Master Thesis

submitted within the UNIGIS Masters's program
"Geographical Information Science & Systems – (UNIGIS MSc)"
to the Department of Geoinformatics – Z_GIS,
Paris-Londron University of Salzburg

Sentinel-2 Time Series Data and Machine Learning Techniques for Sugar Cane Mapping in the Usuthu River Basin, Eswatini

by

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In partial fulfillment of the requirements for
the Degree of
"Master of Science", abbreviated "MSc"

Mbabane, May 2024

Science Pledge

With my signature below, I certify that my thesis is entirely the result of my own work. I have cited all sources I have used.

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Acknowledgements

I thank the Paris Lodron University of Salzburg for providing me with a thorough program for master's degrees in Geospatial Information Science and Systems. Special thanks go to my supervisor, Dr. Neuwirth Christian, for the support he gave me as I worked on my project. I want to thank you Doctor Neuwirth, for your professional experience and guidance in making the study successful.

I want to take the time to say thank you to the River Basin Authority for giving me permission to conduct this study within their river basin and to give me access to their database. Special thanks go to the river basin authority CEO Sindy Mthimkhulu and the other colleagues in the river basin and the informants in ILLOVO sugar mill and Siphofaneni irrigation district. I can never leave out the inspiration and support I received from Dr. Wisdom Dlamini; I appreciate your helping hand.

Lastly, I want to say thank you to my beloved family for the inspiration they gave me while I worked on this project. It would be difficult and almost impossible to accomplish this research without their unfailing support.

Abstract

Agriculture is the primary source of income for most of the residents of Eswatini. The sugar business has a significant economic impact, particularly on neighborhood jobs and incomes in the country. Over the past decades, sugarcane fields' delineation and mapping have been done using conventional techniques, such as the utilization of ground truth facts together with orthophotos which have been proven to be expensive and challenging to employ in remote regions. For accurate management and forecasting of the nation's sugarcane production, charting and tracking the stages of sugarcane development is therefore essential.

This research utilizes the digital mapping technologies with two image classification techniques, support vector machine (SVM) together with the random forest (RF) and using the Sentinel 2 (S2) imageries to categorize and discriminate sugarcane plantations within Usuthu river basin. Supplementary to the S2 images bands, the study looks into how two vegetation indices, enhanced vegetation index (EVI) together with normalized different vegetation index (NDVI), are essential for improving the classification precision. In order to determine the optimal time of year to map sugarcane, four satellite images—germination, tillering, elongation, and ripening—were gathered and analysed for each of the four sugarcane growth stages in the basin.

The highest accuracy was obtained by the SVM model when classifying data for the ripening stage of the sugarcane growing timeline using spectral bands only with an OA of 95% and kappa value of 0.90. The RF method also produced good accuracy with the spectral bands with the highest OA of 92% at the elongation and ripening stages with kappa values of 0.84 and 0.83 at elongation and ripening stages respectively. The vegetation indices (VIs) and spectral bands identification outcomes were marginally inferior to the spectral bands alone. The results show a good improvement as the sugarcane crop matures (ripening stage), suggesting that the last growth stage of the crop is the best time for discriminating sugarcane. Both methods have great potential for discriminating sugarcane, however the SVM portrays superiority over the RF in the classification accuracy as per the results.

Keywords: Sentinel-2; random forests; support vector machine species; sugarcane; phenology; remote sensing

Table of Content

1. Introduction

1.1. Background

Agriculture is the primary source of income for the majority of the residents of Eswatini (Terry and Ogg, 2017, Mamba et al., 2022a). The main export revenue-generating industries in Eswatini are sugar and forestry which accounts for 6 percent and 1.3 percent of the gross domestic product (GDP) of Eswatini respectively (International Finance Corporation Bank (IFB), 2022). As per the Eswatini Sugar Association (ESA) report for the year 2022, approximately 60,000 hectares of land are used to grow sugarcane in the nation, which, depending on the climate, yields an average of 680,000 tonnes of sugar annually.

The fiscal situation and business environment of Eswatini have greatly benefited from the sugar industry over the past years. About 16, 000 people directly employed in the sugar mills and another 20,000 jobs created indirectly, the sugar industry is by far the biggest employer amongst the private sector companies in Eswatini (Nalley et al., 2019). Cane farming and sugar milling both make significant contributions to the production and agricultural businesses, respectively (ESA, 2022). Approximately 92% of the sugar products is exported to foreign nations. The sugar products include direct consumption sugar, bulk raw sugar for further reprocessing and molasses. The direct consumption products are mostly distributed to the European Union countries (EU), World market and to the southern African region countries, mainly Botswana, Eswatini, Lesotho, Namibia and South Africa. While the bulk of the raw sugar is sent to the EU and United States and the molasses is used mainly for domestic purposes (ESA, 2022).

As seen in the areas highlighted in green in Figure 1, sugar cane is cultivated under irrigation in the nation’s eastern region which is classified as the lowveld region based on the climate zones of Eswatini. The lowveld lies in an elevation that ranges between 150 - 600 meters above sea level with a mean annual rainfall of 500mm and temperatures that rise to 39 degrees Celsius. Approximately two hundred thousand hectares, or 12% of Eswatini's total land area, are under cultivation, including both rain-fed and irrigated land (Karimi et al., 2019). Approximately ninety-five percent of the country's water resources above ground are used for irrigation purposes, and over ninety percent of that water is used to grow sugarcane (Karimi et al., 2019).

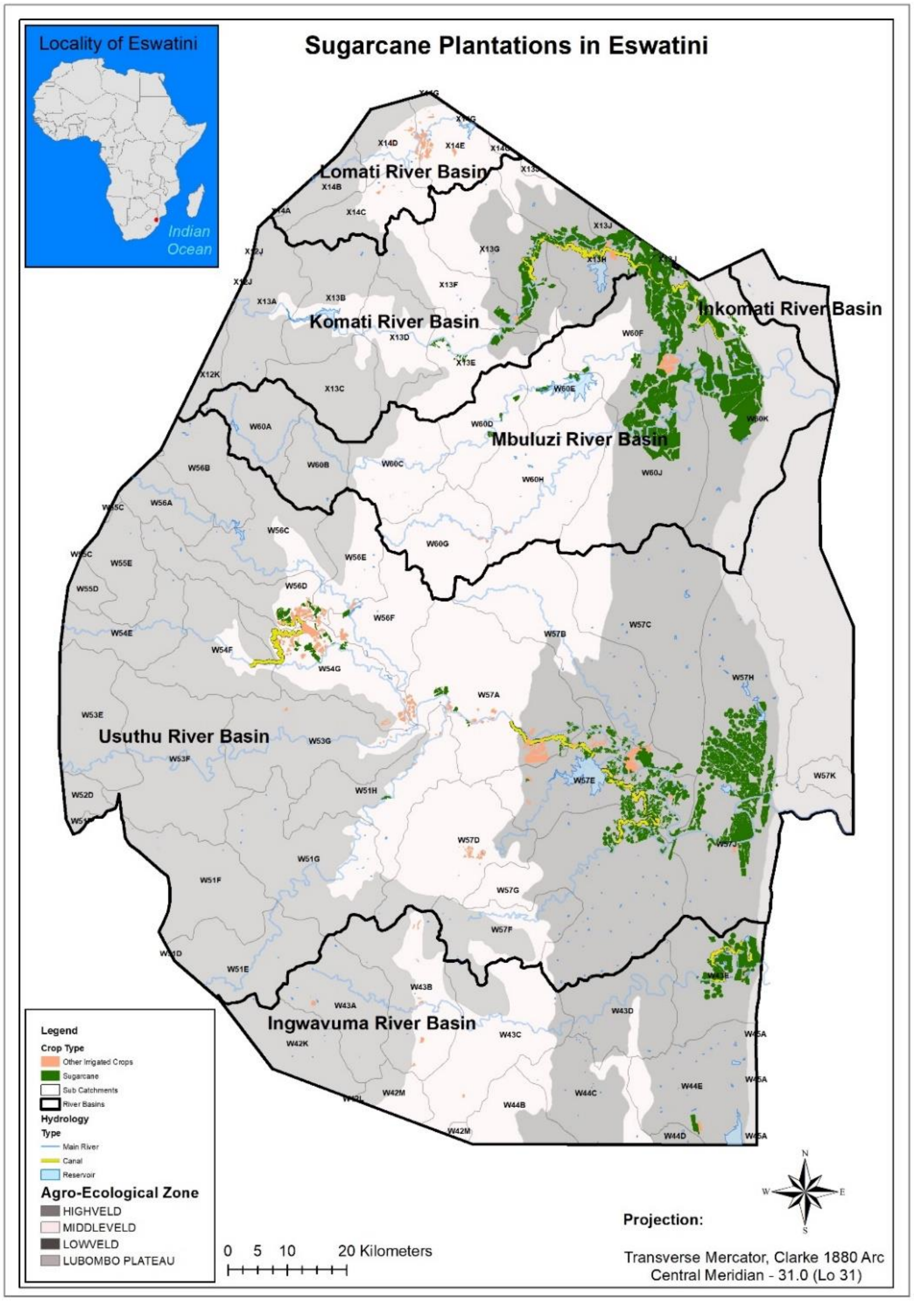


Figure 1: Sugarcane and other irrigated crops map of Eswatini (water use mapping 2021)

Across the country, sugarcane plantations are a significant source of income. All throughout Eswatini, there are sugarcane plantations, with the majority of them located in the eastern region due to the region's more hospitable climate. The country is divided into five river basins for ease of water resource management purposes. The Usuthu river basin is the largest while Lomati is the smallest basin in terms of area allocation. A majority of the sugar cane fields are found in the Usuthu river basin and the least in the Lomati river basin. A total of about 60 000 ha of land in Eswatini is under sugarcane cultivation and a sizeable portion (40%) of the sugar cane fields are found in the Usuthu river basin (ESA, 2022).

In Eswatini, the sugar business has a significant economic impact, particularly on neighborhood jobs and incomes in the rural areas (Mhlanga-Ndlovu, 2022), as it is the same case in other countries (Sawaengsak and Gheewala, 2017). There are direct and indirect benefits from sugarcane farming to society's well-being which includes socio-economic and ecological advantages. These benefits include access to improved infrastructure services, increase in income and wealth, jobs and business opportunities and access to portable water through the dams and canals that are usually constructed for irrigation in the communities where sugar cane plantations exist. Communities around the sugarcane plantations in Eswatini enjoy free access to the canals and dams for fishing and washing their clothes.

A research done by EL CHAMI et al. (2020), found that in Eswatini, like other countries such as Brazil and Mozambique, sugarcane growing communities appear to have higher living standards, with high life expectancy, low poverty, and easy access to resources like electricity, sewage systems, and schools compared to other regions that are not growing sugarcane . In Eswatini, sugarcane farming encourages the emergence of subsidiary companies in a range of industries, such as finance, trading and grocery stores, agricultural businesses support, and other customer-focused industries that weren't previously accessible prior to the establishment of sugarcane plantations. As part of its corporate social responsibility, Eswatini Sugar Association offers the following services to the communities in which it operates: accommodation, parks, clean water, medical care, schooling, and environmental conservation efforts (ESA, 2022). Even if they do not work in the sugar mills or farms, the communities surrounding these sugarcane mills gain from these socioeconomic activities.

Sugarcane plantations typically provide a broad spectrum of ecological benefits, comprising habitat for biodiversity, bioenergy, and recreational areas (Mamba et al., 2022a, Lukhele et al., 2021). One of the most important and effective sources of biomass for the production of biofuel is sugarcane (Mamba et al., 2022a). A variety of insects, birds, and animals can be found in sugarcane plantation as habitat. A study conducted by Lukhele et al. (2021), proved that as much as there is comparatively a higher bird species richness and diversity in savannas than in sugarcane plantations, they showed how different species of birds are attracted to the various growth stages of sugarcane. Their research revealed that different stages of the sugarcane attract different kinds of bird species, as these stages provide suitable conditions for harboring different bird's species which is a benefit to the bird's species.

Despite the aforementioned benefits of sugarcane, there is still a great deal of disagreement in science, particularly when it comes to the conflicting opinions regarding how sugarcane plantations affect different ecological systems, the environment, and the social and economic aspects of society (EL CHAMI et al., 2020). Although sugarcane cultivation has many benefits, changing land use is a major obstacle (Semie et al., 2019). Changes in land use typically has a significant impact on the loss of biodiversity such loss of natural forest land and certain types of species. Research indicates that sugarcane and food crops are becoming more competitive, especially in regions with extensive sugarcane plantations (Harvey and Pilgrim, 2011). This could raise concerns about food security. Since sugarcane requires irrigation, it will have detrimental effects on nations like Eswatini that have limited water supplies, resulting in water stress and water pollution (Mamba et al., 2022a, Nhamo, 2017). Eswatini's population's general socioeconomic well-being depends on striking a balance between development and conservation, which entails the sustainable use of biodiversity.

Details about the dispersion, hectarages, and productivity of sugarcane plantations is essential in managing and monitoring sugarcane growth and its impact on the society. To this end, it is essential to produce precise and current sugarcane distribution maps, particularly at a localized size, in order to apply knowledgeable management techniques and policies. Due to the lack of standardized assessment and monitoring methods, technical and scientific skills, sugarcane plantations classification continue to be a difficult task in Southern Africa as is it based on manual approaches (Mulianga et al., 2015). Therefore, practical as well as economical spatial methods and databases for sugarcane mapping must be developed.

Over the past decades, sugarcane fields' delineation and mapping have been done using conventional techniques, such as the utilization of ground truth facts together with orthophotos. Even though these techniques have been proven to be very precise, they are expensive, cumbersome, and challenging to employ in remote regions (Mulianga et al., 2015). Lately, the integration of field observation and remote sensing techniques has proven effective in delivering the trustworthy data required for sugarcane fields mapping (Mulianga et al., 2015, Wang et al., 2019, Jiang et al., 2019, de Oliveira Maia et al., 2023, Chen et al., 2020). In order to map current sugarcane fields, satellite-based sensor technologies can quickly and cheaply gather the information needed. As a result, local and regional assessments of sugarcane plantations are possible. On the other hand, time series data has become a hot topic in crop classification (Chen et al., 2020). Therefore, building a time series data-based sugarcane identification model can be a useful method for timely and accurate monitoring of sugarcane planting information in Eswatini.

1.2. Literature review

Utilizing Remotely Sensed Information in Sugarcane Production

The simplest and yet most important challenge facing agriculture is mapping crop planted areas with the goal of determining total area, water allocation, and or yield estimation. For these activities, technologies such as satellite imagery and indices of vegetation have become commonplace in the recent past (Nihar et al., 2022, Som-Ard et al., 2021). One of the main industries benefiting from the earth observation (EO) technologies in monitoring plant health, total planted area, and harvest estimates is sugarcane. Satellite sensors are an affordable and less laborious method of gathering crop information because they cover vast territories with finer spatial details (Som-Ard et al., 2021, Hossain et al., 2019, Pinter Jr et al., 2003). Depending on the sensor features, RS is a potent and attractive tool for mapping agricultural inventories, predicting land area, observing, extracting phenology, and forecasting crop yield with acceptable accuracy (Nihar et al., 2022). Inaccurate production forecasts result in incorrect trade and inventory policies for agriculturally based goods. It causes issues for producers, sellers, and consumers by distorting the market (Nihar et al., 2022). Timely and correct information about sugarcane planted area, total harvest, plant growth, and ripening and harvesting time is required for the sugarcane sector's development and oversight. This is essential for the long-lasting production and manufacturing of sugar cane, the entire farming community, economic growth, and the ecosystem (Wang et al., 2020, Mulianga et al., 2015).

From early 1980, remote sensing via satellites has developed into a useful data source for identifying, mapping, and tracking agricultural growth as well as supporting crop yield and wellness monitoring (Som-Ard et al., 2021). Alongside the advancement of sensors, machine learning technology has made significant strides in recent years (Som-Ard et al., 2021, King et al., 1995). Moreover, the availability of essential technological resources has increased (Yao et al., 2019, Chi et al., 2016). Today, numerous types of sensors with diverse spectral, spatial, and temporal qualities are proving successful for applications relating to sugarcane, such as almost real time mapping, growth surveillance, forecasting yields, and emergency preparedness (Ennouri and Kallel, 2019). The most often used satellites for monitoring sugarcane regions are the open SAR images and Sentinel 2 type, along with the vast Landsat imagery database (Som-Ard et al., 2021, Wang et al., 2019, Jiang et al., 2019, Molijn et al., 2019, dos Santos Luciano et al., 2019). Additionally, cutting-edge predictive analytics are presently accessible and have been effectively used for monitoring, mapping, and quick field management (Som-Ard et al., 2021, dos Santos Luciano et al., 2019).

The digital mapping community has used RF and SVM classifiers more frequently during the past ten years due to their speed, ease of use, and satisfying categorization outcomes (Som-Ard et al., 2021). In multiple tests, sugarcane farms were identified using the RF classification algorithm, which yielded good accuracy in classification for sugarcane localization (Som-Ard et al., 2021). To categorise sugarcane and other crops utilising RF, multiple spectrum sensor imagery from Hyperion, L5, L7, L8, S1 SAR, and S2 MSI were employed (dos Santos Luciano et al., 2018, Jiang et al., 2019, Everingham et al., 2007, Schultz et al., 2015). Schultz et al. (2015) analysed numerous potential classifications using the RF technique and error rate measure to determine the best categorization variables for locating sugarcane and the classification outcome was very good with an overall accuracy of up to 98 %. The use of S2 MSI, Hyperion, Landsat 7, and 8 has also been utilised with the SVM learning method to map sugarcane crops with very high classification results (Wang et al., 2019, Everingham et al., 2007, Johnson et al., 2014). These studies reveal that the SVM and the RF classifier produce better results in contrast to other machine learning methods, even though the SVM is more accurate than RF (Wang et al., 2019).

Earlier investigations on sugarcane mapping recognized and utilized the phenology features of sugarcane fields (Jiang et al., 2019, Wang et al., 2020, Nihar et al., 2022, Rao, 2008). From a study by Jiang et al. (2019a), 86.3% accuracy was achieved in mapping sugarcane in a Chinese City, using a collection of S2 imageries and the RF method from 2017 to 2018. In a research conducted by Nihar et al. (2022), using openly accessible S1 and S2 pictures, sugarcane fields were identified at the watershed level, with the help of phenology and spectral-based categorization and the results demonstrated how well the spatiotemporal S2 images distinguish between the newly established and ratoon sugarcane crops at a field level . The classification method using SVM produced a sugarcane mask having a kappa value of 0.95, and the RF method distinguished between the planted crop and ratoon fields with 0.81 kappa value (Nihar et al., 2022).

In further investigations, the spectrum indices NDVI and RVI, were also used to analyze L5 TM and L7 ETM data (Souza et al., 2017) and NDWI (Mulianga et al., 2015) to recognize sugarcane farms by employing crop masking as a standard method (Mulianga et al., 2015, Murillo-Sandoval et al., 2011, Xavier et al., 2006). The crop masking approach was used to analyze satellite data from MODIS data of 250m spatial detail with multiple series vegetation indices such as NDVI and EVI to detect sugarcane farms alongside huge scale field investigations that focused on a specific field level (Souza et al., 2017, Xavier et al., 2006). Additionally, image fusion and the crop masking approach were used to analyze multiple series remote sensing data of MODIS imaging at various spatial details. Because of the abundance of healthy green leaves and high leaf density in the growing to ripening phases, the findings reveal that using the total NDVI values at each of the development phases of sugarcane resulted in favorable precision that reached 80%.

Wang et al. (2019) used Sentinel-2 imagery together with sugarcane phenology information by utilizing composite images to calculate NDVI values of each three sugarcane development phase (the seedling, the elongation, and the harvest phase). In classifying the sugarcane plantations, the study used four automated learning algorithms (artificial neural networks (ANN), SVM, RF, and the decision tree (CART-DT). The outcomes indicated that, except for the ANN classifier, all other classifiers demonstrated exceptionally accurate sugarcane generated maps with overall accuracy above 91%. The SVM (Polynomial-SVM) classifier showed excellent results (95.20%) and a kappa value of 0.88, making it the most preferred classifier for accurately separating sugarcane fields from other crops and vegetation.

A research done by Terry and Ogg, (2017) in regards to the sugar sector's performance in Eswatini indicates that since the year 2001, the sugarcane area coverage expanded strongly in Eswatini with about 28% increase as a result of the introduction of smallholder famers. The Government of Eswatini continues to construct major dams to facilitate irrigation as a poverty alleviation initiative which further suggest an anticipated increase in the agricultural area, particularly sugarcane since these dams are constructed in the sugarcane suitable areas. Simultaneously, the accessibility of digital mapping facilities for agricultural purposes expanded (Atzberger, 2013, dos Santos Luciano et al., 2019), resulting in a wealth of information available about digital mapping technologies (Som-Ard et al., 2021). Most of these studies have demonstrated that multiple dates imagery produces more precise crop categorization results than sole date imagery (Mahmud et al., 2022b, Som-Ard et al., 2021, Wang et al., 2019).

