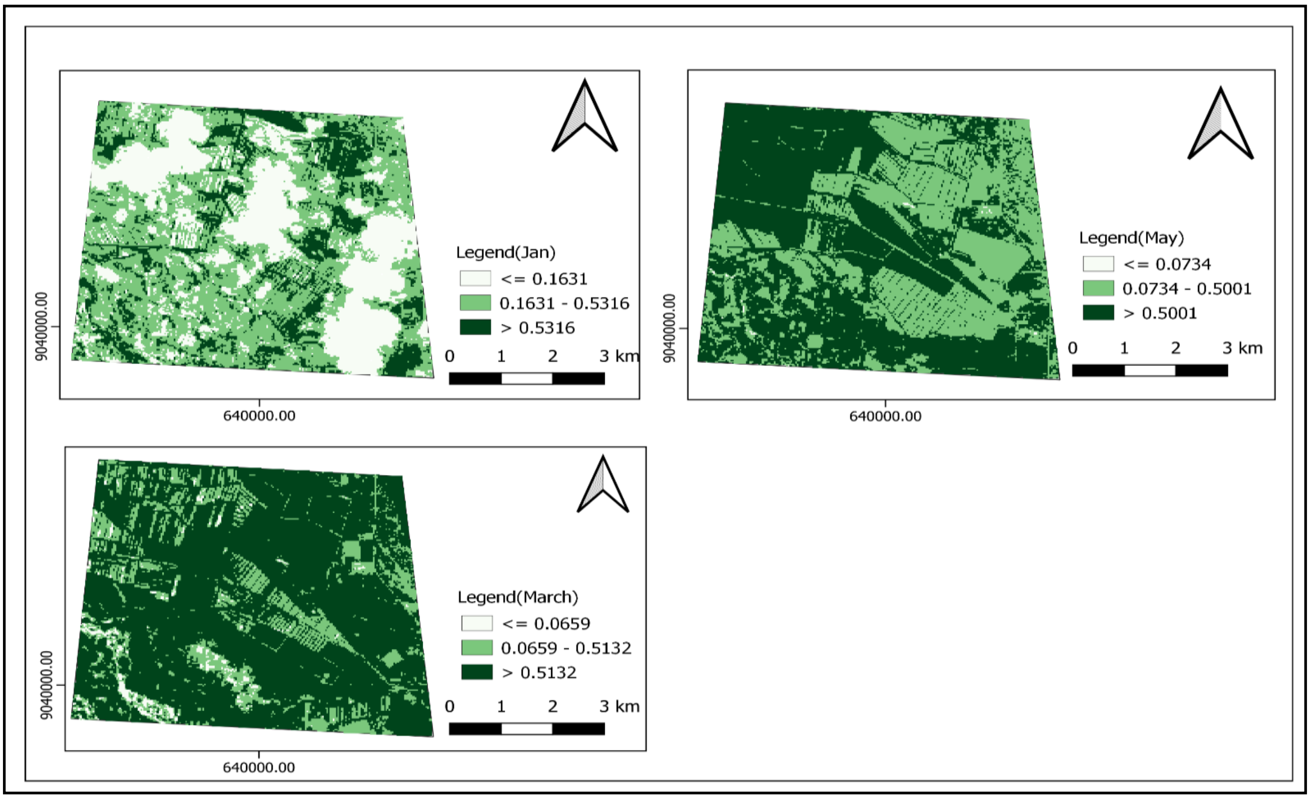

Figure 4.1: NDVI for year 2020

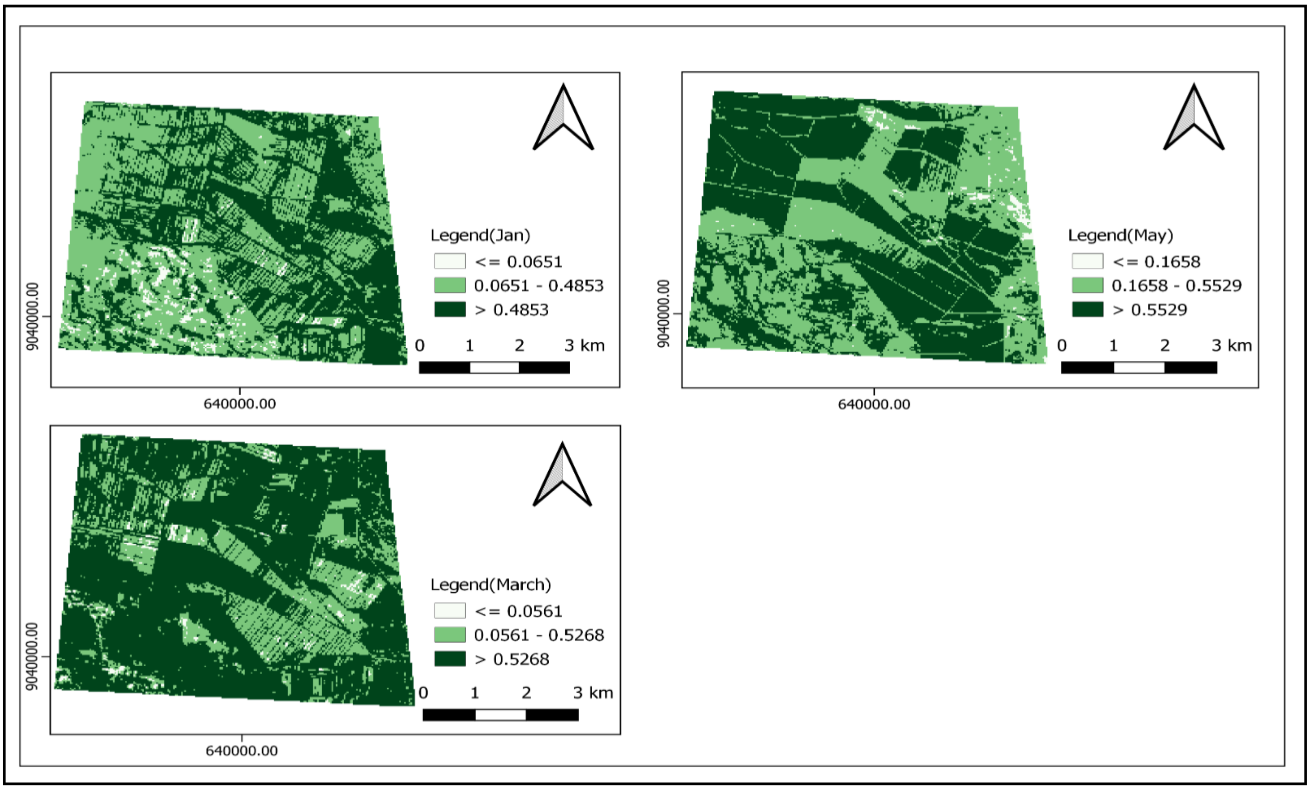

Figure 4. 2: NDVI for year 2021

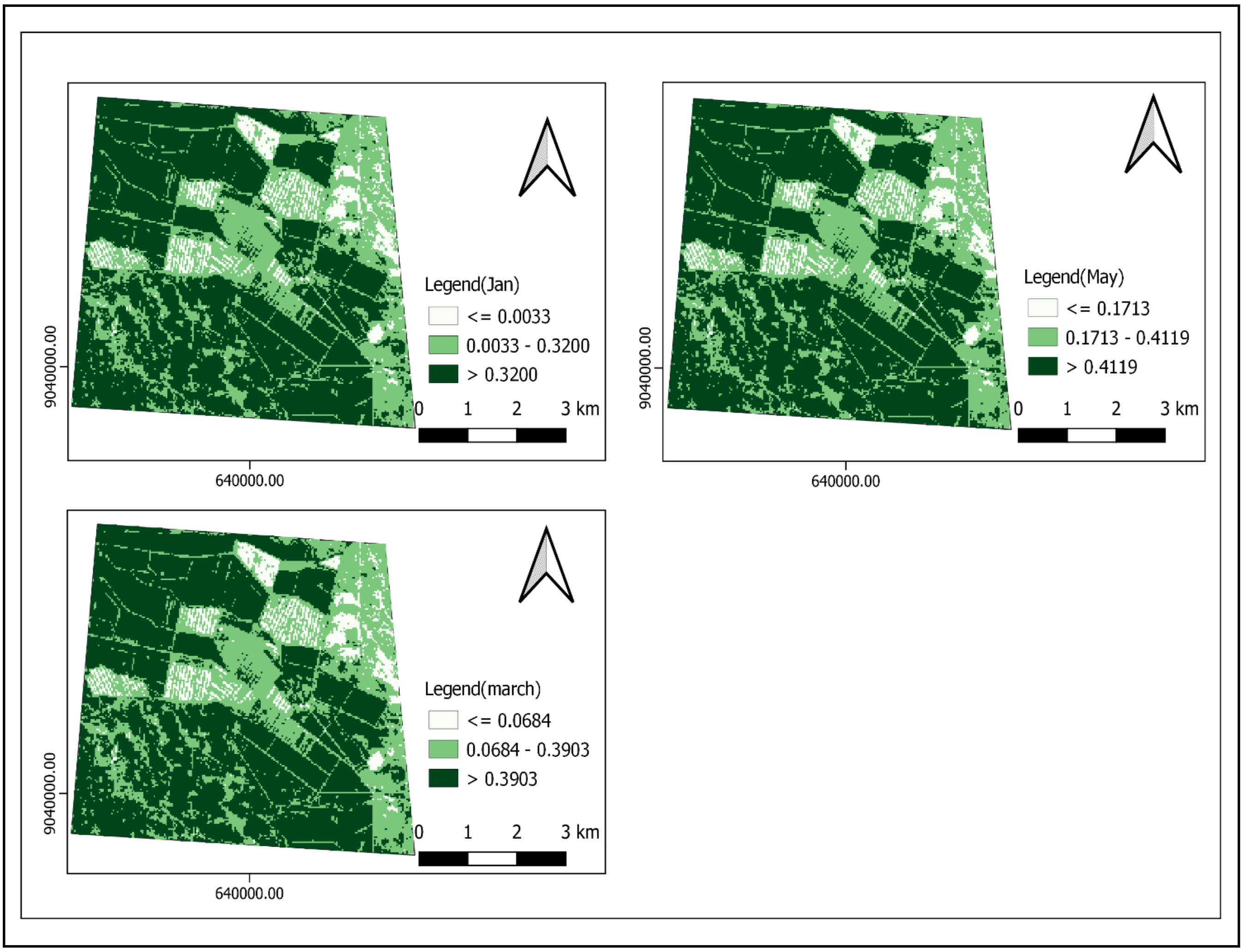

Figure 4. 3: NDVI for year 2022

4.2.2 Normalized difference water index

After of the calculation of NDWI in google earth engine, the results obtained were maps which shows difference in blueness (which symbolizes water) in different stages of rice growth, with its values ranging from -0.2 to 0.3, whereby -0.2 representing areas with less amount of water while 0.3 representing areas with much water, as shown in Figures 4.4, 4.5 and 4.6.

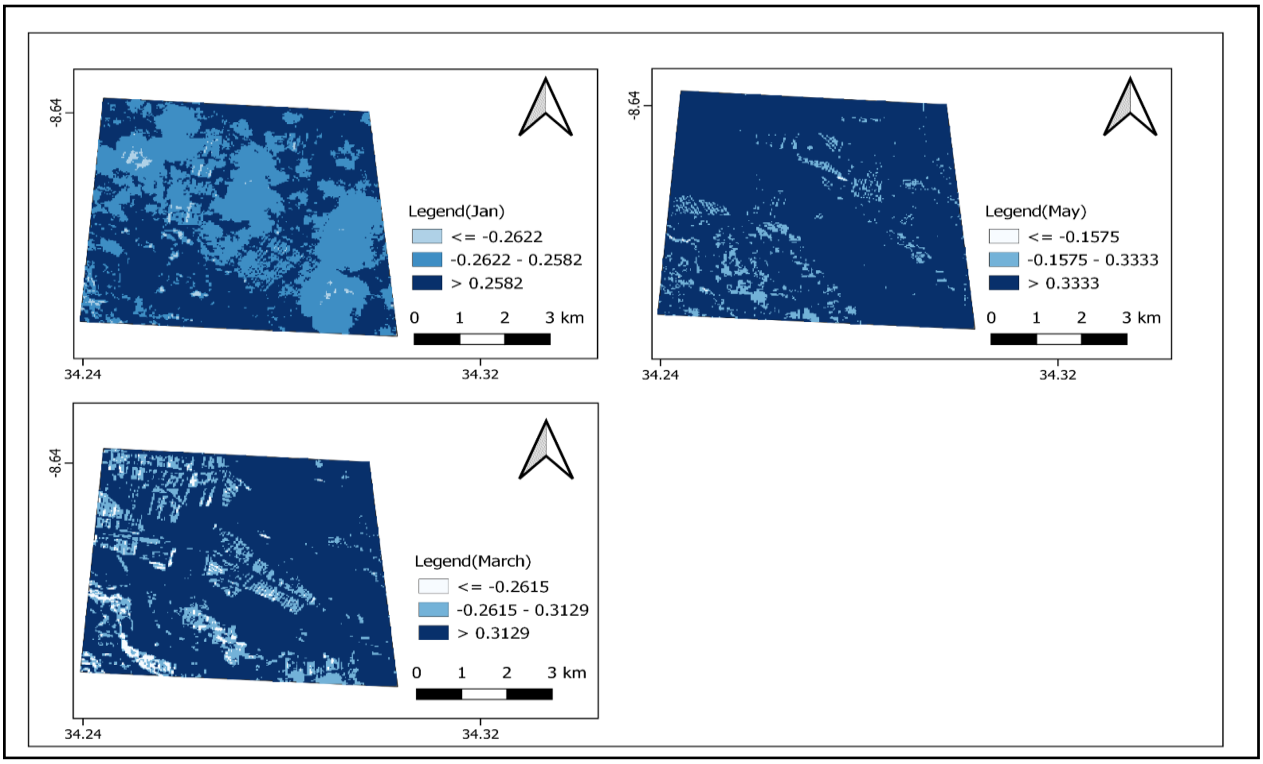

Figure 4. 4: NDWI for year 2020

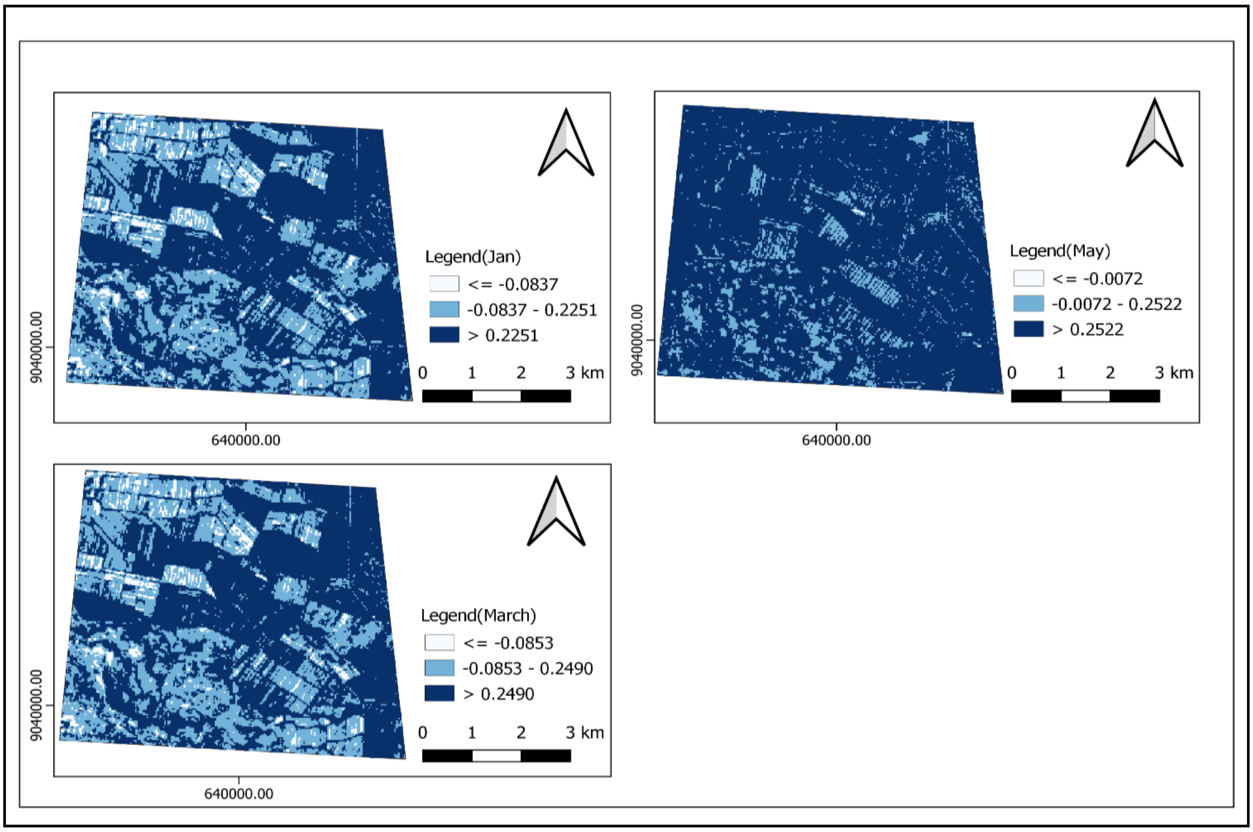

Figure 4. 5: NDWI for year 2021

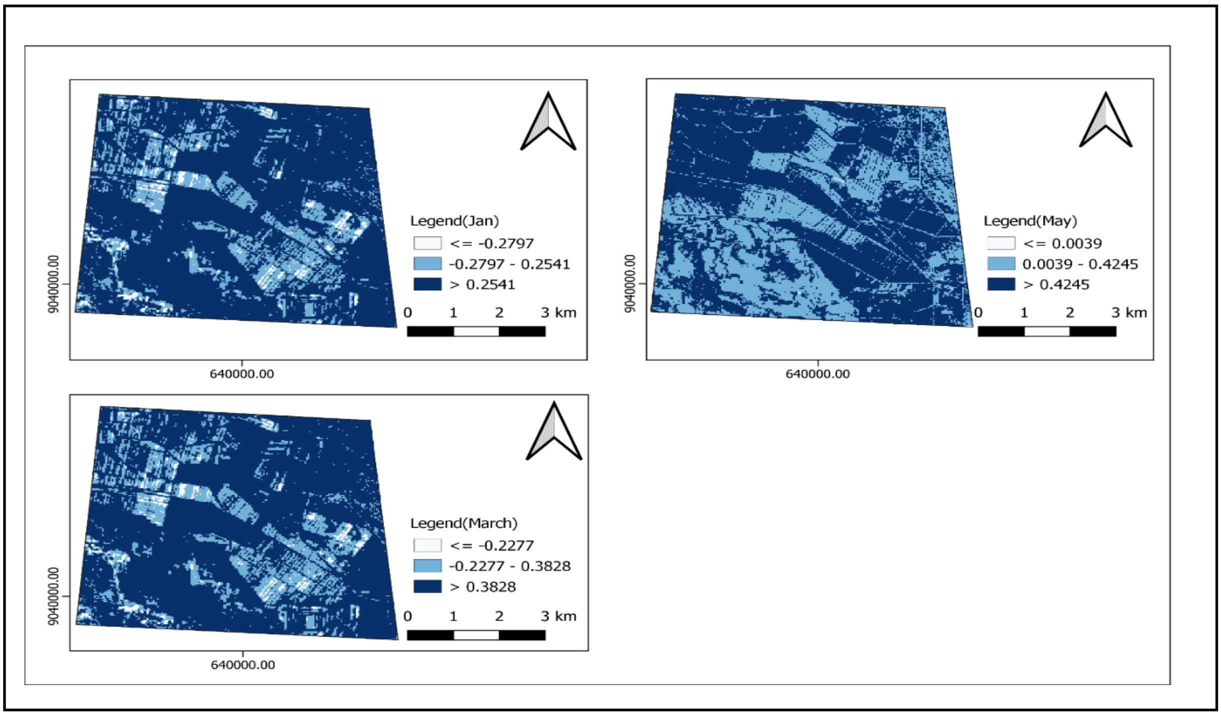

Figure 4. 6: NDWI for year 2022

4.2.3 Modified soil adjusted vegetation index

After of the calculation of MSAVI in google earth engine, the results obtained were maps which shows difference in brownness (which symbolizes soil moisture) in different stages of rice growth, with its values ranging from -0.02 to 0.4, whereby -0.02 representing unhealthy crop while 0.4 representing healthy crops, as shown in Figures 4.7, 4.8 and 4.9.