The availability and advancement of the different sensors are continually being tested for their suitability for sugar cane monitoring. The increasing availability of high-resolution remote sensing data and technological advancement of respective image analysis methods bear a great potential for sugar cane crop mapping. Even though many of S2 capabilities own a positive track record in sugarcane mapping, particularly using multiple date images (Wang et al., 2019, Singh et al., 2020, Jiang et al., 2019), there is no evidence to support its use in identifying and classifying sugarcane fields in Eswatini. Thus, methods that are accurate and computationally efficient are crucial for mapping sugarcane fields with multiple spectral images. Benefits in using S2 imagery include its spatiotemporal coverage, 13 multispectral bands, strategically placed Red-edge bands, global footprint, and the free availability. This study will utilize the RF and SVM classification methods with the phenology-based algorithms using S2 vegetation indices to identify sugarcane fields within the Usutu River basin.

1.3. Motivation to conduct the research

Numerous studies (Wang et al., 2020, Singh et al., 2020, A. Ramezan et al., 2019) show that agricultural statistics used in sugarcane sector comes from field surveys, producer reports, questionnaires, and interviews. This is the same case with the Kingdom of Eswatini whereby sugarcane cane statistics, either published in grey literature and organization’s websites such as the Eswatini Sugar Association (ESA), comes from field surveys and or interviews with the farmers. The ground truthing strategy is laborious and lengthy and it cannot deliver instant information for all the sugarcane areas because it occasionally relies on sampling techniques (Verma et al., 2017). In order to supplement field work statistical information, different kinds of crops can be shown at all levels of detail through the use of passive remote sensors (Wang et al., 2020).

Current and precise sugarcane data are essential for determining sugarcane area and evaluating its effects on economic growth and the ecology at large (Wang et al., 2020). A major shift in the agriculture sector is the drive towards precision farming, which relies on spatial information, GPS technology and remotely sensed data (Liaghat et al., 2010, Palaniswami et al., 2011). Interactive maps of sugarcane fields reveal spatial relationships and trends that are very crucial for sugarcane production, insect management, soil properties and many more (Som-Ard et al., 2021). On the other hand, it is very important to map the location of each sugar cane field so that distance to sugar mill can be estimated since sugar cane contains sucrose which is known to decrease soon as the crop is cut (Solomon et al., 2006). This is confirmed in a research done by Masuku, (2011), who concluded that distance between the farm and the mill is one of many profit determinants for a small holder sugar cane famer in Eswatini. Therefore, estimating the distance to the nearest sugarcane mill is very important.

Local sugar cane farmers use the spatial data to estimate farm inputs needed and the expected yield, while the government need this information for many requirements such as forecasting the total water allocation for each river basin or catchment, quantifying exports, and forecasting profits and revenue. As seen in many research investigations around the country (Jordaan et al., 2019, Mhlanga et al., 2006, Terry and Ogg, 2017), the lack of water resources, as a result of the increasing water demand, particularly for irrigation purpose, is a reason for concern. The sugar sector is thus facing a threat to its overall viability. Therefore, there is a need to employ water management strategies aimed at conserving the already strained water resources in the country as observed by Karimi et al. (2019) in their investigation. While many other studies done in the agriculture sector in Eswatini focus on the water demand and water consumption (Mkhonta, 2015, Mamba et al., 2022b, Mhlanga et al., 2006, Karimi et al., 2019), it is very important to note that these studies depend on spatial datasets of sugarcane field boundaries which also need to be accurately mapped.

Using satellite-based technologies, irrigation water levels can be estimated by mapping the breadth and distribution of agricultural lands and irrigated areas (Halipu et al., 2022). The Department of Water Affairs (DWA) is tasked with issuing irrigation permits which is implemented through the Water Act of 2003. The permit indicates the amount of water to be extracted and the total area to be irrigated. Farmers are expected to possess water measuring devices to enforce compliance to their permitted water volumes but in a recent baseline survey (2021) done by the Joint River Basin Authorities (JRBAs) in the Usuthu River Basin, it was found that famers do not have these devices, meaning their consumption is not measured at all. The JRBA is tasked with managing agricultural activities and water usage in each of the river basins in the country. The 2021 baseline survey done by the JRBA focused on identifying farming activities within the basin and mainly to establish field boundaries. The intended outcome was to establish the total area under irrigation. However, this exercise had a limitation due to some fields having no farming activity at the time of the survey. As a result, some fields would be mapped with the value indicating no farming activity or indicating that the farm is active if there is a farming activity. This implies that systems for measuring water use in each river basin must be established on a constant basis.

The recent survey conducted by the JRBAs utilized the easiest and most reliable method to ascertain water use, which was to consider the field size for each farm to understand if the farmer is irrigating the permitted area or above the permitted hectares. It is therefore very important to accurately map the area under irrigation, even more interesting, to apply the current RS technology to identify these fields in each of the growing stages of the sugarcane life cycle. However, many studies on sugarcane mapping using satellite imagery and machine learning are mostly conducted in the European countries (Som-Ard et al., 2021). In Eswatini there is no study known to this researcher that attempted to identify sugarcane fields using the RS techniques which might be due to the lack of technical expertise on these emerging, quick, and reliable technologies, it is therefore, very important to test these technologies and methods in the local context. Furthermore, the outcome of this scalable research will assist in providing almost real time sugarcane statistics for the country, which will be the first of its kind.

2. Aims and Objectives

2.1. Aims

The aim of this thesis is to demonstrate the capabilities of the Sintenel-2 time series data in mapping sugarcane fields.

2.2. Specific Objectives of the study

1. To map and estimate the total sugar cane planted area in the Usuthu river basin.
2. To extract and classify sentinel 2 vegetation indices from the different phenological stages of the sugar cane crop to select the best time for mapping sugarcane.
3. To select the best time of the year for identifying sugar cane fields in the Usuthu river basin
4. To compare the SVM and RF machine-learning classification methods with respect to their performance in sugarcane mapping.

3. Material and Methods

3.1. Material

3.1.1. Study Area Description

This research was conducted within the Usutu River Basin, Eswatini (26° 38' 2.566" S; 31° 26' 38.395" E) (Figure 2). The area is situated in the nation's center and occupies a total area of 9156.67 km^2 which stretches from west to east of the entire country, encompassing all four ecological zones and, consequently, all the nation's climatic conditions.

The Usuthu River Basin sustains a substantial amount of commercial activity that boosts Eswatini's economy. This includes forestry, industry, and agricultural pursuits like crop farming, which account for a sizable portion of the basin activity. The region was selected because it produces the majority of the nation's sugarcane, offering a chance to assess how well-suited S-2 data are for identifying and mapping sugarcane plantations.

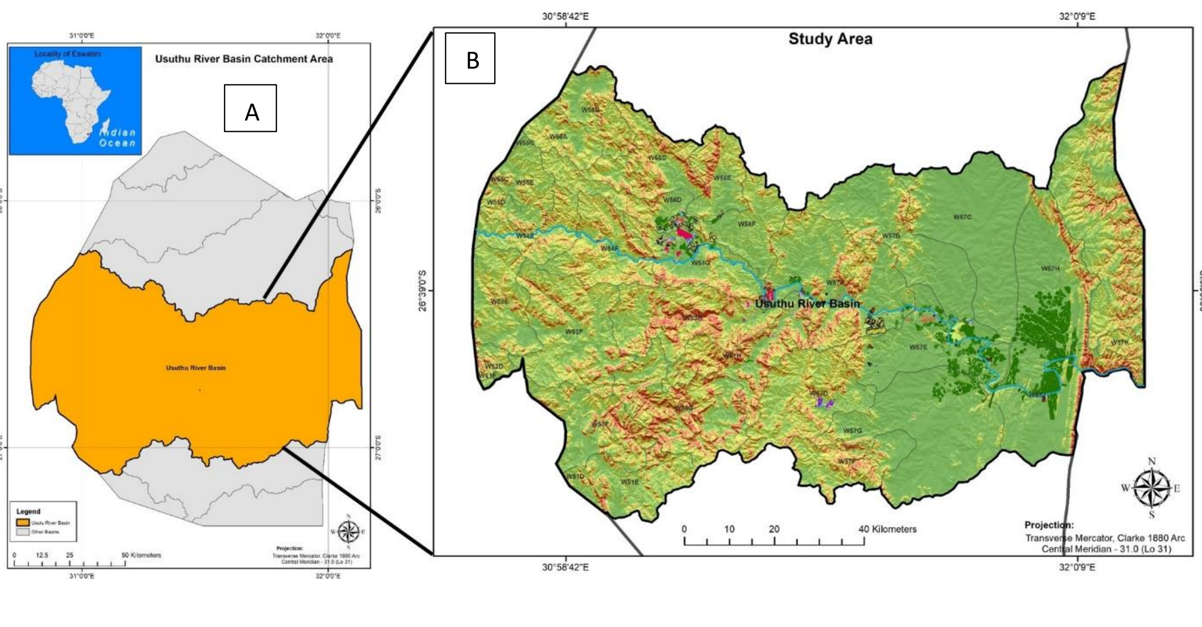


Figure 2: Study site Map

Locality of the Usuthu river basin within Eswatini with other basins and an insert map of the locality of Eswatini in the African region (A), Usuthu river basin (B).

Climate Conditions in the Study Area

Eswatini is separated into multiple agro-ecological zones that stretch from the west to the east (Figure 3). Since the study area covers the entire country, it is also divided into the four ecological zones. On the west there is the mountainous Highveld region which, in comparison to other parts of the nation, is colder and experiences comparatively more rainfall. The primary agricultural pursuits in this area consist of rain-fed maize production and forestry plantations, with smallholder farmers primarily cultivating other crops. The Middleveld, which lies east of the Highveld and is distinguished by rolling hills and level plains, is adjacent to it. Rainfed maize and other crop production is also the primary industry in this region. Generally dry, livestock farming, and irrigated sugarcane plantations predominate in the Lowveld. Finally, the Lubombo plateau is a small strip on the eastern side that borders the Mozambique country. It is similar to the Middleveld in terms of agricultural practices (Tfwala et al., 2020).

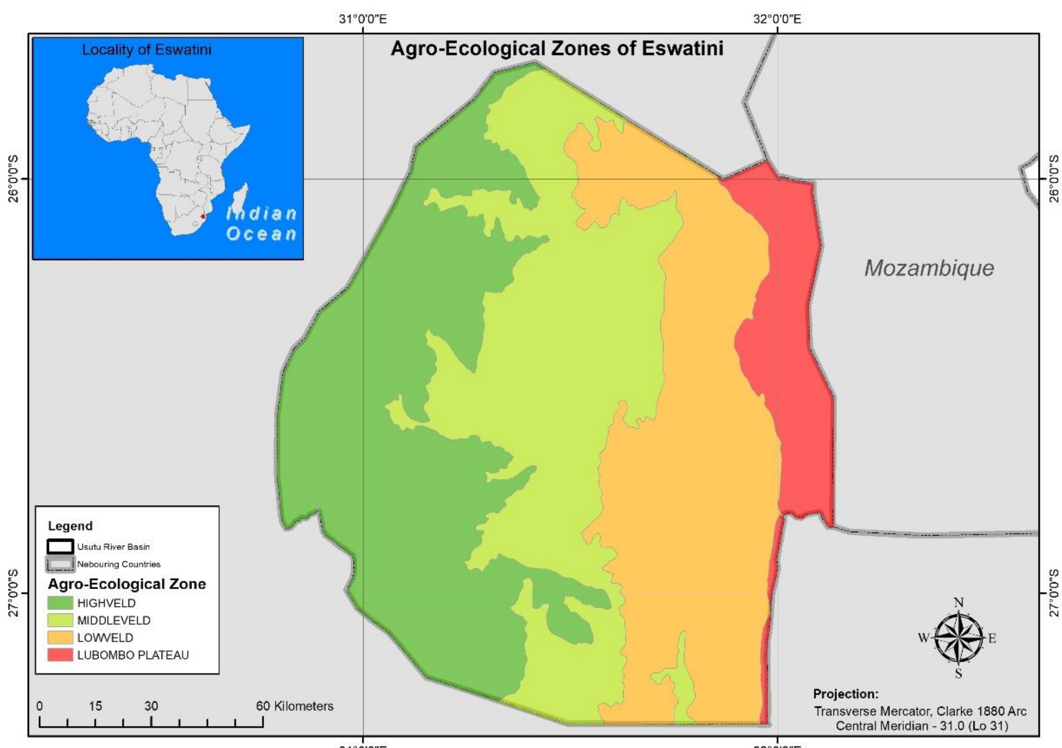


Figure 3: Agro Ecological Zones of Eswatini

Eswatini lies on the southern side of the African continent with a humid subtropical climate with two major seasons (summer and winter). The winter which is normally cold and dry last from April to September and the humid, hot summers extends from October to March (Tfwala et al., 2020). Different climate conditions are evident in the ecological zones; the Highveld is sub-humid and temperate, while the Lowveld is semi-arid and mostly warm (Tfwala et al., 2020). Furthermore, each of the four agro-ecological zones has its own unique vegetation, soils, geology, elevations, and terrain. The areas also experience different rainfall amounts throughout the year with an average rainfall amount of 950 mm for the Highveld, 700 mm for the Middleveld, 475 mm for the Lowveld, and 700 mm for the Lubombo Plateau (Dlamini, 2016). As with the temperatures, each climate zone has a different average, with the Highveld experiencing 17 degrees Celsius on average and the Lubombo plateau experiencing 22 degrees. In the summer, temperatures can soar to 39°C in the Lowveld and as high as 33°C in the Highveld (Dlamini, 2016).

3.1.2. Crops Grown in the Usutu River Basin

Situated in the nation's center, the Usuthu river basin occupies an area of 9156.67 km^2 and stretches from west to east, encompassing all four ecological zones and, consequently, all of the nation's climatic conditions. The Usuthu River Basin has 338 known and documented water users, with a total cropping area of 29889 hectares which were mapped during the water use survey. This information was based on data from the water use database, which is used for managing and monitoring water users that are drawing water from all the rivers and tributaries within the basin. Majority of the farmers are mainly sugar cane farmers, which are highly concentrated towards the eastern part of the region which is the lowveld. A section of cane growers that are growing mainly other types of crops are concentrated in the North West (Highveld) of the basin and some are mostly around the central place (Midleveld). Figure 4 shows the distribution of the 338 water users within the study area by subcatchment as per the water use mapping data.

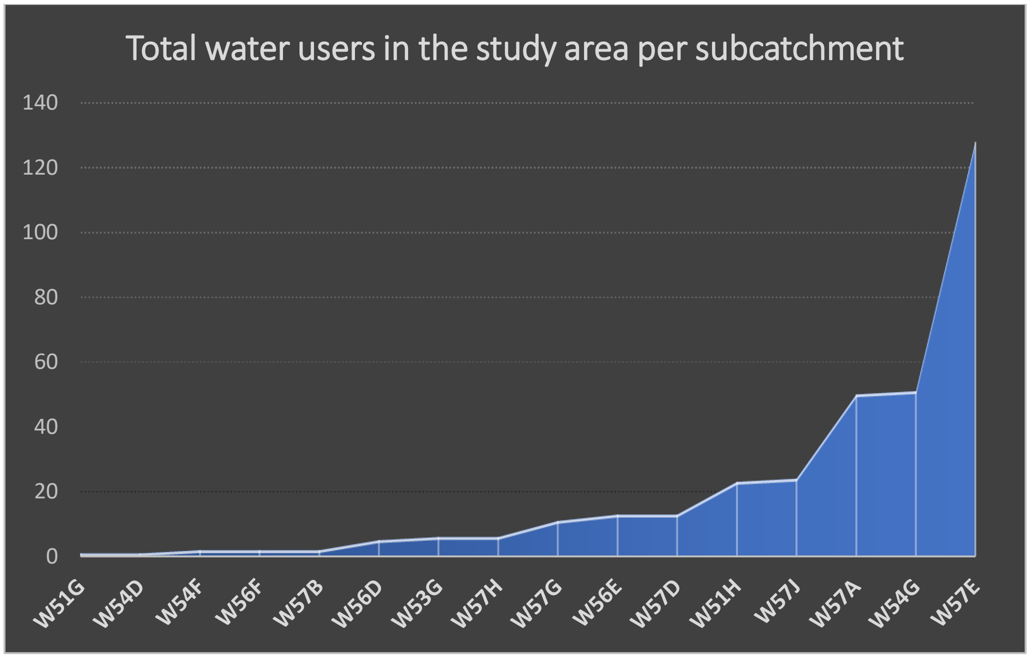


Figure 4: Water users in the Usutu river basin per subcatchment (Joint River Basin Authorities. (2021). Water use Database)

The W57E subcatchment, which is located in the lowveld below the Lubovane dam that was built for the purpose of sugarcane irrigation for the LUSIP project, accommodates majority of famers (nearly 40%) and the W51G subcatment in the highveld has the least number of water users. About 80% of the area under irrigation in the Usuthu river basin is planted with sugarcane, which is mainly concentrated in the lowveld, mangoe is covering the least area at 0.01%. Out of the 29889 hectares mapped sugarcane covers 24048 hectares and the remaining 5840 hectares consist of other crops. Sugarcane irrigation constitutes a major allocation of water at 80.5% than the rest of the crops. Other crops only take 19.5% of the water from Usuthu River Basin. Figure 5 below shows a summary of the crops grown in the basin and the area covered by each of the crops as per the water use mapping data.

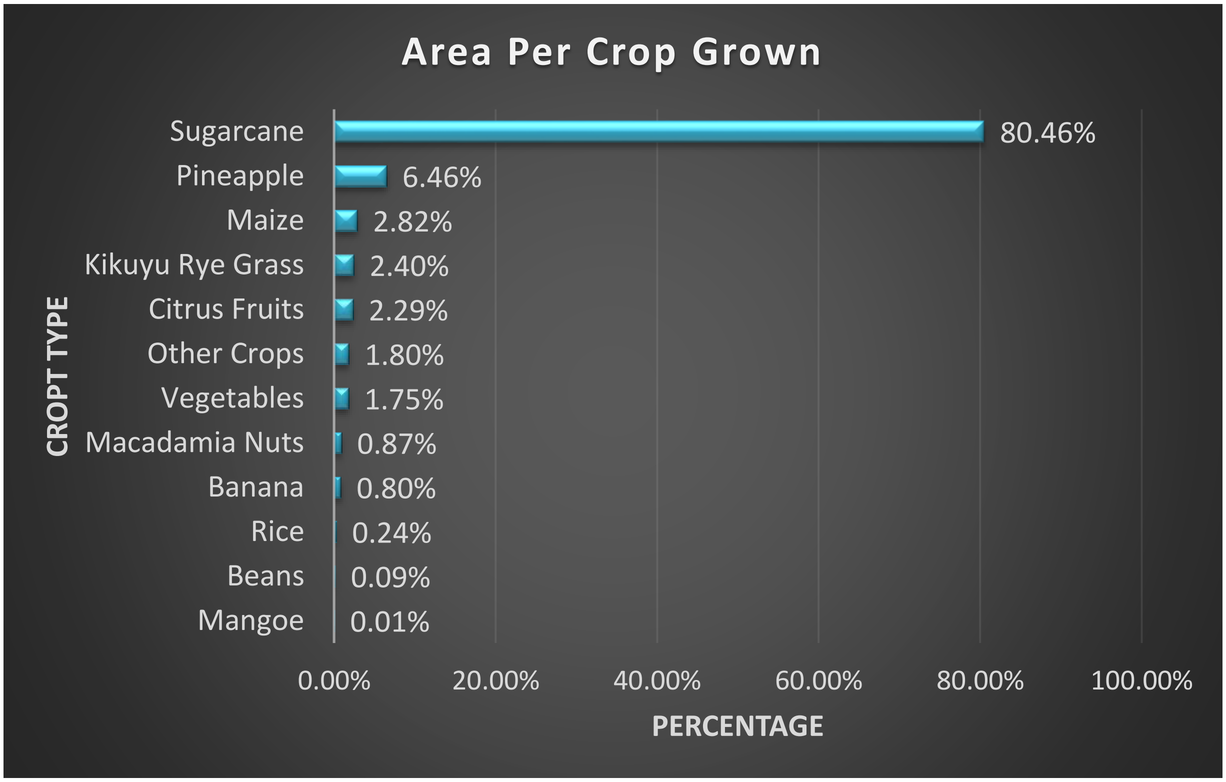


Figure 5: Crops grown in the Usuthu river basin (Joint River Basin Authorities. (2021). Water use Database)

The graph below (Figure 6) shows a summary of sugarcane farmers against the total number of farmers within the basin. About 43% of the water users within the study area are sugarcane farmers. According to the data, sugarcane farmers cover the largest area at a 4:1 ratio (sugarcane – other crops), despite not making up half of all water users in the basin. Figure 6 shows the distribution of sugarcane farmers per subcatchment compared to the total water users in each of the subcatchements as per the water use mapping data. The graph further indicates total cane growers who are actively cultivating their fields.