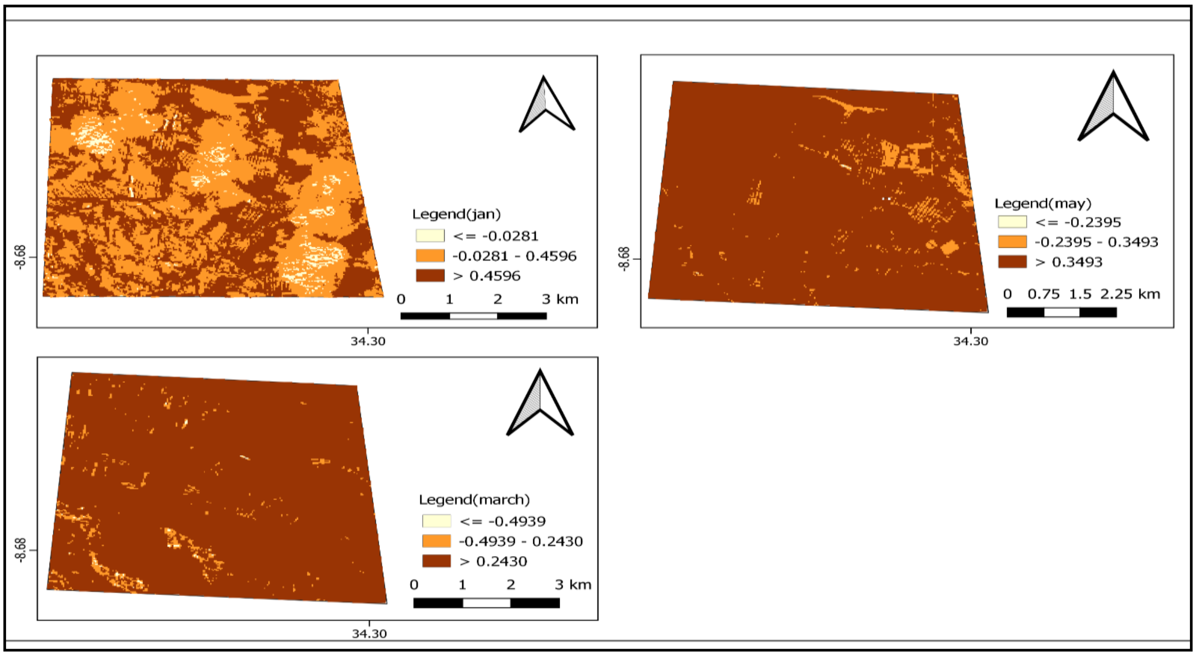

Figure 4.7: MSAVI for year 2020

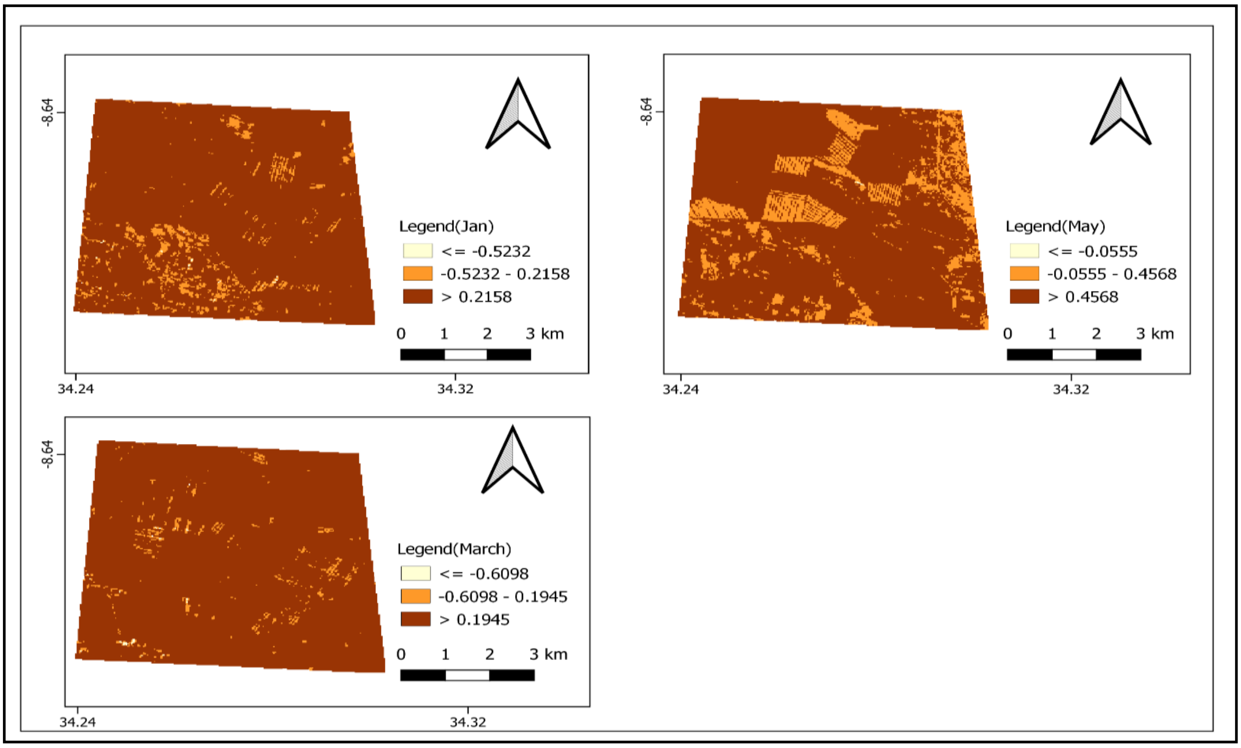

Figure 4.8: MSAVI for year 2021

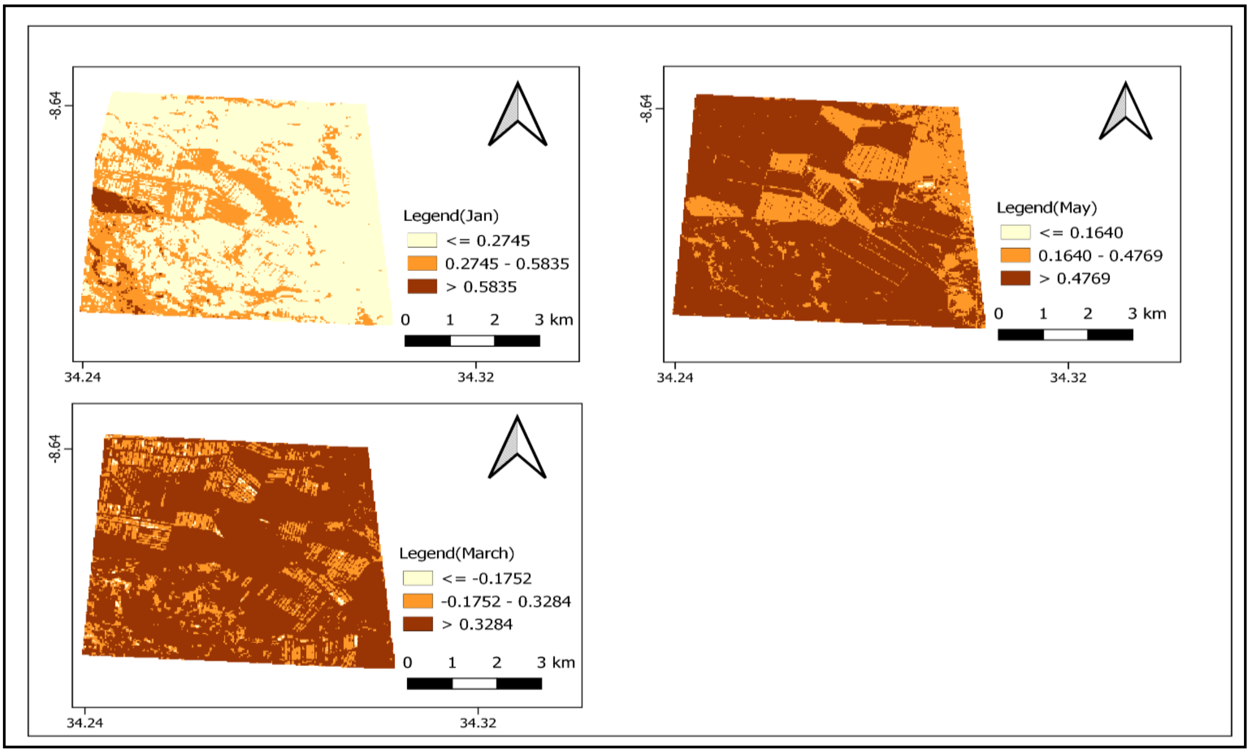

Figure 4.9: MSAVI for year 2022

4.3 Classification

The following were result obtained after classification in which resulting in classified images. Following this classification, a thorough accuracy assessment was conducted to measure the precision of the classified images. This involved complex steps to ensure reliable classifications.

4.3.1 Accuracy assessment

After carrying out accuracy assessment procedures, the accuracy obtained for all three images was above 80% whereby it was 82% for year 2020, 81.8% for year 2021 and 81.6% for year 2022 as shown on Table 4.1, 4.2 and 4.3, this shows how valid the results are, and it shows that the classified images obtained can be used for further analyses.