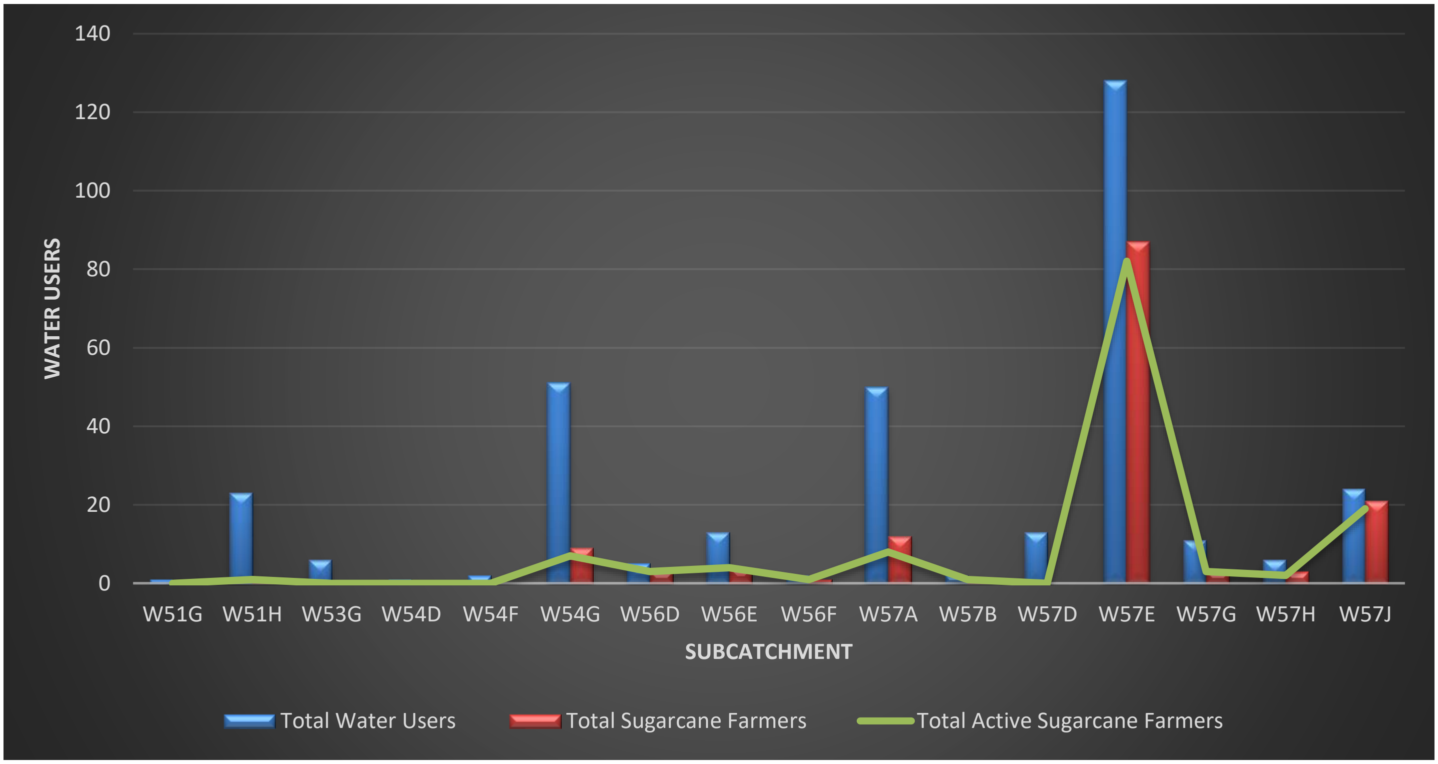


Figure 6: Sugarcane farmers in the Usuthu river basin (Joint River Basin Authorities. (2021). Water use Database)

The map in Figure 7 depicts the distribution of the water users within the study area and the types of crops grown in each of the fields. The map makes it abundantly evident that farming is taking place along the Usuthu River, which flows through the study area. The map also highlights that majority of the sugarcane fields are concentered in the lowveld towards the eastern part of the region and a section of farmers who are growing mainly other types of crops are concentrated in the North West (Highveld) of the basin and some are mostly around the central place (Midleveld).

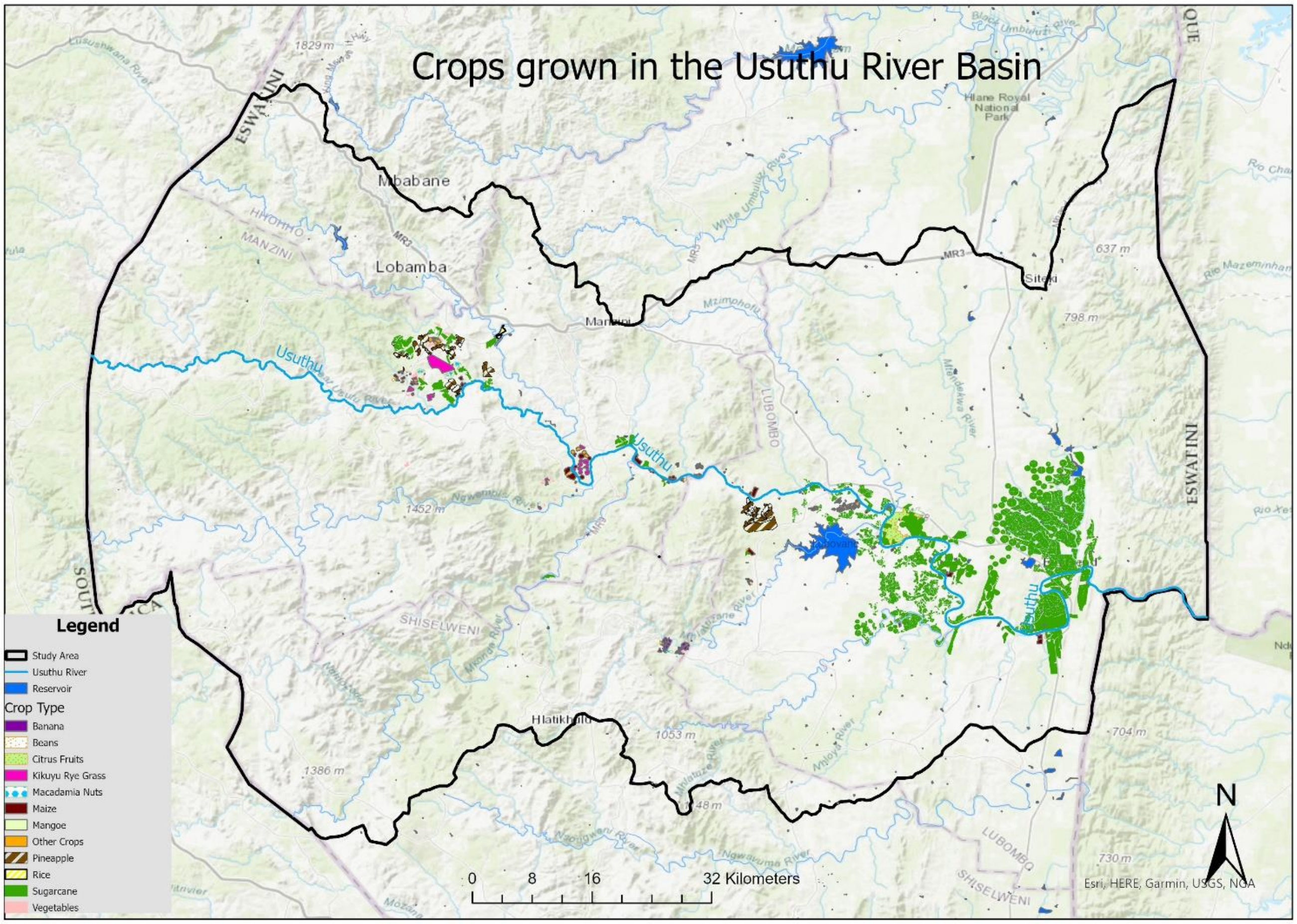


Figure 7: Crops grown in the Usuthu river basin (Joint River Basin Authorities. (2021). Water use Database)

3.1.3. The Sugar Cane Phenology

The southern African region experiences a protracted growth season for sugarcane that lasts roughly ten to twelve months from sowing to maturity, similar to other tropical and subtropical countries including Brazil as well as India (Lukhele et al., 2021). In Eswatini, Sugar cane is an annual crop that takes a lot of sunlight, water, and other resources and grows again after the last harvest. Between 8 and 12 years, the fields are often plowed over and replanted, with most of the fields replanted at 10 years. Based on conversations and correspondence with the Siphofaneni irrigation district manager (Thembeka Nkambule) and the sugarcane agronomists at the ILLOVO sugar mill (Nelson Fakudze), two different timelines in a year are targeted for sugar cane planting within the study area, from February to April (autumn planting) and from July to September (spring planting) and the harvesting period starts from April to December. The researcher visited the sites to evaluate the condition of most sugarcane fields at the time of the research, which verified and confirmed this information from the key informants. The fields' condition matched the sugarcane growth schedules based on conversations with the people who were consulted.

Even though there are two mainly considered seasons for planting, February through April and July to September, each farmer independently decides when to plant and harvest his or her own crop based on the climate, fallow patterns, service provider schedule, availability of planting material, and many other factors. Therefore, the crop phenology of sugar cane in the study area cannot be defined with a single cycle. A report on sugarcane statistics in the country states that the harvest period in the sugar sector is from April to December so that the sugar mill (ILLOVO) can be serviced during the other months (ESA, 2022). As a result, most sugarcane growers are forced to time their planting so that it coincides with the mill's harvest processing schedule, which runs from February to April (ESA, 2022). The ILLOVO sugar mill with vast sugarcane coverage area in the basin aligns the planting and harvesting with the spring plating period. Therefore, as indicated by the key informants described in the previous paragraph, the majority of the farmers in the research area (about 70%) schedule their planting and harvesting around the spring planting period (ESA, 2022). This allows them to harvest their sugar cane during the winter season when there is less rain and the temperatures cold, hence the crop is allowed to grow and mature during the warmer temperatures. The harvest of sugar cane has an extended period, from April to December, because growers can plant at various times. The bulk of harvesting occurs in the month of July and August which allows most of the fields to ratoon around August and September under high irrigation which eases up when the first rains in October begin to fall and the temperatures become warm and more suitable for sugar cane growth.

This research has been aligned with the spring planting timeline where the majority of the farmers prefer to plant their sugar cane. Therefore, the phenology of sugarcane is classified into four categories aligned with the spring planting.

1. The germination period - July to September
2. The tillering period - October to November
3. The elongation period – December to March
4. The ripening or dry of period – April to June

Most of the sugarcane is harvested between July and August, with the harvest lasting from early April through December. This allows the sugar cane phenology in the study area to be defined as per Figure 8 below.

Sugar Cane Crop Cylce	**Jan**	**Feb**	**March**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Planting and Germination stage												
Tillering stage												
Elongation Period												
Ripenning /Dry off Harvest period												
Harvesting												

Figure 8: Sugar cane crop calendar in the Usuthu River Basin

3.1.4. Vegetation Indices Considered in the Study

The physical variations of different land cover types can be captured, and the growth curves of distinct crop kinds can be characterized by using spectral indices that are sensitive to vegetation greenness and water status (Wang et al., 2020, Gonçalves et al., 2012, de Oliveira Maia et al., 2023). The EVI and the NDVI are frequently employed to represent the greenness of the vegetation and have a strong correlation with the index of leaf surface and pigment in the tree crown (Wang et al., 2020).

Numerous studies have demonstrated that the NDVI is a useful tool for measuring vegetation greenness, much like the EVI (Mahmud et al., 2022a, de Oliveira Maia et al., 2023, Xue and Su, 2017, Jiang et al., 2019). However, EVI takes into account specific atmospheric factors and ambient noise from the treetops and is more sensitive in areas with thick vegetation (Zhen et al., 2023, Xue and Su, 2017). In the present investigation, two vegetation indices (Table 1) were evaluated, the NDVI (Wang et al., 2020) and the EVI (Zhen et al., 2023) using the S2 image in each of the sugarcane phenology stages.

Table 1: Vegetation index utilized in this research

Vegetation Index	Equation	Reference
Normalized Difference Vegetation Index	NDVI = (NIR - Red)/(NIR + Red)	(Wang et al., 2020)
Enhanced Vegetation Index	EVI = 2.5 × (NIR - Red)/(NIR + 6xRed - 7.5xBLUE) +1	(Zhen et al., 2023)

3.1.5. Satellite Data

Images of S2 in line with the sugarcane phenology stages were used to conduct the analysis. A mosaic of the images encompassed the whole region of investigation which is the Usuthu river basin. The Planet Labs interface data download platform (https://www.planet.com) which allows users to freely download S2 data that has been processed to level 1C was utilized to collect the S2 images. Sentinels' imageries are delivered fully corrected in 100 km2 tiles using the UTM/WGS84 projection. A subset of the Sentinel 2 data is shown in Figure 9.

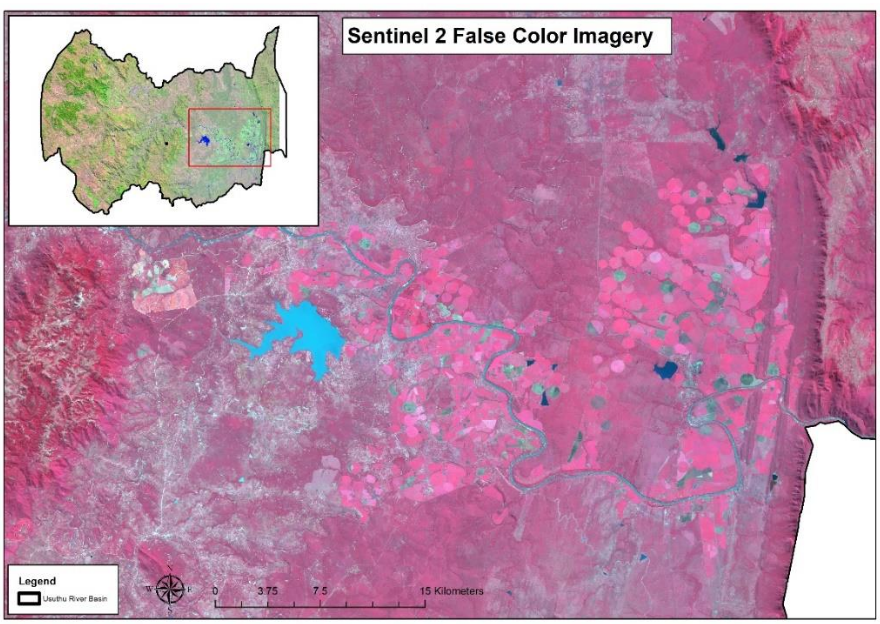


Figure 9: Sentinel 2 False color imagery

Alignment with the water use survey period, the different sugarcane phenology stages identified in this study for ease of reference and verification, accessibility from satellite sensors as well as the associated shade of cloud all played a role in the selection of the images. All of the images were taken on days with little to no cloud cover (5% or less). The images from Sentinel 2 having less cloud coverage (<20 percent), were obtained through planet.com webpage. The 1C collection includes the downloaded data, which has undergone methods for radiometric and atmospheric correction. The Sentinel 2 images comprise thirteen spectral bands, including Coastal Blue (B1-443 nm), Blue (B2-490 nm), Green (B3-560 nm), Red (B4-665 nm), and VNIR (B5-705 nm), VNIR (B6-740 nm), VNIR (B7-783 nm), VNIR (B8-842 nm). Also, this information has been orthorectified, georeferenced, and converted to UTM 36s and WGS 84. Technical details of the Sentinel 2a satellite are available in Table 2 below (Phiri et al., 2020).

Table 2: Sentinel 2 bands

Sentinel – 2 Bands	Description	Resolution	Central Wavelength
B1	Ultra-Blue (Coastal and Aerosol)	60-m	443-nm
B2	Blue	10-m	490-nm
B3	Green	10-m	560-nm
B4	Red	10-m	665-nm
B5	Visible and Near Infrared (VNIR)	20-m	705-nm
B6	Visible and Near Infrared (VNIR)	20-m	740-nm
B7	Visible and Near Infrared (VNIR)	20-m	783-nm
B8	Visible and Near Infrared (VNIR)	10-m	842-nm
B8a	Visible and Near Infrared (VNIR)	20-m	865-nm
B9	Short Wave Infrared (SWIR)	60-m	940-nm
B10	Short Wave Infrared (SWIR)	60-m	1375-nm
B11	Short Wave Infrared (SWIR)	20-m	1610-nm
B12	Short Wave Infrared (SWIR)	20-m	2190-nm

3.1.6. Reference Data

The classified images are verified using reference data. Google Earth data and aerial photography make up the research reference data. Table 3 includes a list of the reference data's specifics.

Table 3: Reference data

REFERENCE DATA				
Data type	**Date of acquisition**	**Features**	**Spatial Resolution**	**Data Source**
Aerial imagery	2021	Colour	10-m	Joint River Basin Authorities
Google Earth images	2021-2022	Colour	1-m	Google Earth Pro

3.1.7. The water use database

The water use database is a geospatial database which is currently utilized by the JRBAs to manage all farmers drawing water from the Usuthu river basin which is stored in a geodatabase format. This database was used for extracting validation and training data for the study. The data is organised into datasets based on pre-defined geodatabase layers, such as field boundaries, water abstraction or diversion point, storage facility, rivers, basin boundary, subcatchment, etc. The water use database also contains details on each farmer or institution that is drawing water from each of the rivers and streams that fall within the Usuthu River Basin. This database contains information such as the type or purpose of the water extraction, large scale or small-scale farmer, permit availability, permitted hectares or volume, field size (mapped, field boundaries (GPS), abstraction point along river (GPS), etc.), availability of water measuring devices, and a lot more information related to water use and water storage.

The spatial data collection for this database was done using the Trimble Juno 3B GPS capable PDAs with quick satellite lock linked to pocket database software (ESRI Arcpad) that captures all questionnaire form information. Enumerators were deployed to collect the data visiting all the water users within the river basin catchment area. The data was then downloaded, collated and processed using ArcGIS 10.8

software into a geodatabase which is currently used for storing and querying water users within the basin.

3.1.8. Software Used

ArcGIS Pro was used to accomplish the segmentation and classification of the satellite images. The ArcGIS Pro was also used for all other spatial data management including sugarcane field boundary adjustments, sugarcane maps development, etc. Other GIS software like QGIS was also used for satellite image preprocessing, image enhancement and mosaicking together with the ESRI ArcGIS software. Microsoft Excel was also utilized to display statistical data from categorization outcomes and other analyses carried out in a form of graphs and charts.

3.2. Methodological approach

This section provides an overview of the image classification approaches utilized in this research, as well as a description of necessary preprocessing steps (geometric correction, reprojection, mosaicking, and clipping).

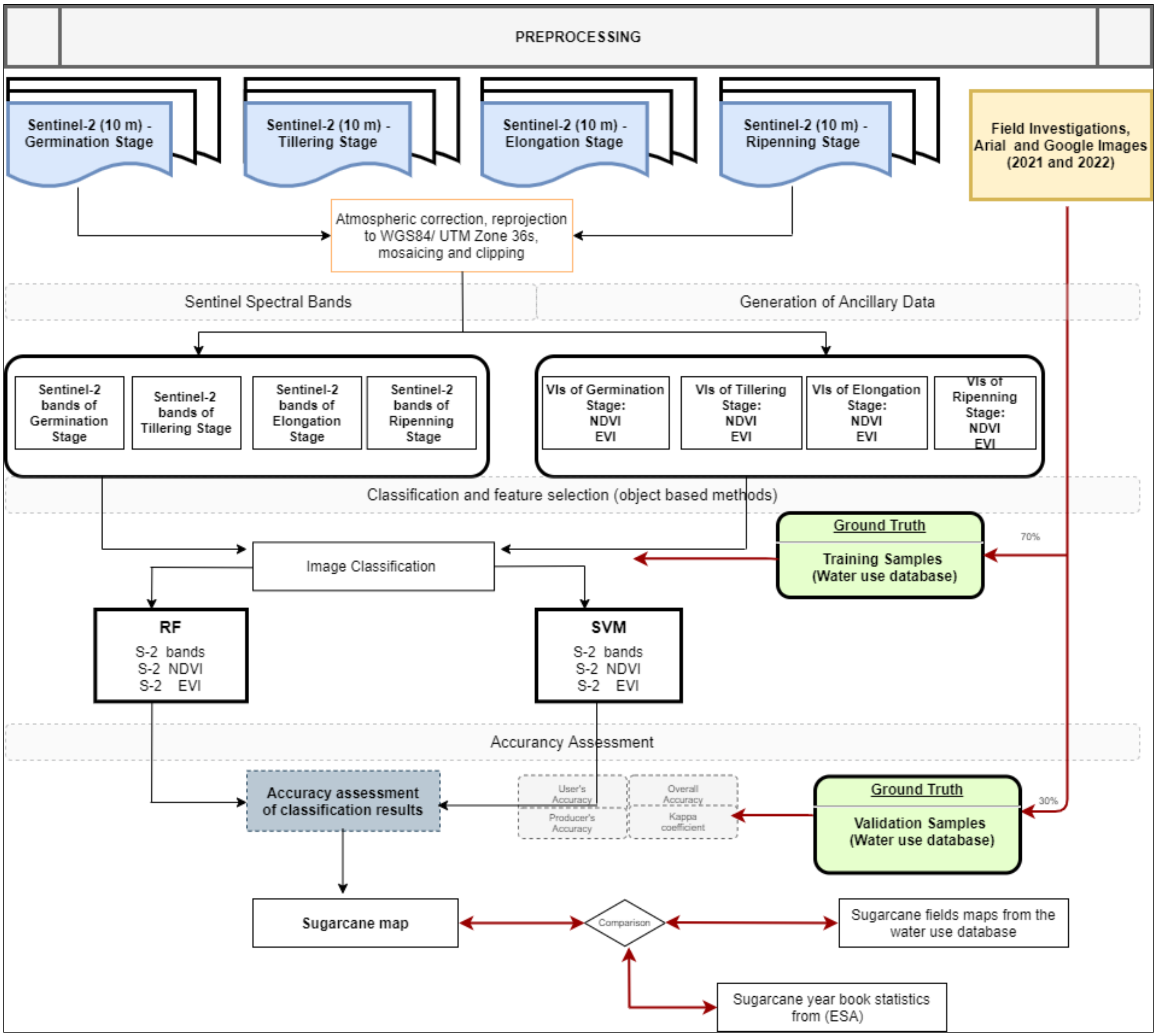


Figure 10: Flowchart of the study methods

One of the pre-processing steps completed prior to classification is geometric rectification of the data. Spatial data that has been acquired through Satellite platforms is more likely to possess different predictions, a key next step is to project the data so that all the spatial data sets that are gathered for a study are all governed by the same coordinate system.

Figure 10 provides a visual presentation of the methodological process flowchart for the study. The key steps involves; a) image download and preprocessing which entails collection of cloud free images and imagery for each of the sugar cane growth cycle, clipping of the data to the study area, projection and mosaicking of the data; b) generation of ancillary data which is mainly generation of the vegetation indices to be utilized in this research; c) sugar cane classification using the RF and SVM algorithms from the S2 spectral bands and the vegetation indices separately; d) accuracy assessment of the classification results using the confusion matrix as well comparison of the result maps to the available data from the water use database collected by the Joint River basin Authorities and the sugar cane statistics from the Eswatini Sugar Association.

3.2.1. Satellite Image pre-processing

To retain the pixel size of the satellite data when conducting the research, the thirteen spectral bands at Level-1C were decreased to 10 bands. The medium resolution bands for the S 2 imagery utilized are displayed in a tabular format (Table 4) (Phiri et al., 2020). Sentinels' imageries were delivered fully corrected in 100 km2 tiles using the WGS84/UTM zone 36S projection, which covers both onshore and offshore locations and is located between 30°E and 36°E in the southern hemisphere. The generated data was trimmed to include only the research area using QGIS and ArcGIS Pro softwares.

Table 4: Sentinel-2 10 bands utilized in this investigation.

Sentinel – 2 Bands	Description	Resolution	Central Wavelength
B2	Blue	10-m	490-nm
B3	Green	10-m	560-nm
B4	Red	10-m	665-nm
B5	Visible and Near Infrared (VNIR)	20-m	705-nm
B6	Visible and Near Infrared (VNIR)	20-m	740-nm
B7	Visible and Near Infrared (VNIR)	20-m	783-nm
B8	Visible and Near Infrared (VNIR)	10-m	842-nm
B11	Short Wave Infrared (SWIR)	20-m	1610-nm
B12	Short Wave Infrared (SWIR)	20-m	2190-nm
B8a	Visible and Near Infrared (VNIR)	20-m	865-nm

3.2.2. Image Segmentation and Vegetation Indices Extraction

The technique of partitioning an Arial imagery into different sections is known as segmentation. Segmentation seeks to streamline or alter the depiction of an image to make it significant and relatable (Sathya et al., 2011). To recognize features and shapes in images, segmentation of the image is widely employed. It is basically grouping of pixels that have the same specific visual characteristics.

The first and most crucial stage in object-based image categorization is segmentation. In order to distinguish between surrounding heterogeneous regions, segmentation algorithms' basic goal is to combine homogeneous pixels into image elements. More and more research has switched from using pixel-based methodologies to object-based ones as high spatial resolution images have become increasingly prevalent. By using high spatial resolution images, prior research has demonstrated that OBIA methods offer highest level of categorization precision than pixel based methods (Wu and Zhang, 2019). One automated image analysis technique is the object-based classification method. The level of categorization precision is subjected to the image segmentation quality (Wu and Zhang, 2019).

NDVI and EVI for each of the sugarcane phenology stages were extracted using the Sentinel 2 imagery for the entire study area. Both vegetation indices extraction and segmentation of the satellite imagery in this study was done using the ArcGIS Pro Software in this research.

3.2.3. Sugar cane map classification

In this work, two supervised classification approaches were utilized for the image categorization. The RF classification method (Jiang et al., 2019) and the SVM (Nihar et al., 2022). Many different applications of remote sensing use the SVM classification technique (Marcinkowska et al., 2014, George et al., 2014, Wang et al., 2019). RF excels at finding important variables and has strong data processing abilities (Mureriwa et al., 2016, Som-Ard et al., 2021). When used with very high spatial resolution satellites, RF is considered to be a reliable classification method for agricultural purposes, especially in heterogeneous environments (Adam et al., 2017, Richard et al., 2017, Som-Ard et al., 2021).

Despite being reliant on a variety of inputs, for example multiband data, RF classification accuracy is frequently very good (Luciano et al., 2018). Due to this classifier's excellent capacity to identify and characterize complicated interactions of variables, ecologists and remote sensing scientists have employed it extensively (Luciano et al., 2018, Wang et al., 2019). Several SVM and RF parameters that have been demonstrated to be accurate have also been used to quantify accuracy. A study by Wang et al. (2019) discovered that the SVM methodology has a higher level of overall precision compared to the RF method. This study utilised the ArcGIS Pro software (Wessel et al., 2018a) for the image classification on the Sentinel-2 imagery.

3.2.4. Sugar cane fields sampling and data collection

A field verification exercise to confirm the sugarcane fields was carried out between the first of September 2023 and thirty first of October 2023 on a sampled list of sugar cane fields in the Usuthu river basin. The purpose of the field verification exercise was to determine if the fields were active with sugar cane crops during the 2020/2021 planting season. A sampled list of sugar cane fields for the training and validation data were chosen using the stratified random selection method. A research organization can branch off the entire sample into numerous distinct, uniform groups called strata then select individuals at random from the various strata for research using stratified random sampling, which lowers costs and increases efficiency. Members of each of these groups should be distinct to ensure that each group member possesses a comparable likelihood of being selected using basic probability. Random quota sampling is another name for this sample technique.

Two distinct forms of stratified random sampling: disproportionate random sampling and proportionate random sampling. Each stratum sample size in the proportionate random sampling approach is directly proportional to the amount of overall population of strata. This implies that all strata samples have the same sampling fraction. The key distinction between proportionate and disproportionate stratified random sampling in the disproportionate case is sampling fraction. In disproportionate sampling, the sampling fraction for each stratum will be different. The accuracy of the researcher's fraction allocation will determine whether this sample technique is successful. The results could be skewed by strata that are either over or underrepresented if the fractions allocated are not exact. For this particular research, the subcatchments within the basin are used as a strata. Therefore, the selection of the sampled fields was proportionate to the total number of sugar cane framers per subcatchment.

The distribution of the sugarcane farmers within the study area is not even, some of the subcatchments have more farmers than other subcatchments. As a result, the proportionate stratified random sampling method was not relevant as it would present a lot of training data within the high farmer concentrated subcatchments. To ensure that the training sets included an adequate sample of the very fewer classes, the stratified random sampling approach (disproportional) was utilized when collecting training data samples, which entails selecting specimens from existing strata in which each member has an equal chance of being chosen, but the analyst determines the size of the strata (Ramezan et al., 2021). The representativeness of the samples is improved by using randomly generated training data, and class imbalance can be decreased by using the disproportional stratified technique (A. Ramezan et al., 2019). Table 5 below provides details of the complete list of sugar cane farmers per subcatchment, total farmers who were active during the data collection and the total number of farmers chosen for the field verification exercise.

Table 5: Sugarcane farmers sampled and utilized in the research.

Basin Name	Sub Catchment	Total WaterUsers (Farmers)	Total Sugarcane farmers	Total Active Sugarcane farmers	Sampled farmers	Used for Training	Used for Validation
Usuthu	*W51H*	23	1	1	1	1	0
Usuthu	*W54G*	51	9	7	3	2	1
Usuthu	*W56D*	5	3	3	1	0	1
Usuthu	*W56E*	13	4	4	2	1	1
Usuthu	*W56F*	2	1	1	1	0	1
Usuthu	*W57A*	50	12	8	3	2	1
Usuthu	*W57B*	2	1	1	1	0	1
Usuthu	*W57E*	128	87	82	16	12	4
Usuthu	*W57G*	11	3	3	3	2	1
Usuthu	W57H	6	3	2	1	0	1
Usuthu	W57J	24	21	19	8	6	2

For this study, overall amount of sugarcane farmers (n) chosen for the investigation was 40, which was sampled from a total of 131 active sugarcane farmers in the study area as per Table 5 above. Using Geographic Information System (GIS) technologies, data was then retrieved at a field scale for the selected farmers. Fields which were found to be inactive (no farming activity) during the survey were not part of the samples for training and validation. These fields were initially mapped to understand the total area per water user or farmer, however they were excluded in the sampling but were vital in testing if the satellite imagery analysis picked some sugarcane activities in these fields or the opposite.

Figure 11 shows the distribution of the 40 sampled sugarcane fields within the Usuthu river basin. A ground truth was then done to verify the status of the field at present and during the time of the water use survey.

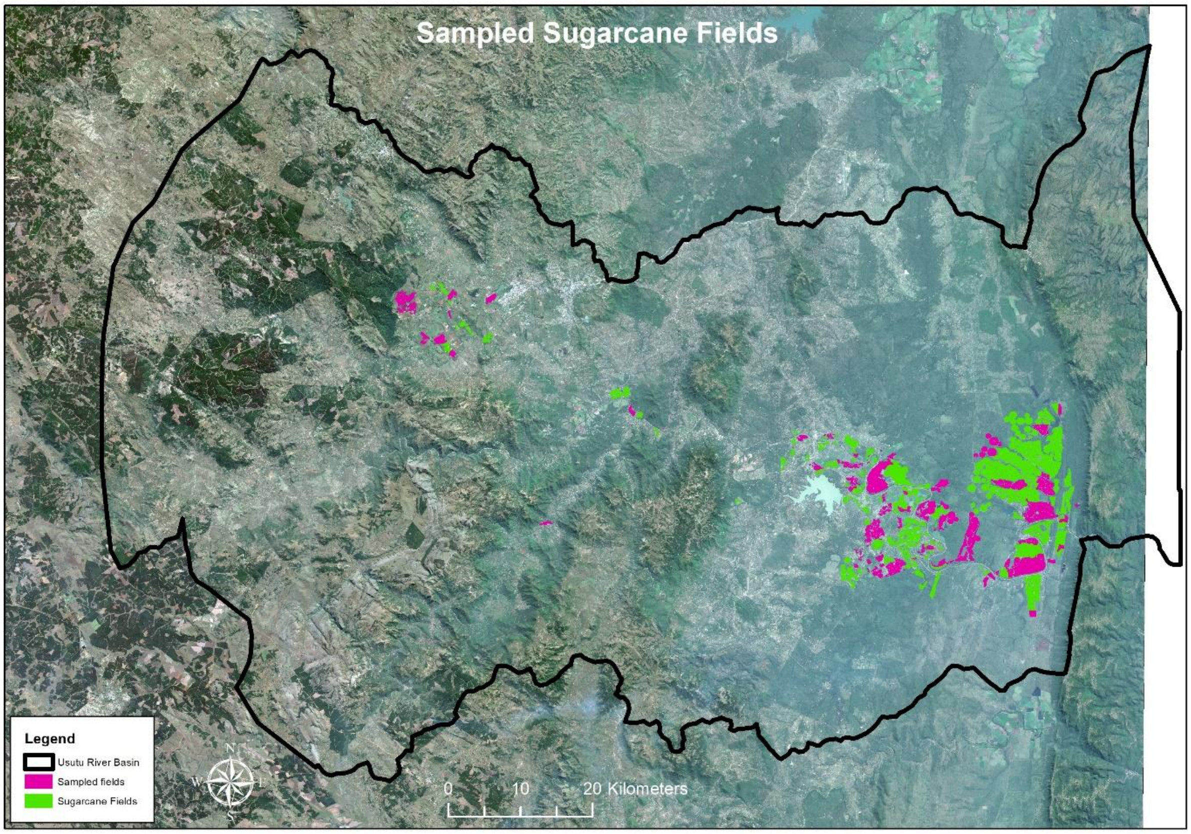


Figure 11: Map of sampled sugarcane fields for verification

Sugarcane field boundaries which were found to be not properly aligned to planted areas were then adjusted using the ArcGIS Pro software with the help of Arial images including Google Earth. This was done to ensure that the training data is accurate to avoid misclassification. Larger fields that belonged to a single farmer who was sampled were adjusted or split into training and validation samples. The sampling approach did not consider the field size per farmer but focused on the number of farmers to be sampled. Some of the fields belonging to one farmer are too large, up to 50 square kilometers in multiple polygons. These were not excluded in the samples but were rather adjusted or split.

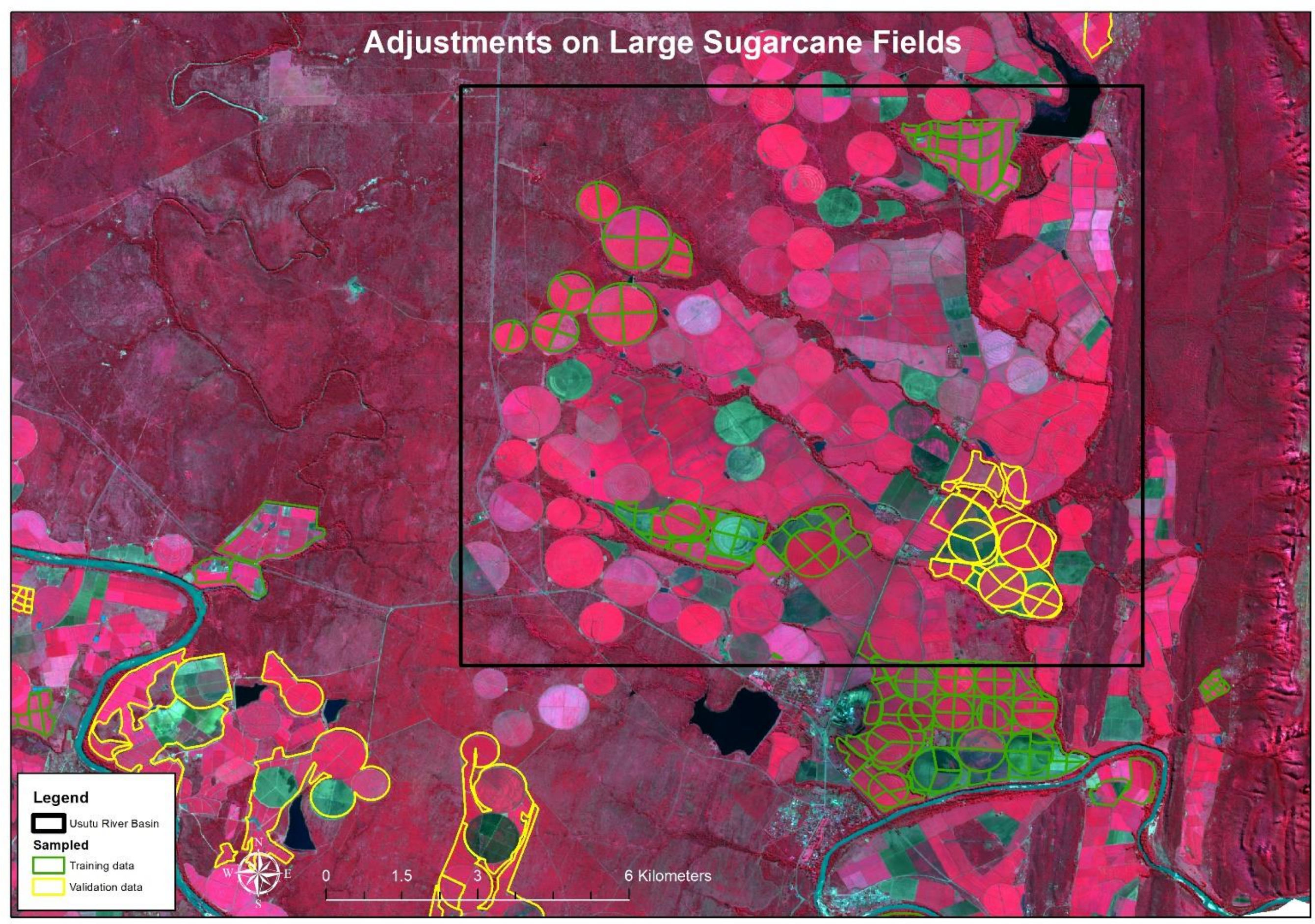


Figure 12: Sugarcane fields for Ubombo Sugar (ILLOVO) which were adjusted and split

Sugarcane fields for the major sugarcane company within the Usuthu river basin (Ubombo Sugar/ILLOVO) were considered for the training samples. However, due to the vast area occupied by the sugarcane fields, only a few polygons were used in the training data. The sampled data was also split into training and validation data. The fields were randomly deleted from the sampled data to only allow a reasonable field size to participate in the training data.

3.2.5. Data extraction and training samples

The training data was extracted from the water use database and a field verification was done to ascertain the field's presence and current state of use. The other purpose for the field verification was to confirm the field boundaries and to check if there are any changes in the boundaries. There were no significant changes in the water use database and the status of the field boundaries on the ground except for minor field adjustments due to GPS mapping errors incurred during the water use survey mapping when compared to Arial imagery. In the verification exercise that took place as part of this research, farmers also attested to the fact that they were actively cultivating sugarcane in the areas that were sampled. The data was split into model-training and verification, with 70% and 30% correspondingly, as was stated in the previous paragraph. Additional data on the other features was also digitized based on Google Earth and Aerial images to be part of the training and validation samples. These include water bodies, grasslands, commercial forests, built up areas and other land use classes other than sugarcane. These features were also split into training and validation samples at the same percentage split as the sugarcane samples. Figure 13 displays the distribution of the investigated region's sampled data by sample type (training or validation).