Table 4.1: Accuracy assessment for year 2020

V_Classified	1	2	5	7	11	Area	Wi
1	0.0001	0.0001	0.0000	0.0000	0.0001	14300.0000	0.0003
2	0.0000	0.0103	0.0073	0.0035	0.0005	1057300.0000	0.0216
5	0.0000	0.0042	0.7454	0.1111	0.0109	42738600.0000	0.8716
7	0.0020	0.0095	0.0051	0.0277	0.0012	2235300.0000	0.0456
11	0.0008	0.0009	0.0149	0.0077	0.0366	2990200.0000	0.0610
Total	0.0030	0.0251	0.7726	0.1500	0.0493	49035700.0000	
Area	146628	1228380	37886667	7357806	2416219	49035700	
SE	0.0001	0.0002	0.0006	0.0006	0.0003		
SE area	4696	11216	30939	29507	14898		
95% CI area	9204	21983	60640	57833	29199		
PA [%]	3.7984	41.1864	96.4716	18.4892	74.3622		
UA [%]	38.9474	47.8507	85.5195	60.8598	60.0880		
Kappa hat	0.3876	0.4651	0.3631	0.5395	0.5802		

Overall accuracy [%] = 82.0188
Kappa hat classification = 0.4313

Area unit = metre^2
SE = standard error
CI = confidence interval
PA = producer's accuracy
UA = user's accuracy

Table 4.2: Accuracy assessment for year 2021

> AREA BASED ERROR MATRIX
> Reference

V_Classified	1	2	5	7	8	11	Area
1	0.0001	0.0001	0.0000	0.0000	0.0000	0.0001	11300.0000
2	0.0000	0.0084	0.0069	0.0022	0.0000	0.0002	866200.000
5	0.0002	0.0063	0.7471	0.1111	0.0000	0.0101	42889500.0
7	0.0026	0.0102	0.0058	0.0296	0.0000	0.0022	2475000.00
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1300.0000
11	0.0001	0.0014	0.0136	0.0083	0.0000	0.0335	2792400.00
Total	0.0030	0.0264	0.7734	0.1512	0.0000	0.0460	49035700.0
Area	144878	1295382	37922507	7415079	0	2256554	49035700
SE	0.0001	0.0002	0.0006	0.0006	0.0000	0.0003	
SE area	4605	12106	30870	29623	0	14244	
95% CI area	9026	23727	60505	58060	0	27919	
PA [%]	2.2437	31.8430	96.6024	19.6011	nan	72.7776	
UA [%]	28.7671	47.6204	85.4150	58.7247	nan	58.8120	
Kappa hat	0.2856	0.4620	0.3565	0.5137	nan	0.5683	

Overall accuracy [%] = 81.8700
Kappa hat classification = 0.4205

Area unit = metre^2
SE = standard error
CI = confidence interval
PA = producer's accuracy
UA = user's accuracy

Table 4.3: Accuracy assessment for year 2022

V_Classified	1	2	5	7	11	Area	Wi
1	0.0001	0.0001	0.0000	0.0000	0.0001	15100.0000	0.0003
2	0.0000	0.0075	0.0059	0.0023	0.0000	777400.0000	0.0159
5	0.0000	0.0065	0.7454	0.1123	0.0100	42867300.0000	0.8742
7	0.0027	0.0102	0.0055	0.0285	0.0015	2373700.0000	0.0484
11	0.0001	0.0012	0.0174	0.0073	0.0352	3002200.0000	0.0612
Total	0.0029	0.0256	0.7742	0.1505	0.0468	49035700.0000	
Area	142425	1254290	37964405	7379369	2295212	49035700	
SE	0.0001	0.0002	0.0006	0.0006	0.0003		
SE area	4493	11840	31178	29577	14435		
95% CI area	8807	23206	61109	57971	28293		
PA [%]	3.9900	29.5043	96.2725	18.9217	75.1998		
UA [%]	37.6344	47.6035	85.2615	58.8239	57.4910		
Kappa hat	0.3745	0.4623	0.3472	0.5153	0.5540		

Overall accuracy [%] = 81.6697
Kappa hat classification = 0.4136

Area unit = metre^2
SE = standard error
CI = confidence interval
PA = producer's accuracy
UA = user's accuracy

After performing the classification process, and after obtaining the valid accuracy assessment for maps of all years which was above 80%, the classified maps were obtained for all three years, as shown on Figure 4.10, which shows two classes which are the area which is covered with rice and the area which is not covered with rice.