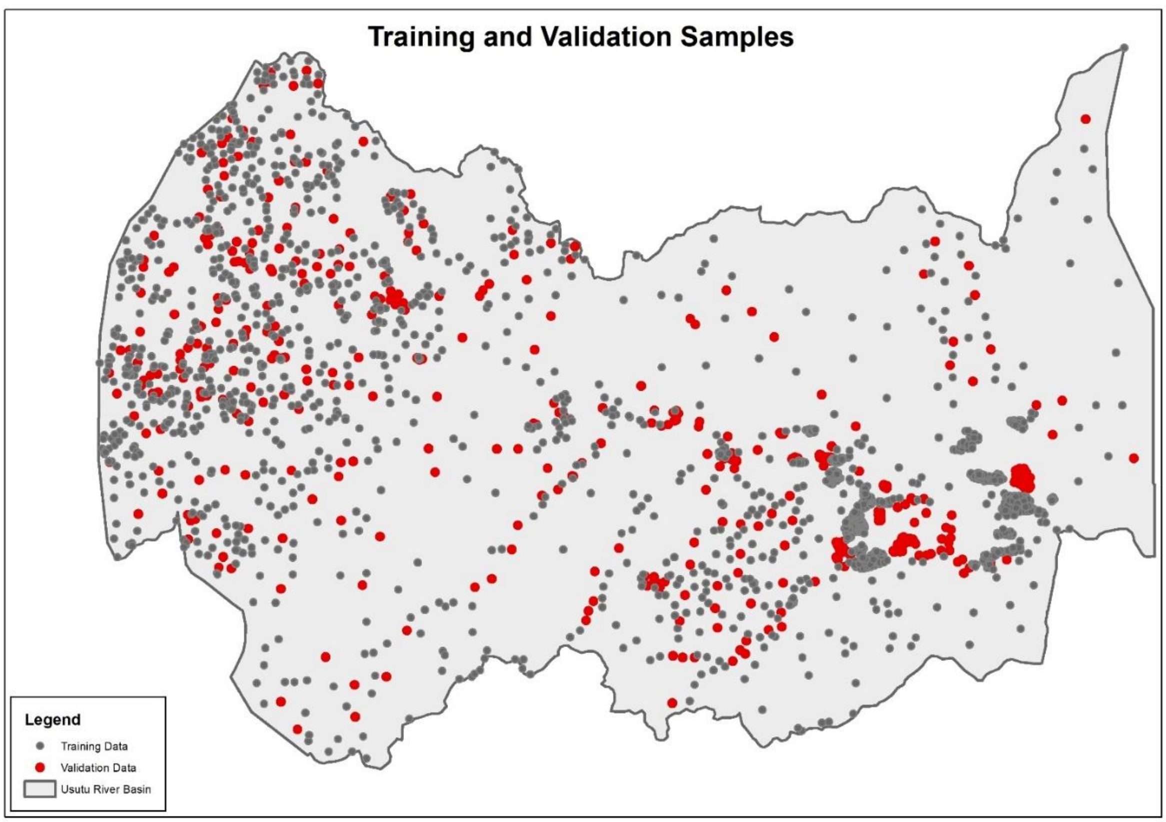


Figure 13: Training and validation samples

3.2.6. Accuracy assessment

Using the water use survey database, accuracy evaluation was done to gauge how well each classification experiment performed. A field verification exercise was conducted for a sampled list of farmer fields which were chosen at random in the study region to confirm their existence and activeness on the ground.

A sampling size of 70% data for training and 30% for validation was obtained. The image acquisition date was aligned with the water use survey data collection to facilitate ease of validation. Then, for each experiment (Random Forest and the Support Vector Machine), the Kappa coefficient, producer accuracy, overall accuracy, and user accuracy were computed to select top-performing model for recognizing sugarcane fields.

A confusion matrix has typically been used for accuracy evaluations (Stehman and Foody, 2019), which measures the integrity associated with the produced categories to the source dataset (Xie et al., 2008, ED Chaves et al., 2020). Percentage of the research area that is successfully classified is directly connected with OA, and kappa measures the effectiveness of the classification algorithm (Stehman and Foody, 2019). Whereas producers accuracy and users accuracy, respectively, offer precision on the reference and categorized area per class that is particular to each class , the overall classification accuracy is a very coarse measurement because it does not do so (Stehman and Foody, 2019). According to Story et al. (1986), AO, PA, and UA may regard accuracy above 79% to be of high precision, while kappa values above 80% indicate high levels of agreement (Landis and Koch, 1977).

Extremely high (>90 percent), high (80-89 percent), acceptable (70-79 percent), and low (< 69 percent) accuracy can be used to classify the AO, PA, and UA (Story et al., 1986). A measure of map accuracy most commonly employed in remote sensing is the Kappa Coefficient (k) (van Vliet et al., 2011). The Kappa coefficient (Foody and Mathur, 2004, Story et al., 1986), believes that figures higher than 0.8 offer thematic maps having a significant amount of concordance between the generated map and the actual map (van Vliet et al., 2011).

A visual inspection of the classification outcome was also performed against the Google Earth images and aerial photos to determine whether the categorisation was accurate. Google Earth images (2021) and Arial imagery for 2021 were used as reference data. Imagery from Google Earth can be used to verify the accuracy of categorized pictures, according to several studies (Tilahun and Teferie, 2015, Hu et al., 2013, Pulighe et al., 2016, Knorn et al., 2009). Sugarcane crop classification maps were then produced in ArcGIS Pro software and compared to the sugarcane crop map generated from the water use database.

4. Results

This chapter discusses two classification approaches in identifying and mapping sugarcane fields in each of the four sugarcane growing stages in the Usuthu river basin. The chapter is divided into two sections: Sentinel 2 classification results for the RF classification method as well as the SVM. In each of the two image classification methods, S2 images were tested for the precision of the classification for each of the sugarcane phenology stages. To determine the most accurate estimation of the sugarcane fields in the basin, accuracy assessment results for each method and growing timeline are also provided in each section. These results compare the accuracy of the sugarcane classification to each method as well as the results for each growth stage. The comparison aims to assess the role that phenology plays in sugarcane plantation classification. The chapter goes on to the contribution of vegetation indices in discriminating sugarcane fields in the study area. The second one presents a comparison of the outcomes which is the performance of each method and then the comparison of the classification results to the reference database, which is the water use database, mapped sugarcane fields in the Usuthu river basin.

The study area sustains a substantial amount of commercial activity which includes forestry, industry, and agricultural pursuits like crop farming. The two most common agricultural practices in the basin are sugarcane and forestry, with sugarcane concentrated in the region's warm western section and forestry concentrated in its wet eastern section. The basin is made up of constructed areas, water bodies, and other natural forests in addition to large grasslands and woodland areas. This research primarily aims to discriminate sugarcane plantations, therefore, all the other land use types besides sugarcane were classified and grouped into other. The classification of the sugarcane plantations is shown in the results, with all other features that are present being grouped and classified as other. In order to choose the most accurate classification method and the ideal time of the sugarcane growing stage for identifying sugarcane fields in the Usuthu river basin, the results present a classification of the four phonological growth stages for each of the two image classification methods.

4.1. Sugar cane classification results from Sentinel 2

The highest accuracy was obtained by the SVM model when classifying data for the ripening stage of the sugarcane growing time using the Sentinel 2 imagery spectral bands. The overall classification accuracy was 95% (Kappa—0.90) (Table. 13). The classification performed on the same imagery for the other growth stages ranged from OA of 91% and kappa (0.80) (SVM) to OA of 94% and kappa (0.88) (SVM). Classification of the Sentinel 2 image using the RF classification method also produced highly acceptable but lower accuracy levels than the SVM classification method. The highest classification accuracy was obtained for the elongation stage with a user accuracy of 92% (Kappa – 0.84) (Table. 8). The other growth stages ranged from OA of 90% and Kappa (0.80) (RF) to OA of 92% and kappa (0.83). This shows a significant amount of classification precision for SVM method than RF which has been observed throughout the four growth stages of the sugarcane crop.

The SVM method had the highest UA of 96% and lowest UA (90%) when classifying all other features and a highest UA of 95% and lowest UA (92%) when classifying sugarcane plantations. UA of 93% is the highest obtained by the RF method and a lowest UA of 89% was obtained when classifying all other features in the study area. Sugarcane classification also had a highest UA of 93% and a lowest UA of 89% when using the RF method of classification. Although the accuracy levels for each growth stage vary, both classification methods show an improvement in accuracy as the sugarcane ages.

4.1.1. Classification by Random Forest

4.1.1.1. Classification using spectral bands

After utilizing the RF with the object-oriented categorization for Sentinel 2 imagery, a final classification raster was produced, representing the established optimal model conditions for the all the four stages of the sugarcane growth cycle in the basin. The map in Figure 14 displays the distribution of sugarcane plantations in the study area as per the RF classification method in all four phases of sugarcane development.

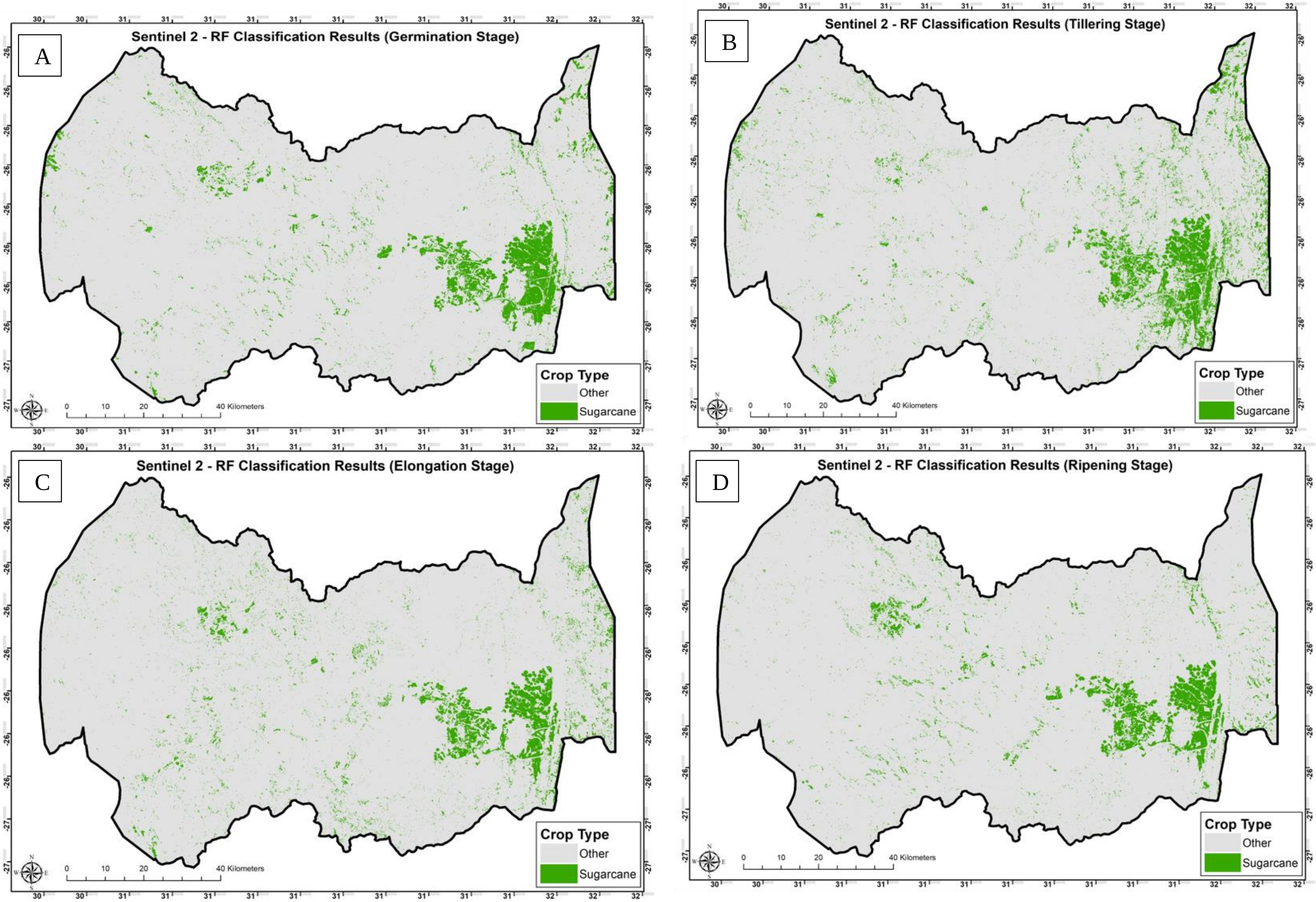


Figure 14: Sentinel 2 -RF classification results for all four phases of sugarcane development (*A-germination, B -tillering, C-elongation and D – ripening stage)*

a) Germination Stage

The sugarcane plantation's classification accuracy at this growth stage was assessed using a confusion matrix. Overall accuracy, Producer's accuracy, User's Accuracy, and kappa measures rely upon the confusion matrix, which was used for assessing and evaluating the classification accuracy. The confusion matrix in Table 6 has columns for the reference classification and rows for the map classification. The matrix's diagonal cells display the proper classifications, whereas off-diagonal cells show incorrect classifications. The germination stage map had an OA of 91% and 0.81 kappa value, according to the cross-validation results. In Table 6, confusion matrix is displayed. Users' accuracy ranged from 92% for other to 89% for the sugarcane plantations, and producer's accuracy varied between 93% for other and 87% for sugarcane. Some sugarcane fields were confused with other vegetation types, while some non-sugarcane areas were confused with sugarcane.

Table 6: RF categorization Confusion Matrix for germination stage

Crop Type	Sugarcane	Other	Total	U_Accuracy	Kappa
Sugarcane	**186**	22	208	89%	0%
Other	27	**309**	336	92%	0%
Total	213	331	**544**	0%	0%
P_Accuracy	87%	93%	0%	**91%**	0%
Kappa	0	0	0	0%	**81%**

b) Tillering Stage

For the tillering stage, overall accuracy, Producer's accuracy, User's Accuracy, and kappa were also computed. The tillering stage map had an OA of 90% and 0.80 kappa value, according to the cross-validation results. In Table 7, confusion matrix is displayed. Users' accuracy ranged from 93% for sugarcane to 89% for other classes, and producer's accuracy varied between 96% for other and 82% for sugarcane. Some sugarcane fields were confused with other vegetation types, while some non-sugarcane areas were confused with sugarcane.

Table 7: RF categorization Confusion Matrix for tillering stage

Crop Type	Sugarcane	Other	Total	U_Accuracy	Kappa
Sugarcane	**175**	14	189	93%	0%
Other	38	**317**	355	89%	0%
Total	213	331	**544**	0%	0%
P_Accuracy	82%	96%	0%	**90%**	0%
Kappa	0	0	0	0%	**80%**

c) Elongation Stage

For the elongation stage, overall accuracy, Producer's accuracy, User's Accuracy, and kappa were also computed. The elongation stage map had an OA of 92% and 0.84 kappa value, according to the cross-validation results. In Table 8, confusion matrix is displayed. Users' accuracy ranged from 93% for other to 92% for sugarcane plantations, and producer's accuracy varied between 95% for other and 89% for sugarcane. Again, some sugarcane fields were confused with other vegetation types, while some non-sugarcane areas were also confused with sugarcane.

Table 8: RF categorization Confusion Matrix for elongation stage

Crop Type	Sugarcane	Other	Total	U_Accuracy	Kappa
Sugarcane	**189**	17	206	92%	0%
Other	24	**314**	338	93%	0%
Total	213	331	**544**	0%	0%
P_Accuracy	89%	95%	0%	**92%**	0%
Kappa	0	0	0	0%	**84%**

d) Ripening Stage

Overall accuracy, Producer's accuracy, User's Accuracy, and kappa were also computed for the ripening stage. The ripening stage map had an OA of 92% and 0.83 kappa value, according to the cross-validation results. In Table 9, confusion matrix is displayed. Users' accuracy ranged from 93% for other to 90% for sugarcane fields, and producer's accuracy varied between 93% for other and

89% for sugarcane. Some sugarcane fields were also confused with other vegetation types, while some non-sugarcane areas were confused with sugarcane in the ripening stage.

Table 9: RF categorization Confusion Matrix for ripening stage

Crop Type	Sugarcane	Other	Total	U_Accuracy	Kappa
Sugarcane	**190**	22	212	90%	0%
Other	23	**309**	332	93%	0%
Total	213	331	**544**	0%	0%
P_Accuracy	89%	93%	0%	**92%**	0%
Kappa	0	0	0	0%	**83%**

4.1.2. Classification by Support Vector Machine

4.1.2.1. Classification using spectral bands

After utilizing the SVM with the object-oriented categorization for Sentinel 2 imagery, a final classification raster was produced, representing the established optimal model conditions for the all the four stages of the sugarcane growth cycle in the basin. The map in Figure 15 shows the relative distribution of sugarcane plantations in the study area as per the SVM classification method in each of all four phases of sugarcane development stages.

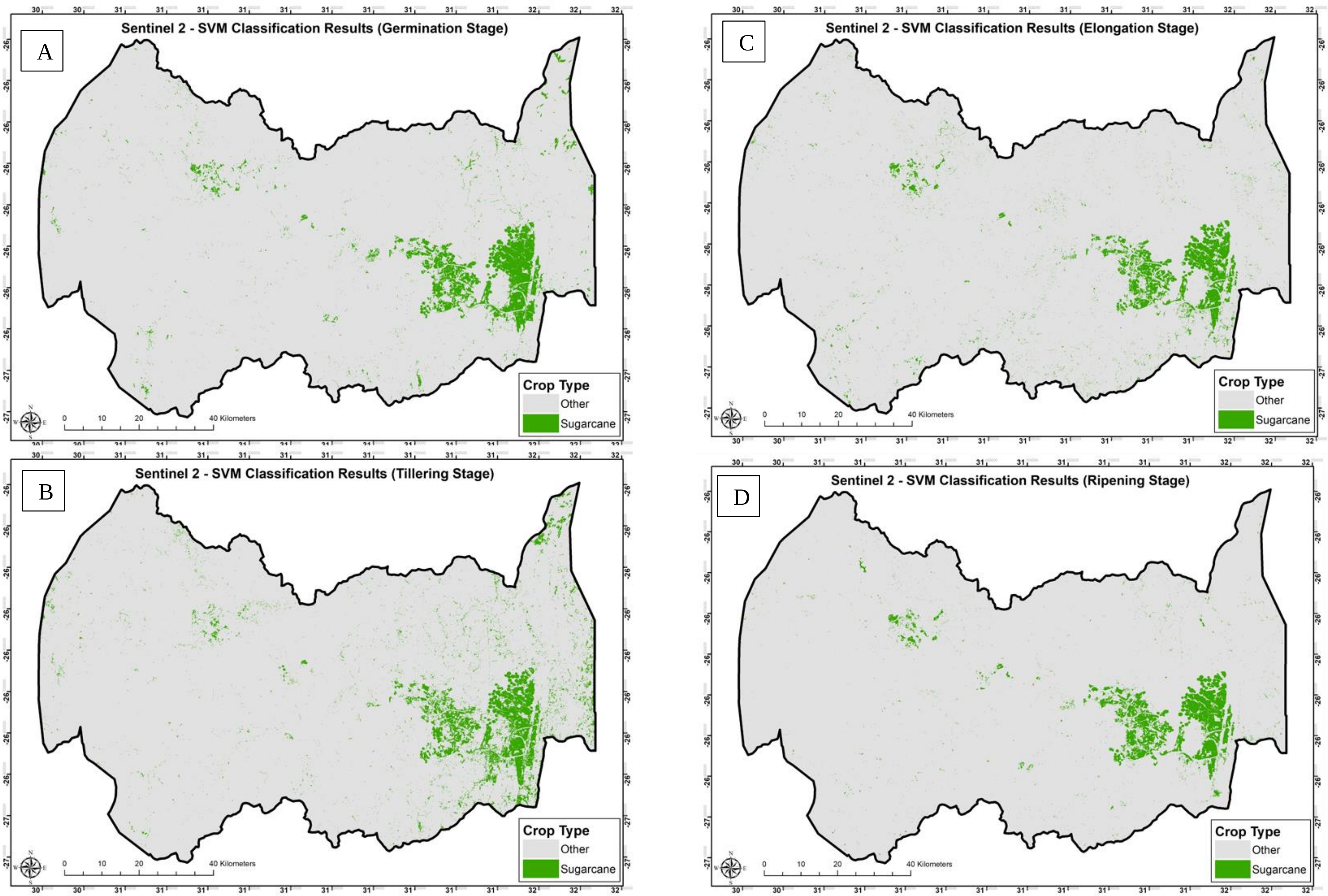


Figure 15: Sentinel 2 -RF classification results for the four phases of sugarcane development (A-germination, B -tillering, C-elongation and D – ripening stage)

Y06.01a	B06.10a
C06.07	B06.10b

a) Germination Stage

For the SVM classification method, the sugarcane plantation's classification accuracy at this growth stage was assessed using a confusion matrix. Overall accuracy, Producer's accuracy, User's Accuracy, and kappa measures rely upon the confusion matrix, which was used for assessing and evaluating the classification accuracy. The confusion matrix in Table 10 has columns for the reference classification and rows for the map classification. The matrix's diagonal cells display the proper classifications, whereas off-diagonal cells show incorrect classifications. The germination stage map produced when using the SVM classifier had an OA of 94% and 0.88 kappa value, according to the cross-validation results. In Table 10, confusion matrix is displayed. Users' accuracy ranged from 98% for other to 94% for the sugarcane plantations, and producer's accuracy varied between 96% for other and 92% for sugarcane. Some sugarcane fields were confused with other vegetation types, while a few non-sugarcane areas were also confused with sugarcane.

Table 10: SVM categorization Confusion Matrix for germination stage

Crop Type	Sugarcane	Other	Total	U_Accuracy	Kappa
Sugarcane	**195**	12	207	94%	0%
Other	18	**319**	337	95%	0%
Total	213	331	**544**	0%	0%
P_Accuracy	92%	96%	0%	**94%**	0%
Kappa	0	0	0	0%	**88%**

b) Tillering Stage

For the tillering stage, overall accuracy, Producer's accuracy, User's Accuracy, and kappa were also computed. The tillering stage map had an OA of 91% and 0.80 kappa value, according to the cross-validation results. In Table 11, confusion matrix is displayed. Users' accuracy ranged from 92% for sugarcane to 90% for other classes, and producer's accuracy varied between 95% for other and 84% for sugarcane. Some sugarcane fields were confused with other vegetation types, while some non-sugarcane areas were confused with sugarcane.

Table 11: SVM categorization Confusion Matrix for tillering stage

Crop Type	Sugarcane	Other	Total	U_Accuracy	Kappa
Sugarcane	**178**	16	194	92%	0%
Other	35	**315**	350	90%	0%
Total	213	331	**544**	0%	0%
P_Accuracy	84%	95%	0%	**91%**	0%
Kappa	0	0	0	0%	**80%**

c) Elongation Stage

For the elongation stage, overall accuracy, Producer's accuracy, User's Accuracy, and kappa were also computed. The elongation stage map had an OA of 94% and 0.86 kappa value, according to the cross-validation results. In Table 12, confusion matrix is displayed. Users' accuracy ranged from 95% for sugarcane plantations to 93% all other classes, and producer's accuracy varied between 97% for other and 88% for sugarcane. Again, some sugarcane fields were confused with other vegetation types, while some non-sugarcane areas were also confused with sugarcane.

Table 12: SVM categorization Confusion Matrix for elongation stage

Crop Type	Sugarcane	Other	Total	U_Accuracy	Kappa
Sugarcane	**187**	10	197	95%	0%
Other	25	**322**	347	93%	0%
Total	212	332	**544**	0%	0%
P_Accuracy	88%	97%	0%	**94%**	0%
Kappa	0	0	0	0%	**86%**

d) Ripening Stage

Overall accuracy, Producer's accuracy, User's Accuracy, and kappa were also computed for the ripening stage. The ripening stage map had an OA of 95% and 0.90 kappa value, according to the cross-validation results. In Table 13, confusion matrix is displayed. Users' accuracy ranged from 96% for other to 93% for sugarcane fields, and producer's accuracy varied between 96% for other and

94% for sugarcane. Some sugarcane fields were also confused with other vegetation types, while some non-sugarcane areas were confused with sugarcane in the ripening stage.

Table 13: SVM categorization Confusion Matrix for ripening stage

Crop Type	Sugarcane	Other	Total	U_Accuracy	Kappa
Sugarcane	**201**	14	215	93%	0%
Other	12	**317**	329	96%	0%
Total	213	331	**544**	0%	0%
P_Accuracy	94%	96%	0%	**95%**	0%
Kappa	0	0	0	0%	**90%**

4.1.3. Comparison of the classification methods based on vegetation indices

The accuracy of the vegetation indices varies in each of the four stages of the sugarcane crop's growth, much like the spectral bands. However, the accuracy of the results' classification was not increased by the VIs. A very good classification accuracy, OA of 95% was achieved with the SVM when applied on the spectral bands only at the last growth stage of the sugarcane crop. At the early stage of the sugarcane crop (germination stage), the results from the vegetation indices demonstrate a good classification accuracy for both the EVI and the NDVI. The EVI has an OA of 89% and 88% for the SVM and the RF, respectively, and the NDVI has a high OA of 93% for both the RF and the SVM.

The findings for both the NDVI and EVI indicated a decrease in accuracy at the tillering stage due to high spectral reflectance competence from other crops. The results also show that sugarcane can be accurately classified during the elongation and ripening stages of its growth as it is also the case with the spectral bands only. This implies that the final stage of the crop is the ideal time to distinguish sugarcane from other features. The results from the spectral bands alone outperform the classification outcome from the vegetation indices, despite the fact that the results from the vegetation indices are also good. This implies that spectral bands can be used in the Usuthu river basin for sugarcane discrimination. Table 14 uses the kappa values and overall accuracy to compare and summarize the vegetation indices' outcomes.

Table 14: Confusion matrix summary for the SVM and RF based on vegetation indices

Confusion Matrix for the vegetation indices per classification method in each of the four sugarcane growth stages										
			Germination		Tillering		Elongation		Ripening	
		Crop Type	PA	UA	PA	UA	PA	UA	PA	UA
	SVM	Sugarcane	92%	91%	81%	90%	89%	95%	90%	92%
NDVI		Other	94%	95%	94%	89%	97%	93%	95%	94%
		OA	**93%**		**89%**		**94%**		**93%**	
		Kappa	**86%**		**77%**		**87%**		**86%**	
		Crop Type	PA	UA	PA	UA	PA	UA	PA	UA
	RF	Sugarcane	91%	91%	81%	89%	88%	90%	89%	86%
		Other	94%	94%	93%	89%	94%	93%	91%	93%
		OA	**93%**		**89%**		**92%**		**90%**	
		Kappa	**85%**		**76%**		**82%**		**79%**	
		Crop Type	PA	UA	PA	UA	PA	UA	PA	UA
	SVM	Sugarcane	80%	92%	57%	80%	75%	95%	91%	92%
		Other	95%	88%	91%	77%	98%	86%	95%	94%
EVI		OA	**89%**		**78%**		**89%**		**93%**	
		Kappa	**77%**		**51%**		**76%**		**86%**	
		Crop Type	PA	UA	PA	UA	PA	UA	PA	UA
	RF	Sugarcane	75%	93%	60%	72%	76%	90%	88%	90%
		Other	96%	86%	85%	77%	95%	86%	93%	93%
		OA	**88%**		**75%**		**87%**		**91%**	
		Kappa	**74%**		**46%**		**73%**		**82%**	

4.1.4. Spectral Profiles for features of interest

Figure 16 shows the spectral profiles for the features of interest in each of the sugarcane growth stages. A study done by Jiang et al. (2019) when mapping sugarcane crop using S2 images and machine learning algorithms proved that every crop has a different backscattering coefficient temporal profile due to its unique phenological evolution. As a result, the period of time in connection to crop characteristics is essential information for differentiating between crop types (Jiang et al., 2019). The spectral profiles (Figure 16), taken at different stages of the sugarcane crop in this research shows a similar pattern to the study done by Jiang et al. (2019). The profiles indicate that at the early stages (germination and tillering) of the sugarcane crop, the spectral reflectance values for the sugarcane are lower when compared to the later stages (elongation and ripening). As a result, the classification accuracy of the sugarcane crop is improved at the last stage as indicated by the high spectral reflectance in the red edge and near infrared bands.

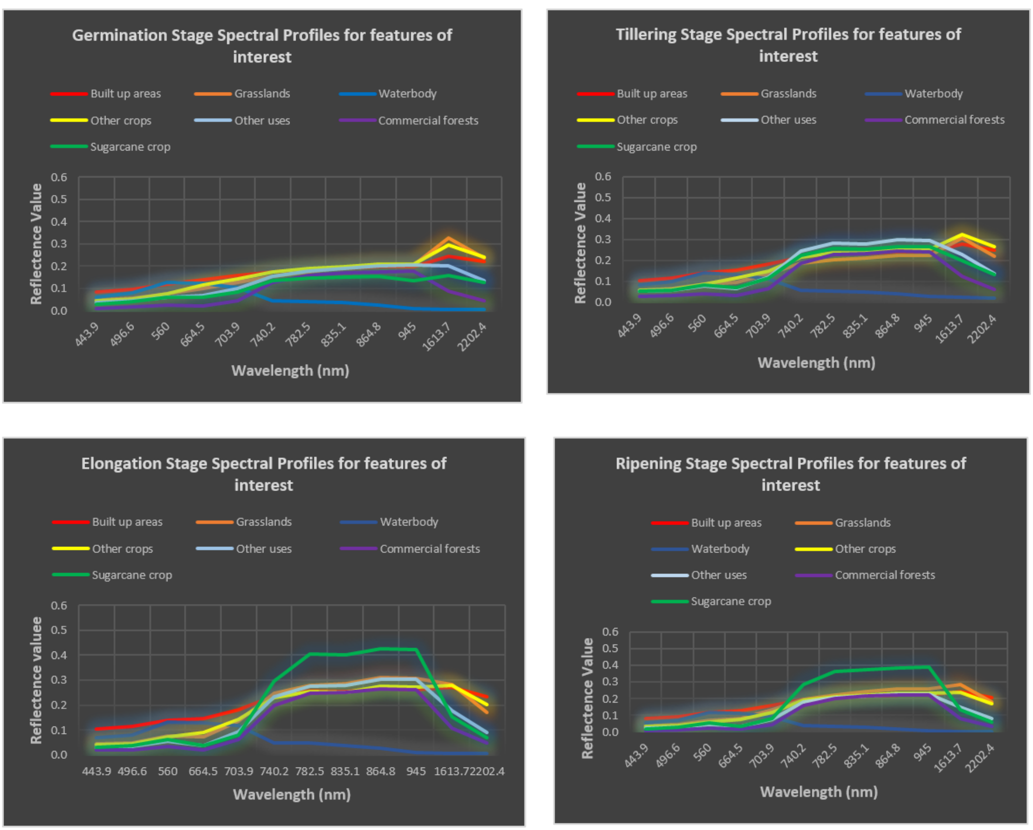


Figure 16: Spectral profiles for features of interest in the study area in each of the phenology stages

4.1.5. Contribution of the crop phenology in the classification outcome

Many studies have demonstrated that collecting plant information at multiple dates offer a comprehensive assessment of how the ecosystem reacts to climatic elements like humidity, moisture, flames, and human disturbance at different seasons of the plant growth period (Luciano et al., 2018, Aji et al., 2023). It creates the possibility of identifying specific species that might have distinct biophysical properties in remote sensing products during a given time frame (Aji et al., 2023). In this research, the months from April to June (ripening stage) are the best months for discrimination of sugarcane crop in the Usutu river basin. During these months, it is winter in Eswatini and most vegetation starts to lose their green leaves, except for sugarcane. Sugarcane is an evergreen crop as it is an irrigated crop. Even though the irrigation is reduced during this time to allow for drying up in readiness for harvesting, the crop is usually green and showing healthy leaves.

A research done by Luciano et al. (2018), found that April is the best single date for tree species discrimination in the savannah of southern Africa since April is a transitional month between aging and the full green canopy of plants. In this research, the multi-temporal approach showed that, the time between green canopy and senescence offers superior opportunities for separating the sugarcane crop than does the peak productivity period (the time between germination and tillering stages). During this period, other vegetation is also growing in the intense summer rains and they tend to have spectral reflectance which creates competition with the sugarcane crop.

Table 15 summarizes the classification accuracy for the RF classifier in each of the various phases of sugarcane development in the study area. The results from the RF method do not show any visible differences in the classification accuracy, all stages have good classification accuracy.

Table 15: RF categorization Confusion Matrix for different phonological stages

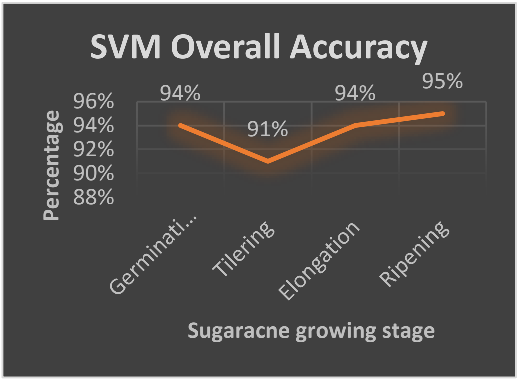
Confusion matrix summary for the RF classifier in all sugarcane growth stages								
	Germination		**Tillering**		**Elongation**		**Ripening**	
Crop Type	PA	UA	PA	UA	PA	UA	PA	UA
Sugarcane	87%	89%	82%	93%	89%	92%	90%	90%
Other	93%	92%	96%	89%	95%	93%	93%	93%
OA	**91%**		**90%**		**92%**		**92%**	
Kappa	**0.81**		**0.80**		**0.84**		**0.83**	

Table 16, shows the SVM classifier with a very good classification accuracy of 0.90 kappa value at the ripening stage of the sugarcane growth which is the highest amongst all the growth stages and highest between the two different classifiers when using the spectral bands only.

Table 16: SVM categorization Confusion Matrix for different phonological stages

Confusion matrix summary for the SVM classifier in all sugarcane growth stages								
	Germination		**Tillering**		**Elongation**		**Ripening**	
Crop Type	PA	UA	PA	UA	PA	UA	PA	UA
Sugarcane	92%	94%	84%	92%	88%	95%	94%	93%
Other	96%	95%	95%	90%	97%	93%	96%	96%
OA	**94%**		**91%**		**94%**		**95%**	
Kappa	**0.88**		**0.80**		**0.86**		**0.90**	

The classification results from the two methods in each of the sugarcane growth stages suggest that it is very important to consider the different phenology stages of the sugarcane growth for an improved classification accuracy. The results prove that during the elongation stage (March – April) and ripening stage (May – June) the sugarcane crop has green healthy leaves while other vegetation shows signs of water stress as it is winter in the country with no rains for the non-irrigated plants. This allows for ease of separating the sugarcane from other vegetation when there is less spectral reflectance competence among the sugarcane crop and the other vegetation. It is also anticipated that during the dry season, it is a period with reduced cloud influence thus allowing ease of image classification. Figure 17 below compares the overall classification accuracy achieved by both classifiers in each of the growth stages with SVM showing high accuracy across all stages.



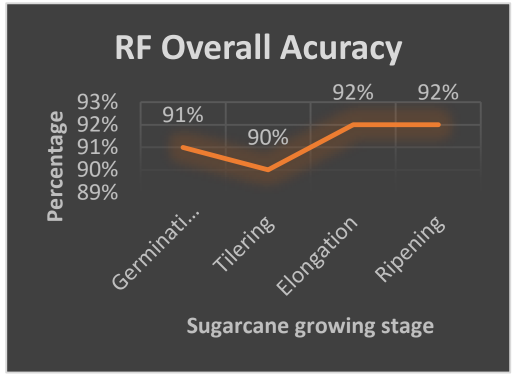


Figure 17: SVM vs. RF classification method overall accuracy

4.2. Comparison of Classified Data

4.2.1. Classification methods comparison

The effectiveness of the RF and SVM classification approaches in identifying sugarcane fields was tested. The classification was performed in each of the four sugarcane growing stages. Table 17 presents a comparison of the confusion matrix values obtained by each of the methods in in the germination stage of the sugarcane growth using the S2 imagery spectral bands.

Table 17: Confusion matrix and statistical measures for Sentinel 2 at germination stage

Sugarcane Classification at Germination Stage				
	SVM Germination		RF Germination	
Crop Type	PA	UA	PA	UA
Sugarcane	92%	94%	87%	89%
Other	96%	95%	93%	92%
OA	**94%**		**91%**	
Kappa	**0.88**		**0.81**	

As shown in Table 17, the SVM classification methods achieved the highest OA of 94% and kappa of 0.88 for the S2 imagery at germination stage. An OA of 91% and kappa of 0.81 was obtained with Random Forest. SVM performed better than RF as it obtained higher accuracy value when classifying the data during this phase of sugarcane development.

Table 18: Confusion matrix and statistical measures for Sentinel 2 at tillering stage

Sugarcane Classification at Tillering Stage				
	SVM Tillering		RF Tillering	
Crop Type	PA	UA	PA	UA
Sugarcane	84%	92%	82%	93%
Other	95%	90%	96%	89%
OA	**91%**		**90%**	
Kappa	**0.80**		**0.80**	

As shown in Table 18, the SVM classification methods achieved the highest OA of 91% and kappa of 0.80 for the S2 imagery at the tillering stage. A slightly lower OA of 90% and kappa of 0.80 was obtained with Random Forest. SVM performed better than RF as it obtained higher accuracy value when classifying the data during this phase of sugarcane development.

Table 19: Confusion matrix and statistical measures for Sentinel 2 at elongation stage

Sugarcane Classification at Elongation Stage				
	SVM Elongation		RF Elongation	
Crop Type	PA	UA	PA	UA
Sugarcane	88%	95%	89%	92%
Other	97%	93%	95%	93%
OA	**94%**		**92%**	
Kappa	**0.86**		**0.84**	

In Table 19, the SVM classification methods achieved the highest OA of 94% and kappa of 0.86 for the S2 imagery at the elongation stage. A slightly lower OA of 92% and kappa of 0.84 was obtained with Random Forest. SVM performed better than RF as it obtained higher accuracy value when classifying the data during this phase of sugarcane development.

Table 20: Confusion matrix and statistical measures for Sentinel 2 at ripening stage

Sugarcane Classification at Ripening Stage				
	SVM Ripening		RF Ripening	
Crop Type	PA	UA	PA	UA
Sugarcane	94%	93%	89%	90%
Other	96%	96%	93%	93%
OA	**95%**		**92%**	
Kappa	**0.90**		**0.83**	

In Table 20, the SVM classification methods achieved the highest OA of 95% and kappa of 0.90 for the S2 imagery at the ripening stage. A slightly lower OA of 92% and kappa of 0.83 was obtained with Random Forest. SVM performed better than RF as it obtained higher accuracy value when classifying the data during this phase of sugarcane development. The classified map of sugarcane plantations for the ILLOVO sugar mill at ripening stage is closely compared to the mapped sugarcane field boundaries in Figure 18 below.

The SVM method Figure 18 B, demonstrated its robustness in accurately mapping sugarcane fields by producing a highly accurate map with no outliers from the classified map. Although there are a few obvious outliers of incorrectly classified sugarcane, the RF on the left exhibits good classification accuracy. These outliers could compromise the reliability of the estimation of the total sugarcane area in the research site, resulting in overestimated totals. The accuracy of the two image classification techniques in sugarcane mapping is demonstrated by the black outlines that closely encircle the classified sugarcane fields shown in green, which are the ILLOVO sugarcane fields' GPS boundaries.

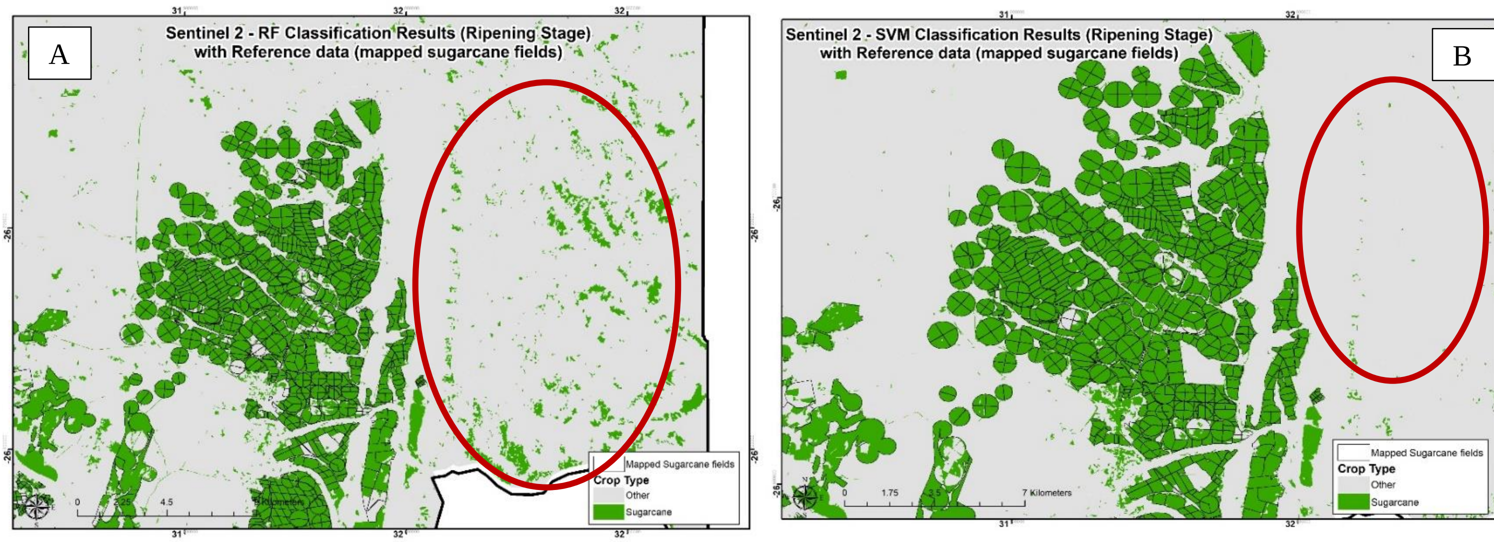


Figure 18: Sentinel 2 -RF classification results (A) and SVM classification results (B) with reference data

4.3.2. Comparison of remote sensing products with water use database

The area covered by the sugarcane fields from the categorized data alongside the water use database is shown in a graph (Figure 19). By comparing the total amount of classified sugarcane to the reference data for each growth stage, the graph makes it possible to see the classification accuracy or error. Figure 20 shows the classified sugarcane map using the RF and SVM methods with the spectral bands only compared to the sugarcane map from the water use mapped data.