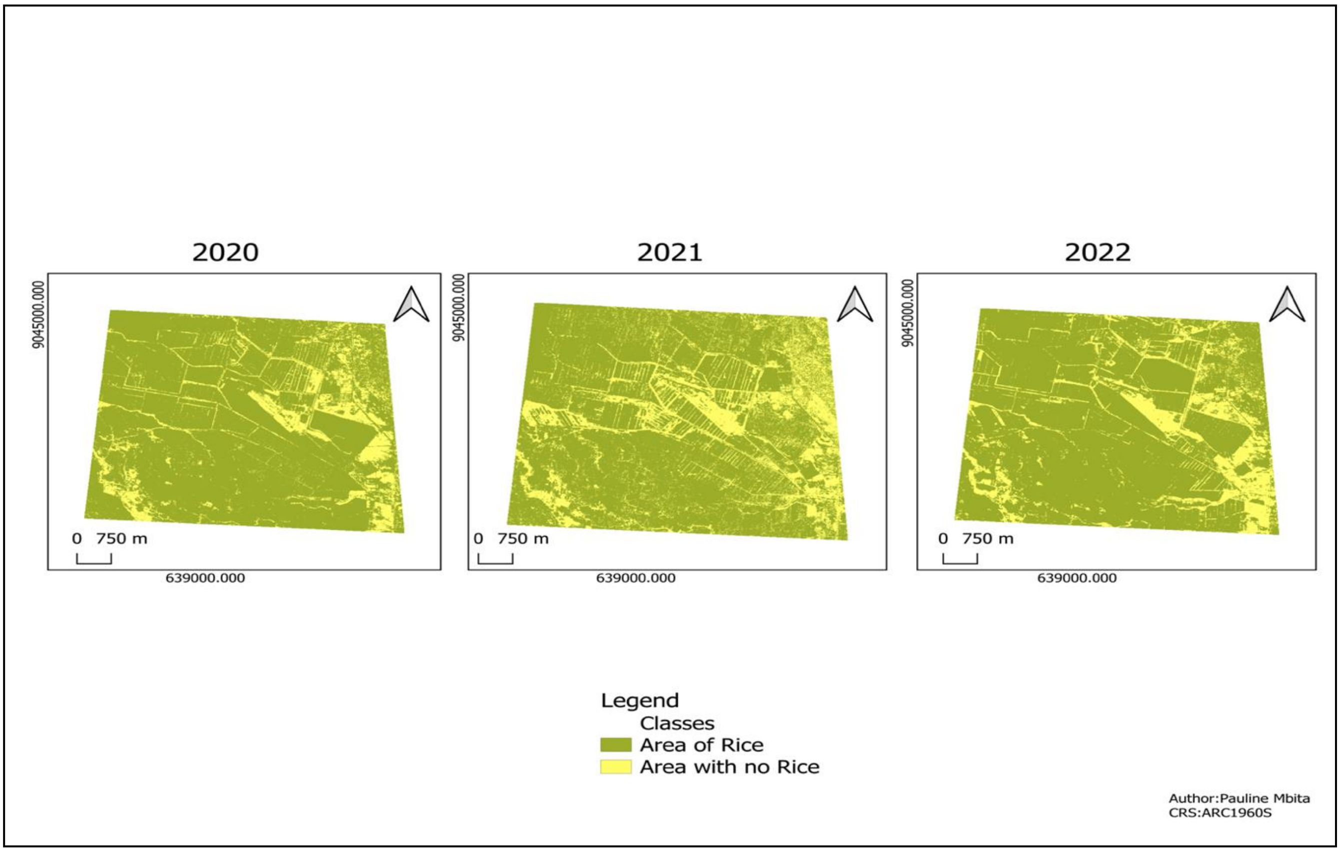

Figure 4.10: Classification for year 2020,2021 and 2022

4.3.2 Rice yield estimation

After the classification process, the area covered with rice was obtained through raster unique value reports, as shown on Tables 4.4, 4.5 and 4.6. Area covered with rice was then converted into acres through mathematical conversions as it was in meter squares. Then the obtained results were multiplied by the constant of production of rice per acre which is 3700 (Kimutai et al., 2022).

Table 4.4: showing area (m^2) for all classes after classification (year 2020)

class	Area (m^2)	Area in hectares
Area with rice	29,722,100	2972.21
Area with no rice	9,134,600	913.46

For yield estimation;

Rice area *constant production per acre

=7344.4908585*3700

=27,174,616.1

Therefore, yield estimation for year 2020 is 27,174,616.1per 3885.67 hectares

Table 4.5: showing area (m^2) for all classes after classification (year 2021)

class	Area (m^2)	Area in hectares
Area with rice	29,531,800	2953.18
Area with no rice	9,324,900	932.49

For yield estimation;

Rice area *constant production per acre

=7297.4667044*3700

=27,000,626.8

Therefore, yield estimation for year 2021 is 27,000,626.8 per 3885.67 hectares

Table 4.6: showing area (m^2) for all classes after classification (year 2022)

Class	Area (m^2)	Area in hectares
Area with rice	31,839,700	3183.97
Area with no rice	7,017,000	701.7

For yield estimation;

Rice area *constant production per acre

=7867.7612143*3700

=29,110,716.5

Therefore, yield estimation for year 2022 is 29,110,716.5 per 3885.67 hectares

4.4 Discussion of the results

From the research objectives, the requirements are to show how remote sensing techniques can solve the problem of high capital in terms of labor and assessing time, through the use vegetation indices and random forest classification method to assess and estimate yield production of rice crop.

4.4.1 Assessing rice health

Spectral reflectance-based vegetation indices have sensitive characteristics to crop growth and health conditions. The performance of each vegetation index to a certain condition is different and needs to be interpreted, correspondingly (Ryu et al., 2020). In this study, the results obtained through indices clearly shows how vegetation indices can be used in assessing rice health throughout its growth.

For NDVI; it shows how greenness increases from January towards may, this symbolized the proper growing of rice throughout its growth, and good yield production to be expected. For NDWI it shows how the blueness increases from January to May, as blueness symbolizes water, then the results shows that rice needs enough water throughout its growth, and the yield obtained in year

2020, 2021 and 2022 will be sufficient in relevance to rice planted. For MSAVI it shows how the brownness increases from January to May, as brown indicates healthy vegetation, therefore this indicated a proper growing of rice throughout its growth. Therefore, during rice growth, incase farmers will assess the indices and determine any divergence in any of the indices, this will help farmers to easily determine any abnormality in rice growth, and work on it to ensure more and sufficient yield is obtained and hence ensure food security.

4.4.2 Rice yield estimation

The outcomes derived from the random forest classification applied to the years 2020, 2021, and 2022 in this investigation offer a clear demonstration of the potential utility of remote sensing techniques in yield estimation. These results illustrate the feasibility of estimating yield based on the constant yield production concept outlined by FAO. The findings serve to delineate areas under cultivation (characterized by rice coverage) and areas not under cultivation (lacking rice coverage). The outcomes of this study shed light on the methodology for yield estimation, which doesn't necessitate access to historical production data from preceding years or reliance on models such as the linear regression approach frequently cited by researchers, this can also help in reducing the gap on unavailability of data as the form of crop insurance preferred by clients and industry, is constrained by the limited availability of detailed historical yield records (Setiyono et al., 2018), Since remote sensing can provide information on the actual status of an agricultural crop, the integration between remote sensing data and crop growth simulation models has become an important trend for yield estimation and prediction (Jeong et al., 2016).

The results obtained from both indices and random forest classification algorithm, shows that, in year 2022 there was much rice yield compared to year 2020, compared to year 2021. As the results obtained from classification shows that there was much area covered with rice in year 2022, followed by year 2020 then less area covered with rice in 2021 meaning that there was less rice yield in year 2021. And the range values of indices shows that in year 2022 much yield was to be expected compared to year 2020 compared to year 2021 and the values are high in 2022, followed by 2020, followed by 2021. These results were further confirmed and approved by one of the workers from Mbarali highland estates rice farm, which concluded how accurate the methods can be used in estimation of yields.

CHAPTER FIVE

CONCLUSION, CHALLENGES AND RECOMMENDATION

5.0 Overview

This chapter is based on the finding from the results and discussion chapter, showing how the results answers the research objectives, where the explanation is summarized in the conclusion. This chapter contains conclusion, limitations and recommendation.

5.1 Conclusion

Based on the objectives of this research, the results and discussion analyzed shows how the problem of lack of sufficient information showing how farmers can handle large-scale farms by the use of remote sensing techniques, can be handled as Most farmers in Tanzania hesitate in engaging themselves into large scale rice farming due to having inadequate capital in terms of time and labor.