The estimated area for the RF method is slightly above double for the germination stage and doubled for both the elongation and ripening stages. The graph also indicates a consistent inflation of the area under sugarcane for the RF methods, up to three times the reference data for the tillering stage. As the sugarcane ages, the accuracy of classification is increasing. The same findings have been noted for the SVM method, which shows that as the sugarcane ages, the estimated area grows closer to the reference data. For the SVM classification method, at the tillering stage, there is an observed overestimation of nearly twice the reference database area, despite the fact that the SVM method produced a closer estimate. Compared to the tillering stage, the germination and elongation stages yielded more accurate estimates for the SVM method. The optimum area estimate was achieved when classifying the ripening stage for the SVM method. This is consistent with the confusion matrix, which shows that out of all growth stages, the ripening stage had the highest kappa value of 0.90 among all SVM and RF classification results.

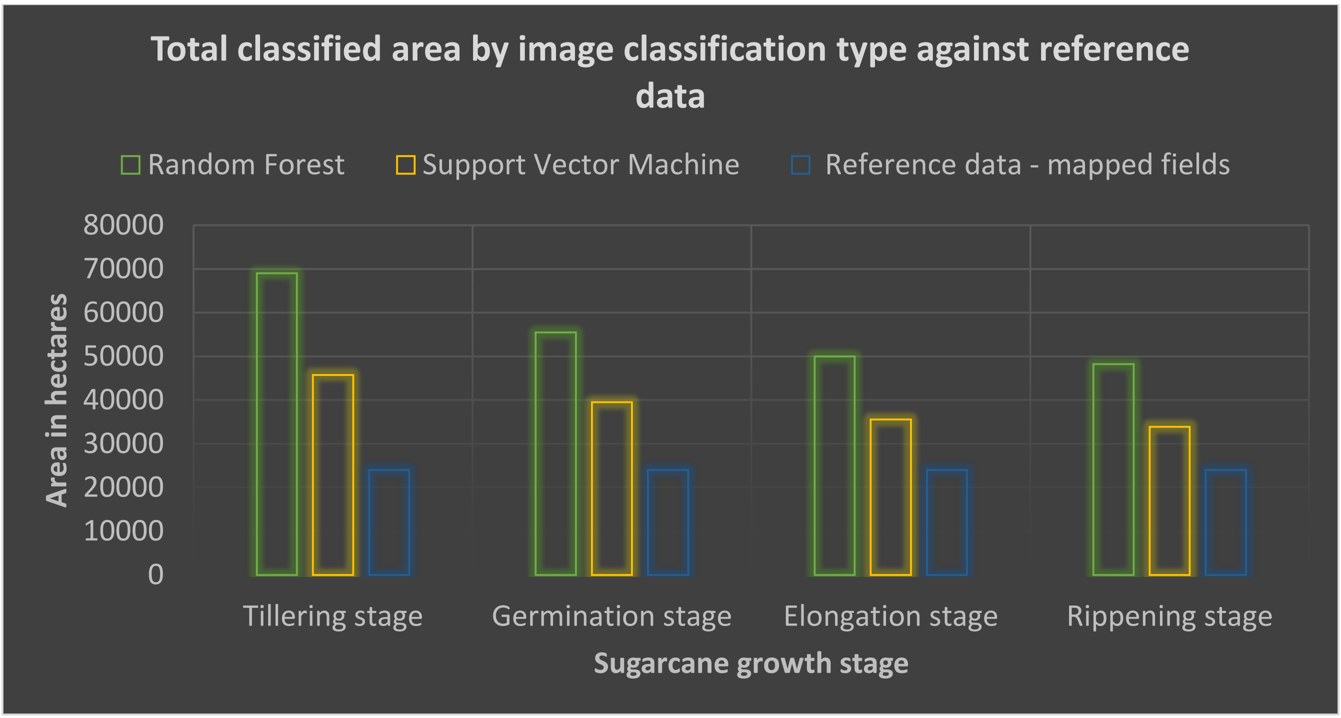


Figure 19: Sentinel 2 -RF and SVM classification results compared to the water use database

A map that contrasts the results of satellite imagery with the source data, displayed in Figure 20, shows that most of the variances were negligible, producing an identical map to the reference data for the RF classification method. The area difference between the reference data and the categorised data illustrates the differences between the two products. Besides the area differences, the confusion matrix shows good classification accuracy and the maps looks the same as the reference data maps. Even though the classified maps match the reference data maps exactly, the RF classifier produced outcome maps with more area covered by sugarcane due to the obvious outliers seen on the maps.

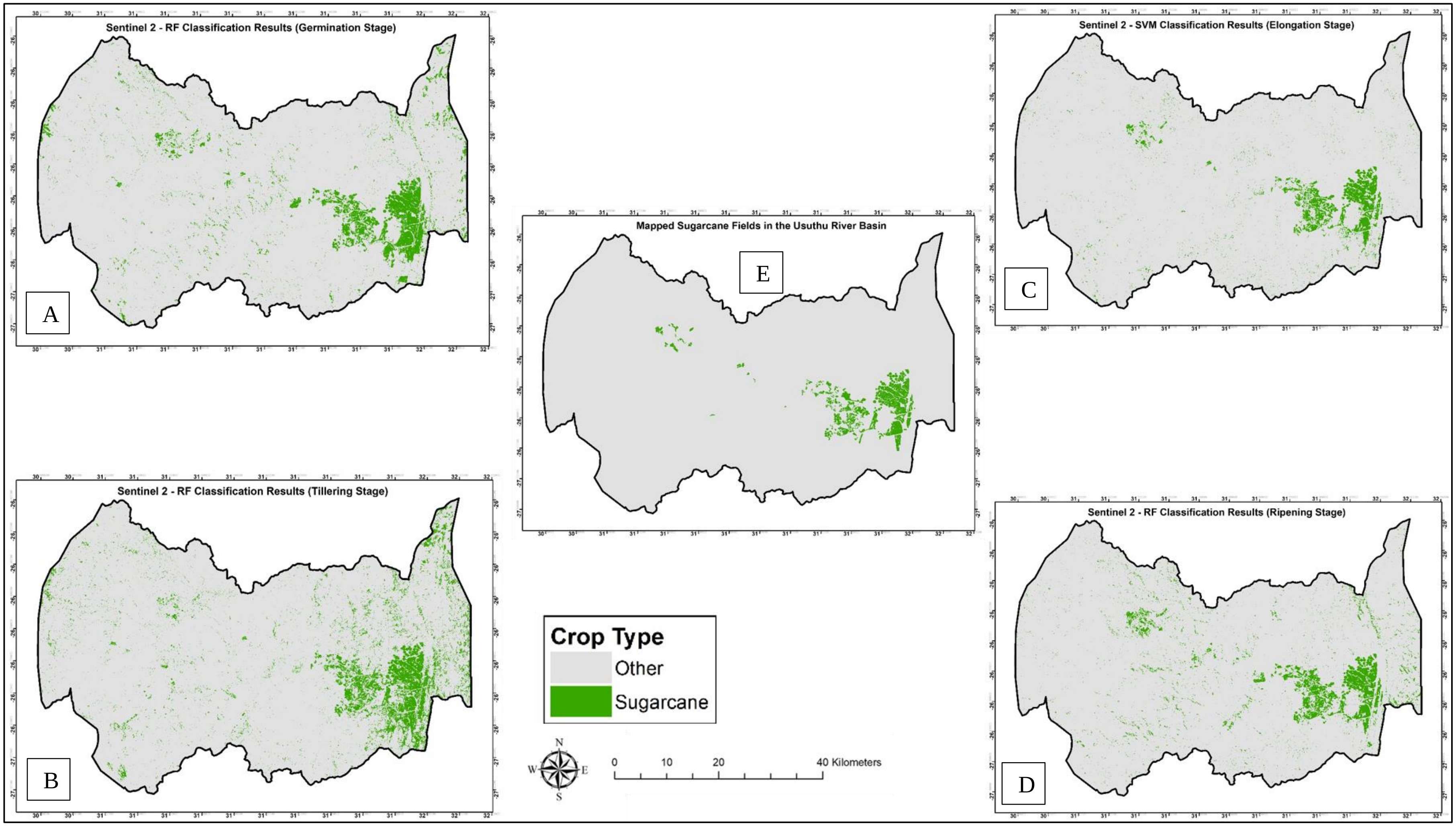


Figure 20: Map comparison of Sentinel 2 -RF classification results to water use database map (A-germination, B - tillering, C-elongation and D – ripening stage) E- reference database map

A map that contrasts the results of satellite imagery with the source data, displayed in Figure 21, shows an identical map to the reference data for the SVM classification method. An estimate of the sugarcane area that is closer to the reference data is produced by the categorized data, especially during the ripening stage, which displays a smooth map of the sugarcane fields without any expected classified outliers in grasslands and other landuse classifications. Besides the area differences, the confusion matrix shows good classification accuracy, and the maps looks the same as the reference data maps.

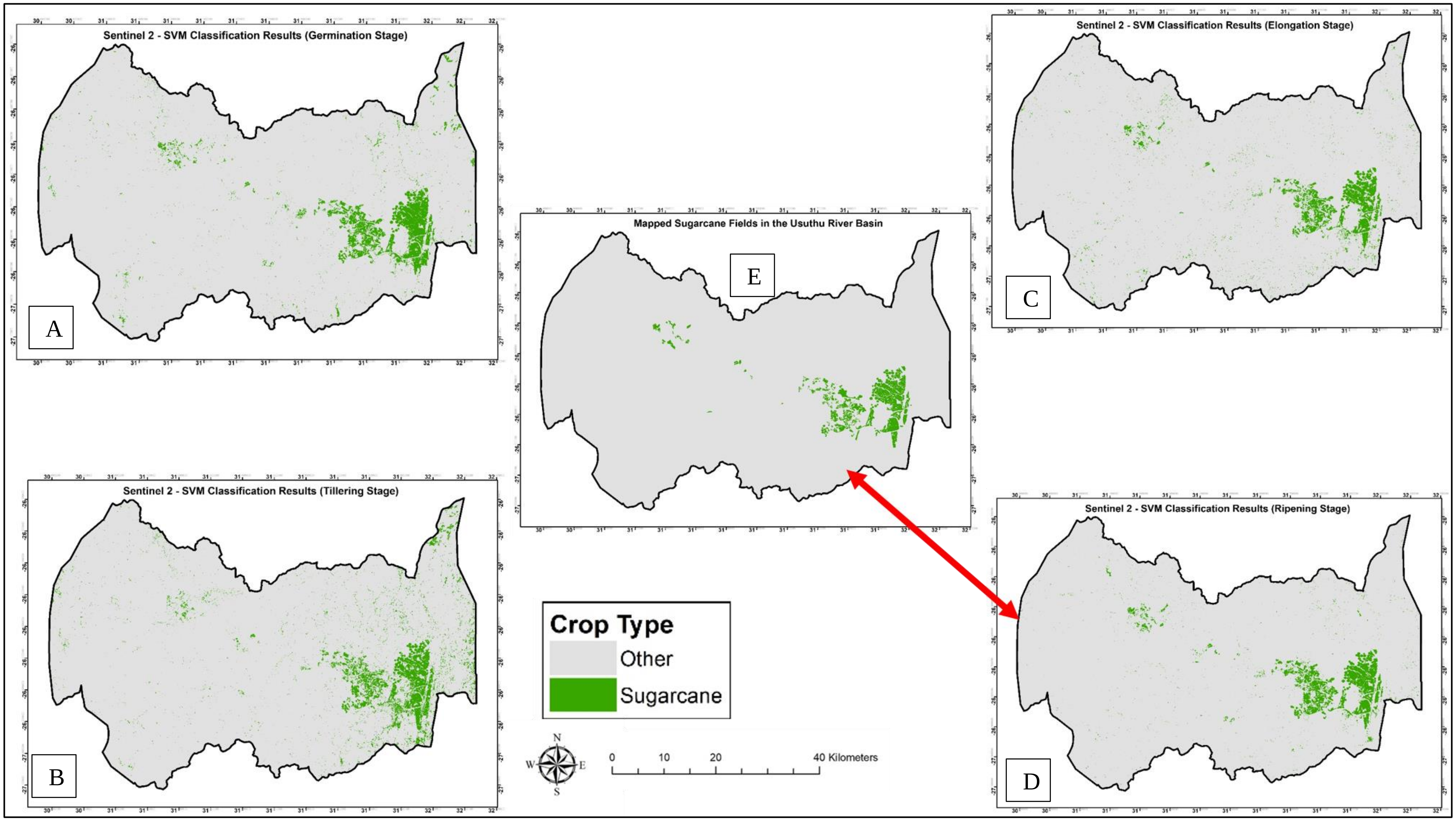


Figure 21: Map comparison of Sentinel 2 - SVM classification results to water use database map (A-germination, B -tillering, C-elongation and D – ripening stage), E- reference database map

5. Discussions

The aim of this thesis is to demonstrate the capabilities of the Sintenel-2 time series data in mapping sugarcane fields. Specifically, the study's objective is to determine the best time to map sugarcane fields during their growth stage and to determine the most reliable classification technique for differentiating sugarcane fields in the Usuthu river basin based on S2 images. The results in chapter four present a classification of the four phenological growth stages for each of the two image classification methods and further shows the growth stage with the most accurate classification outcome.

The highest accuracy was obtained by the SVM model when classifying data for the ripening stage of the sugarcane growing timeline using the Sentinel 2 imagery spectral bands only with an OA of 95% and kappa value of 0.90. The lowest classification accuracy achieved by the SVM was 91% OA (0.80) kappa value at tillering stage. The RF method also produced good accuracy with the spectral bands with the highest OA of 92% at the elongation and ripening stages with kappa values of 0.84 and 0.83 at elongation and ripening stages respectively. The lowest classification results achieved by the RF method was 90% OA with a kappa value of 0.80 at tillering stage. The results show a good improvement as the sugarcane crop matures (ripening stage) and this suggest that the last growth stage of the crop is the best time for discriminating sugarcane in the Usuthu basin using the SVM classification method. At both the elongation and ripening stage, there was an observed consistency in accuracy for both the RF and the SVM methods, however the SVM portrays superiority over the RF in the classification accuracy.

Even though both the SVM and the RF produced highly acceptable results with the SVM having a slightly more accurate results at the ripening stage, the resultant maps and the overall classified sugarcane area for the SVM proved to be more comparable to the reference database, making the SVM method the preferred choice for mapping sugarcane fields. The ability of the SVM to eliminate outliers caused by electromagnetic interference on sugarcane mapping was very influential in obtaining a much closer estimate of sugarcane area to the reference database. This is in line with findings from other researchers, such as (Kai et al., 2022, Wang et al., 2019), who found that object-oriented visual analysis can be effectively processed using Support Vector Machine techniques.

The results from this research prove that the months from April to June (ripening stage) are the best months for discrimination of sugarcane crop in the Usutu river basin. During these months, it is winter in Eswatini and most vegetation starts to lose their green leaves, except for sugarcane which is an irrigated crop. Even though the irrigation is reduced during this time to allow for drying up in readiness for harvesting, the crop is usually green and showing healthy leaves. A study done by Bappel et al. (2003) concluded that Significant differences are seen in the Near-IR reflectance's, having lower reflectance values which are associated with sugar cane at early stage of development (less than six months), while higher reflectance values are associated with later stage of sugar cane, between 9 and 12 months. There is a very close relationship between the lifespan of sugarcane and the spectral reflectance from plant biomass present in the crop canopy. The study's findings demonstrate that evaluating the classification accuracy at each stage of growth reveals patterns that would be challenging to spot with just one date's worth of imagery. Verma et al.'s (2017) study found that the IRS-P6, 5.8 m resolution LISS IV sensor imagery produced satisfactory results for the peak growing stage of sugarcane. This implies that the plant growth stage affects classification accuracy in different climate conditions and regions, so it's important to take the crop's growth stage into account when classifying satellite imagery.

There was no significant contribution of the VIs in the classification accuracy of the results. The spectral bands produced the best accuracy results which are highly comparable to the reference water use database maps. A key observation made is that the sugarcane classification accuracy showed great improvement in areas with large sugarcane fields or sugarcane fields covering a large area. The ILLOVO sugarcane plantations show a very good classification accuracy in all the four sugarcane growth stages. These are fields with less or no intercropping that are mainly sugarcane, making it highly possible to identify the sugarcane crop. Besides the outliers due to noise and electromagnetic interference both the RF and SVM classification methods shows highly acceptable results for the sugar mill fields that is identical to the reference data.

The study aims to demonstrate the validity of remote sensing together with machine learning methodologies in mapping of sugarcane fields, especially the awkward and difficult to reach places by the JRBA officers. These are the areas where farmers are using water from the rivers without water permits, unfortunately these are small scale farmers with small sugarcane fields that are not easily identified by the digital mapping technologies due to the high spectral competence from other crops grown with the sugarcane fields.

6. Conclusion

In this study, two image classification methods were applied in Sentinel 2 imageries taken at four different growth stages of the sugarcane crop in the Usuthu river basin. The study attempted to identify the best time of the year for discriminating and mapping sugarcane fields and to select the best classification method to be used for accurate separation of the sugarcane crop. The study further looks into how vegetation indices are essential for improving the classification accuracy of the sugarcane plantations. The findings suggest that phenology in conjunction with spectral bands can yield very satisfactory outcomes. It was found that spectral bands by themselves were more accurate than additional vegetation indicators. The results reported in section 4 suggest that the SVM classifier can achieve highly acceptable classification accuracy level in all the four sugarcane growth stages with the spectral bands only. The RF classifier on the other hand shows very good classification results across the sugarcane growth stages but lower than the SVM method. Both methods showed slightly lower classification accuracies at the early stage of the sugarcane growth compared to the later stages.

It is anticipated that the samples used to train the prediction models, is probably what accounts for the SVM classifier's somewhat improved performance as other studies show that machine learning algorithms heavily rely on the caliber of training data as well as the chosen areas (Wessel et al., 2018b).

In conclusion:

- The results show that Sentinel 2 sensor could discriminate the sugarcane crop from other features with high accuracy and the resultant maps are comparable to the reference map.
- The SVM classifier produced highly acceptable results when classifying the Sentinel 2 imagery at the final growth stage of the sugarcane crop (ripening stage) with OA of 95% and kappa value of 0.90 utilizing the spectral bands only for S2.
- When spectral bands alone were used as opposed to indices of vegetation, the classification results were not enhanced.

- Using different imagery dates played a pivotal role in identifying the best time of the year for discriminating sugarcane crop in the study area. The accuracy of the classification showed great improvement as the sugarcane cane crop ages, as a result, the study reveals that the last stage of the sugarcane growth is the best time for discriminating sugarcane fields.

In conclusion, the maps that are produced provide essential information for research on the impact of sugarcane growing on Eswatini's economy and ecology, and the results provides valuable information and resources to the daily operations of the Joint River Basin Authorities office. As a result of easy availability of Sentinel-2 data, this method of categorization is especially appropriate towards future research and ongoing mapping of sugarcane fields and other crops grown in the basin. By lowering resources needed for mapping sugarcane and other crops grown in the basin and serve as a reference in cases of crops grown uncertainty, the final sugarcane distribution map will aid in the entire basin management. Moreover, upcoming studies in other basins or regions can apply the specified categorization method for discrimination of sugarcane. The methods applied in this research can be easily transferred or adopted by the sugar mills such as ILLOVO to accurately and promptly classify sugarcane fields as the methods depend on S2 imagery which is available for free.

References

A. RAMEZAN, C., A. WARNER, T. & E. MAXWELL, A. J. R. S. 2019. Evaluation of sampling and cross-validation tuning strategies for regional-scale machine learning classification. 11**,** 185.

ADAM, E., DENG, H., ODINDI, J., ABDEL-RAHMAN, E. M. & MUTANGA, O. 2017. Detecting the early stage of phaeosphaeria leaf spot infestations in maize crop using in situ hyperspectral data and guided regularized random forest algorithm. *Journal of Spectroscopy,* 2017.

AJI, M. A. P., KAMAL, M., FARDA, N. M. J. R. S. A. S. & ENVIRONMENT 2023. Mangrove species mapping through phenological analysis using random forest algorithm on Google Earth Engine. 30**,** 100978.

ATZBERGER, C. J. R. S. 2013. Advances in remote sensing of agriculture: Context description, existing operational monitoring systems and major information needs. 5**,** 949-981.

BAPPEL, E., BÉGUÉ, A., DESPINOY, M., BUCHON, Y. & SIEGMUND, B. Spectral indices as bio-indicators of sugar cane crop condition from hyperspectral CASI data. IGARSS 2003. 2003 IEEE International Geoscience and Remote Sensing Symposium. Proceedings (IEEE Cat. No. 03CH37477), 2003. IEEE, 561-563.

CHEN, Y., FENG, L., MO, J., MO, W., DING, M. & LIU, Z. J. J. O. T. I. S. O. R. S. 2020. Identification of sugarcane with NDVI time series based on HJ-1 CCD and MODIS fusion. 48**,** 249-262.