5.1.1 Assessing rice health

Various factors including water presence and vegetation greenness can affect yield production, and some of these factors are explained and can be shown through the use of vegetation indices. The study came to conclusion that vegetation indices can be used in assessing rice health throughout its growing season from January to May, whereby the indices used was NDVI, NDWI and MSAVI. As NDVI shows difference in greenness between healthy and unhealthy vegetation, as rice needs enough water NDWI shows differences in water content and MSAVI shows amount of soil moisture and vegetation health. Therefore, divergence in greenness, blueness, or brownness while carrying out the indices will help farmers in determine whether there is any problem during rice growth and this will help in ensuring that sufficient yield is obtained per rice season.

5.1.2 Rice yield estimation

The research also came to conclusion that random forest algorithm which is one of the remote sensing techniques, can be used in estimating and providing early information about rice yields, more precisely without the use of historical records and models. The study further shows how random forest algorithm can be used in showing number of hectares that a farm holds.

The results obtained clearly shows, how farmers can manage large scale rice farming with less labor and within a short period of time. This can help in enhancing advancements in agricultural sectors and ensuring adequate food security in country and regional level.

5.2 Challenges and limitations

While carrying out this study, the challenge faced was on data availability, as Mbarali highland estates rice farm is among the biggest rice farms in Tanzania, but the farm is divided into plots which are controlled by different independent farmers, therefore it was difficult in obtained data of how many tons of rice was harvested in different years including the studied years (2020, 2021 & 2022), this is because it was difficult in obtaining data and information from each farmer, therefore it was a limitation in validation purpose, and in carrying out predictions and estimations by using models, example linear regression model.

5.3 Recommendation

Based on the findings and conclusion of this research, farmers and investors can be recommended to use the results obtained in assessing rice health and yield to reduce a gap in labor and assessing time required while engaging in large scale farming. Also, further studies on crops other than rice should be done, in order to increase and provide knowledge to farmers dealing with all type of crops, so that farmers can be comfortable in investing in large scale farming, in order to promote the increase in production for all crops and assure food security within the nation.

Also, further researches should be conducted showing how GIS and remote sensing technologies can be used in estimating and predicting rice yield, through the use of simplified models of data and machine learning techniques so that to simplify and advance more the agricultural sector.

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APPENDIX

Ground truthing data collected by using hand held GPS with Arc1960 as a reference coordinate system.

1	x	y,	Name
2	642476.520	9044972.987	Bare land
3	642753.355	9044632.150	Bare land
4	642111.458	9044293.225	Bare land
5	642008.756	9044827.251	Bare land
6	642313.376	9044784.575	Bare land
7	642224.559	9044926.717	Bare land
8	641950.152	9043901.719	Bare land
9	642889.914	9044322.996	Bare land
10	642353.487	9044257.163	Bare land
11	642838.698	9044284.974	Bare land
12	642346.761	9044079.112	Bare land
13	642033.611	9044319.081	Bare land
14	642175.444	9043953.503	Bare land
15	643096.676	9043855.728	Bare land
16	642736.271	9044578.232	Bare land
17	642646.056	9043997.650	Bare land
18	642193.713	9044719.044	Bare land
19	642422.225	9043742.661	Bare land
20	642467.233	9044343.003	Bare land
21	642851.527	9044435.302	Bare land
22	642311.376	9042565.285	Built up
23	643310.286	9042164.489	Built up
24	642994.013	9043526.520	Built up
25	643174.241	9042553.209	Built up
26	643410.313	9039989.368	Built up
27	641654.478	9042418.246	Built up
28	642824.092	9042584.978	Built up
29	642619.206	9043498.271	Built up
30	642927.770	9042490.515	Built up
31	641637.146	9042549.129	Built up
32	643427.760	9040338.452	Built up
33	643107.978	9041370.622	Built up
34	643426.115	9041059.814	Built up
35	643252.606	9042129.823	Built up
36	643247.840	9041591.196	Built up
37	642451.728	9043572.800	Built up
38	643428.919	9041243.035	Built up
39	642342.167	9042753.298	Built up
40	643318.447	9041990.657	Built up
41	642088.516	9042650.998	Built up
42	643454.724	9040776.223	Built up
43	643222.813	9041038.730	Built up
44	642465.898	9043248.806	Built up
45	643402.213	9041506.198	Built up

51	642180.961	9042614.035	Built up
52	637671.360	9039940.723	Rice
53	636623.860	9040504.817	Rice
54	638748.450	9040613.286	Rice
55	638640.102	9038907.441	Rice
56	640678.213	9043430.501	Rice
57	641883.180	9040275.294	Rice
58	642938.244	9038963.666	Rice
59	636689.803	9044362.726	Rice
60	641136.342	9045069.238	Rice
61	636270.836	9040006.840	Rice
62	641778.735	9040123.088	Rice
63	641317.214	9042931.338	Rice
64	642027.530	9040641.398	Rice
65	638722.405	9041260.080	Rice
66	640392.156	9038966.245	Rice
67	637173.664	9044014.010	Rice
68	639752.998	9041264.935	Rice
69	640697.012	9039592.411	Rice
70	637432.055	9038405.029	Rice
71	640487.456	9038880.714	Rice
72	641231.050	9043815.572	Rice
73	642019.273	9041306.312	Rice

100	638034.646	9044144.049	Rice
101	640626.927	9042243.384	Rice
102	642389.028	9041029.157	Vegetation
103	642433.413	9041028.374	Vegetation
104	642787.153	9041479.089	Vegetation
105	642497.977	9041145.542	Vegetation
106	642632.356	9041143.383	Vegetation
107	642473.989	9040858.769	Vegetation
108	642558.207	9041216.484	Vegetation
109	642516.102	9041196.583	Vegetation
110	642659.973	9040932.830	Vegetation
111	642594.613	9041228.837	Vegetation
112	642467.471	9040862.105	Vegetation
113	642776.461	9041348.396	Vegetation
114	642589.100	9041198.889	Vegetation
115	642474.435	9041087.240	Vegetation
116	642681.262	9041245.492	Vegetation
117	642473.234	9040955.240	Vegetation
118	642705.985	9040862.379	Vegetation
119	642680.565	9041325.092	Vegetation
120	642441.286	9040926.382	Vegetation
121	642450.316	9041046.464	Vegetation
122	640366.997	9042817.111	water