CHI, M., PLAZA, A., BENEDIKTSSON, J. A., SUN, Z., SHEN, J. & ZHU, Y. J. P. O. T. I. 2016. Big data for remote sensing: Challenges and opportunities. 104**,** 2207-2219.

DE OLIVEIRA MAIA, F. C., BUFON, V. B. & LEÃO, T. P. J. P. A. 2023. Vegetation indices as a Tool for Mapping Sugarcane Management Zones. 24**,** 213-234.

DLAMINI, W. M. J. M. E. S. & ENVIRONMENT 2016. Analysis of deforestation patterns and drivers in Swaziland using efficient Bayesian multivariate classifiers. 2**,** 1-14.

DOS SANTOS LUCIANO, A. C., PICOLI, M. C. A., ROCHA, J. V., DUFT, D. G., LAMPARELLI, R. A. C., LEAL, M. R. L. V., LE MAIRE, G. J. I. J. O. A. E. O. & GEOINFORMATION 2019. A generalized space-time OBIA classification scheme to map sugarcane areas at regional scale, using Landsat images time-series and the random forest algorithm. 80**,** 127-136.

DOS SANTOS LUCIANO, A. C., PICOLI, M. C. A., ROCHA, J. V., FRANCO, H. C. J., SANCHES, G. M., LEAL, M. R. L. V. & LE MAIRE, G. J. R. S. O. E. 2018. Generalized space-time classifiers for monitoring sugarcane areas in Brazil. 215**,** 438-451.

ED CHAVES, M., CA PICOLI, M. & D. SANCHES, I. J. R. S. 2020. Recent applications of Landsat 8/OLI and Sentinel-2/MSI for land use and land cover mapping: A systematic review. 12**,** 3062.

EL CHAMI, D., DACCACHE, A. & EL MOUJABBER, M. 2020. What are the impacts of sugarcane production on ecosystem services? A Review.

ENNOURI, K. & KALLEL, A. J. M. P. I. E. 2019. Remote sensing: An advanced technique for crop condition assessment. 2019.

Eswatini Sugar Association (ESA), 2022. Eswatini Sugar Journal. Mbabane, Eswatini.

EVERINGHAM, Y., LOWE, K., DONALD, D., COOMANS, D. & MARKLEY, J. J. A. F. S. D. 2007. Advanced satellite imagery to classify sugarcane crop characteristics. 27**,** 111-117.

FOODY, G. M. & MATHUR, A. J. R. S. O. E. 2004. Toward intelligent training of supervised image classifications: directing training data acquisition for SVM classification. 93**,** 107-117.

GEORGE, R., PADALIA, H., KUSHWAHA, S. J. I. J. O. A. E. O. & GEOINFORMATION 2014. Forest tree species discrimination in western Himalaya using EO-1 Hyperion. 28**,** 140-149.

GONÇALVES, R. R., ZULLO JR, J., ROMANI, L. A., NASCIMENTO, C. R. & TRAINA, A. J. J. I. J. O. R. S. 2012. Analysis of NDVI time series using cross-correlation and forecasting methods for monitoring sugarcane fields in Brazil. 33**,** 4653-4672.

International Finance Corporation Bank (IFB), 2022. Country Private Sector Diagnostic: Creating Markets in Eswatini-Strengthening the Private Sector to Grow Export Markets and Create Jobs. Mbabane, Eswatini.

HALIPU, A., WANG, X., IWASAKI, E., YANG, W. & KONDOH, A. J. R. S. 2022. Quantifying Water Consumption through the Satellite Estimation of Land Use/Land Cover and Groundwater Storage Changes in a Hyper-Arid Region of Egypt. 14**,** 2608.

HARVEY, M. & PILGRIM, S. J. F. P. 2011. The new competition for land: Food, energy, and climate change. 36**,** S40-S51.

HOSSAIN, M. D., CHEN, D. J. I. J. O. P. & SENSING, R. 2019. Segmentation for Object-Based Image Analysis (OBIA): A review of algorithms and challenges from remote sensing perspective. 150**,** 115-134.

HU, Q., WU, W., XIA, T., YU, Q., YANG, P., LI, Z. & SONG, Q. J. R. S. 2013. Exploring the use of Google Earth imagery and object-based methods in land use/cover mapping. 5**,** 6026-6042.

JIANG, H., LI, D., JING, W., XU, J., HUANG, J., YANG, J. & CHEN, S. J. R. S. 2019. Early season mapping of sugarcane by applying machine learning algorithms to Sentinel-1A/2 time series data: a case study in Zhanjiang City, China. 11**,** 861.

JOHNSON, B. A., SCHEYVENS, H., SHIVAKOTI, B. R. J. I. J. O. A. E. O. & GEOINFORMATION 2014. An ensemble pansharpening approach for finer-scale mapping of sugarcane with Landsat 8 imagery. 33**,** 218-225.

JORDAAN, A. J., MLENGA, D. H. & MANDEBVU, B. J. J. J. O. D. R. S. 2019. Monitoring droughts in Eswatini: A spatiotemporal variability analysis using the Standard Precipitation Index. 11**,** 1-11.

KAI, P. M., DE OLIVEIRA, B. M. & DA COSTA, R. M. J. A. 2022. Deep learning-based method for classification of sugarcane varieties. 12**,** 2722.

KARIMI, P., BONGANI, B., BLATCHFORD, M. & DE FRAITURE, C. J. R. S. 2019. Global satellite-based ET products for the local level irrigation management: An application of irrigation performance assessment in the Sugarbelt of Swaziland. 11**,** 705.

KING, R. D., FENG, C. & SUTHERLAND, A. J. A. A. I. A. I. J. 1995. Statlog: comparison of classification algorithms on large real-world problems. 9**,** 289-333.

KNORN, J., RABE, A., RADELOFF, V. C., KUEMMERLE, T., KOZAK, J. & HOSTERT, P. J. R. S. O. E. 2009. Land cover mapping of large areas using chain classification of neighboring Landsat satellite images. 113**,** 957-964.

LIAGHAT, S., BALASUNDRAM, S. K. J. A. J. O. A. & SCIENCES, B. 2010. A review: The role of remote sensing in precision agriculture. 5**,** 50-55.

LUCIANO, A. D. S., PICOLI, M. C. A., ROCHA, J. V., FRANCO, H. C. J., SANCHES, G. M., LEAL, M. R. L. V. & MAIRE, G. L. J. R. S. O. E. 2018. Generalized space-time classifiers for monitoring sugarcane areas in Brazil. 215**,** 438-451.

LUKHELE, S. M., SHAPIRO, J. T., THEMB'ALILAHLWA, A., SIBIYA, M. D., MCCLEERY, R. A., FLETCHER, R. J. & MONADJEM, A. J. H. 2021. Influence of sugarcane growth stages on bird diversity and community structure in an agricultural-savanna environment. 7.

MAHMUD, S., REDOWAN, M., AHMED, R., KHAN, A. A. & RAHMAN, M. M. J. G. I. 2022a. Phenology-based classification of Sentinel-2 data to detect coastal mangroves. 37**,** 14335-14354.

MAHMUD, S., REDOWAN, M., AHMED, R., KHAN, A. A. & RAHMAN, M. M. J. G. I. 2022b. Phenology-based classification of Sentinel-2 data to detect coastal mangroves. 1-20.

MAMBA, M. P., SHONGWE, M. I. J. M. E. S. & ENVIRONMENT 2022a. Spatial variability assessment of irrigation performance in the Lower Usuthu Smallholder Irrigation Project (LUSIP) in Eswatini. 8**,** 4455-4465.

MAMBA, M. P., SHONGWE, M. I. J. M. E. S. & ENVIRONMENT 2022b. Spatial variability assessment of irrigation performance in the Lower Usuthu Smallholder Irrigation Project (LUSIP) in Eswatini. 1-11.

MARCINKOWSKA, A., ZAGAJEWSKI, B., OCHTYRA, A., JAROCIŃSKA, A., RACZKO, E., KUPKOVÁ, L., STYCH, P. & MEULEMAN, K. J. M. G. R. S. O. D. 2014. Mapping vegetation communities of the Karkonosze National Park using APEX hyperspectral data and Support Vector Machines. 18**,** 23-29.

MASUKU, M. J. A. J. O. A. S. 2011. Determinants of sugarcane profitability: the case of smallholder cane growers in Swaziland. 3**,** 210-214.

MHLANGA-NDLOVU, N. 2022. Socio-Economic Effects of Neoliberal Transformation on Irrigated Agriculture in Eswatini: A Case of Sugarcane Farmers' Groups in the Komati Downstream Development Project. *Capital Penetration and the Peasantry in Southern and Eastern Africa: Neoliberal Restructuring.* Springer.

MHLANGA, B., NDLOVU, L., SENZANJE, A. J. P. & CHEMISTRY OF THE EARTH, P. A. B. C. 2006. Impacts of irrigation return flows on the quality of the receiving waters: A case of sugarcane irrigated fields at the Royal Swaziland Sugar Corporation (RSSC) in the Mbuluzi River Basin (Swaziland). 31**,** 804-813.

MKHONTA, B. E. 2015. Hydraulic performance and productivity for large commercial and smallholder sub surface drip irrigation systems for sugarcane: a case study of the Royal Swaziland Sugar Corporation (RSSC), Cathula and Manzana farmer associations in Swaziland.

MOLIJN, R. A., IANNINI, L., VIEIRA ROCHA, J. & HANSSEN, R. F. J. R. S. 2019. Sugarcane productivity mapping through C-band and L-band SAR and optical satellite imagery. 11**,** 1109.

MULIANGA, B., BÉGUÉ, A., CLOUVEL, P. & TODOROFF, P. J. R. S. 2015. Mapping cropping practices of a sugarcane-based cropping system in Kenya using remote sensing. 7**,** 14428-14444.

MURERIWA, N., ADAM, E., SAHU, A. & TESFAMICHAEL, S. 2016. Examining the spectral separability of Prosopis glandulosa from co-existent species using field spectral measurement and guided regularized random forest. *Remote Sensing,* 8**,** 144.

MURILLO-SANDOVAL, P., CARBONELL-GONZALEZ, J. & OSORIO-MURILLO, C. J. J. A. S. T. 2011. Evaluation of landsat 7 etm+ data for spectral discrimination and classification of sugarcane varieties in colombia. 5**,** 101-107.

NALLEY, L., ANDERSON, B., PRICE, H. & DALMINI, T. 2019. Revenue implications associated with climate change for sugar producers in Eswatini.

NHAMO, G. 2017. An assessment of Swaziland sugarcane farmer associations' vulnerability to climate change.

NIHAR, A., PATEL, N., POKHARIYAL, S. & DANODIA, A. J. J. O. T. I. S. O. R. S. 2022. Sugarcane crop type discrimination and area mapping at field scale using sentinel images and machine learning methods. 1-9.

PALANISWAMI, C., GOPALASUNDARAM, P. & BHASKARAN, A. J. S. T. 2011. Application of GPS and GIS in Sugarcane Agriculture. 13**,** 360-365.

PHIRI, D., SIMWANDA, M., SALEKIN, S., NYIRENDA, V. R., MURAYAMA, Y. & RANAGALAGE, M. J. R. S. 2020. Sentinel-2 data for land cover/use mapping: A review. 12**,** 2291.

PINTER JR, P. J., HATFIELD, J. L., SCHEPERS, J. S., BARNES, E. M., MORAN, M. S., DAUGHTRY, C. S. & UPCHURCH, D. R. 2003. Remote sensing for crop management.

PULIGHE, G., BAIOCCHI, V. & LUPIA, F. J. I. J. O. D. E. 2016. Horizontal accuracy assessment of very high resolution Google Earth images in the city of Rome, Italy. 9**,** 342-362.

RAMEZAN, C. A., WARNER, T. A., MAXWELL, A. E. & PRICE, B. S. J. R. S. 2021. Effects of training set size on supervised machine-learning land-cover classification of large-area high-resolution remotely sensed data. 13**,** 368.

RAO, N. R. J. I. J. O. R. S. 2008. Development of a crop-specific spectral library and discrimination of various agricultural crop varieties using hyperspectral imagery. 29**,** 131-144.

RICHARD, K., ABDEL-RAHMAN, E. M., SUBRAMANIAN, S., NYASANI, J. O., THIEL, M., JOZANI, H., BORGEMEISTER, C. & LANDMANN, T. 2017. Maize cropping systems mapping using rapideye observations in agro-ecological landscapes in Kenya. *Sensors,* 17**,** 2537.

SATHYA, P., MALATHI, L. J. I. J. O. M. L. & COMPUTING 2011. Classification and segmentation in satellite imagery using back propagation algorithm of ann and k-means algorithm. 1**,** 422.

SAWAENGSAK, W. & GHEEWALA, S. H. J. J. O. C. P. 2017. Analysis of social and socio-economic impacts of sugarcane production: A case study in Nakhon Ratchasima province of Thailand. 142**,** 1169-1175.

SCHULTZ, B., IMMITZER, M., ROBERTO FORMAGGIO, A., DEL'ARCO SANCHES, I., JOSÉ BARRETO LUIZ, A. & ATZBERGER, C. J. R. S. 2015. Self-guided segmentation and classification of multi-temporal Landsat 8 images for crop type mapping in Southeastern Brazil. 7**,** 14482-14508.

SEMIE, T. K., SILALERTRUKSA, T., GHEEWALA, S. H. J. G. E. & CONSERVATION 2019. The impact of sugarcane production on biodiversity related to land use change in Ethiopia. 18**,** e00650.

SINGH, R., PATEL, N., DANODIA, A. J. R. S. A. S. & ENVIRONMENT 2020. Mapping of sugarcane crop types from multi-date IRS-Resourcesat satellite data by various classification methods and field-level GPS survey. 19**,** 100340.

SOLOMON, S., BANERJI, R., SHRIVASTAVA, A. K., SINGH, P., SINGH, I., VERMA, M., PRAJAPATI, C. & SAWNANI, A. J. S. T. 2006. Post-harvest deterioration of sugarcane and chemical methods to minimize sucrose losses. 8**,** 74-78.

SOM-ARD, J., ATZBERGER, C., IZQUIERDO-VERDIGUIER, E., VUOLO, F. & IMMITZER, M. J. R. S. 2021. Remote sensing applications in sugarcane cultivation: A review. 13**,** 4040.

SOUZA, C. H. W. D., CERVI, W. R., BROWN, J. C., ROCHA, J. V. & LAMPARELLI, R. A. C. J. J. O. L. U. S. 2017. Mapping and evaluating sugarcane expansion in Brazil's savanna using MODIS and intensity analysis: A case-study from the state of Tocantins. 12**,** 457-476.

STEHMAN, S. V. & FOODY, G. M. J. R. S. O. E. 2019. Key issues in rigorous accuracy assessment of land cover products. 231**,** 111199.

STORY, M., CONGALTON, R. G. J. P. E. & SENSING, R. 1986. Accuracy assessment: a user's perspective. 52**,** 397-399.

TERRY, A. & OGG, M. J. J. O. S. A. S. 2017. Restructuring the Swazi sugar industry: the changing role and political significance of smallholders. 43**,** 585-603.

TFWALA, C., MENGISTU, A., SEYAMA, E., MOSIA, M., VAN RENSBURG, L., MVUBU, B., MBINGO, M. & DLAMINI, P. J. H. 2020. Nationwide temporal variability of droughts in the Kingdom of Eswatini: 1981–2018. 6.

TILAHUN, A. & TEFERIE, B. J. A. J. O. E. P. 2015. Accuracy assessment of land use land cover classification using Google Earth. 4**,** 193-198.

VAN VLIET, J., BREGT, A. K. & HAGEN-ZANKER, A. J. E. M. 2011. Revisiting Kappa to account for change in the accuracy assessment of land-use change models. 222**,** 1367-1375.

VERMA, A. K., GARG, P. K. & HARI PRASAD, K. J. A. J. O. G. 2017. Sugarcane crop identification from LISS IV data using ISODATA, MLC, and indices based decision tree approach. 10**,** 1-17.

WANG, J., XIAO, X., LIU, L., WU, X., QIN, Y., STEINER, J. L. & DONG, J. J. R. S. O. E. 2020. Mapping sugarcane plantation dynamics in Guangxi, China, by time series Sentinel-1, Sentinel-2 and Landsat images. 247**,** 111951.

WANG, M., LIU, Z., BAIG, M. H. A., WANG, Y., LI, Y. & CHEN, Y. J. L. U. P. 2019. Mapping sugarcane in complex landscapes by integrating multi-temporal Sentinel-2 images and machine learning algorithms. 88**,** 104190.

WESSEL, M., BRANDMEIER, M. & TIEDE, D. 2018a. Evaluation of different machine learning algorithms for scalable classification of tree types and tree species based on Sentinel-2 data. *Remote Sensing,* 10**,** 1419.

WESSEL, M., BRANDMEIER, M. & TIEDE, D. J. R. S. 2018b. Evaluation of different machine learning algorithms for scalable classification of tree types and tree species based on Sentinel-2 data. 10**,** 1419.

WU, Y. & ZHANG, X. J. F. 2019. Object-Based tree species classification using airborne hyperspectral images and LiDAR data. 11**,** 32.

XAVIER, A. C., RUDORFF, B. F., SHIMABUKURO, Y. E., BERKA, L. M. S. & MOREIRA, M. A. J. I. J. O. R. S. 2006. Multi-temporal analysis of MODIS data to classify sugarcane crop. 27**,** 755-768.

XIE, Y., SHA, Z. & YU, M. J. J. O. P. E. 2008. Remote sensing imagery in vegetation mapping: a review. 1**,** 9-23.

XUE, J. & SU, B. J. J. O. S. 2017. Significant remote sensing vegetation indices: A review of developments and applications. 2017.

YAO, X., LI, G., XIA, J., BEN, J., CAO, Q., ZHAO, L., MA, Y., ZHANG, L. & ZHU, D. J. R. S. 2019. Enabling the big earth observation data via cloud computing and DGGS: Opportunities and challenges. 12**,** 62.

ZHEN, Z., CHEN, S., YIN, T., GASTELLU-ETCHEGORRY, J.-P. J. I. J. O. P. & SENSING, R. 2023. Globally quantitative analysis of the impact of atmosphere and spectral response function on 2-band enhanced vegetation index (EVI2) over Sentinel-2 and Landsat-8. 205**,** 206-226.

Appendices

Appendix A: Pictures taken in field during the field verification exercise, showing the sugar cane growth stages. Due to the flexibility for farmers to decide when to plant, different sugarcane fields are always at different growth stages as per the discussion in section 3.1.3 (sugarcane phenology in the study area)

Germination stage

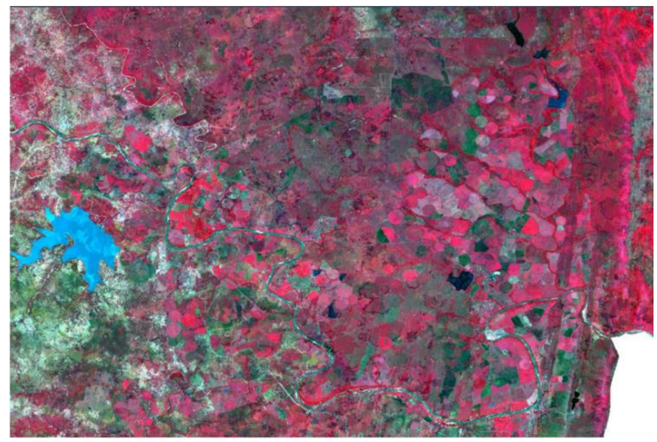
Tillering stage

Elongation stage

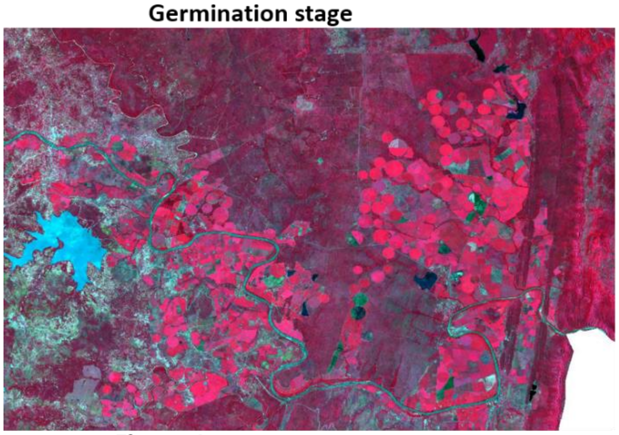
Ripening stage

Appendix B: False color images of Sentinel 2 data captured in each of the four sugarcane growth stages in the study area. The imgeries shows healthier vergetation and sugarcane crops in the last stages (elongationa and ripening) compared to the early growth stages (germination and tillering) as indicated by the near infrared band. Harvested sugarcane fields can be easily identified in these images.

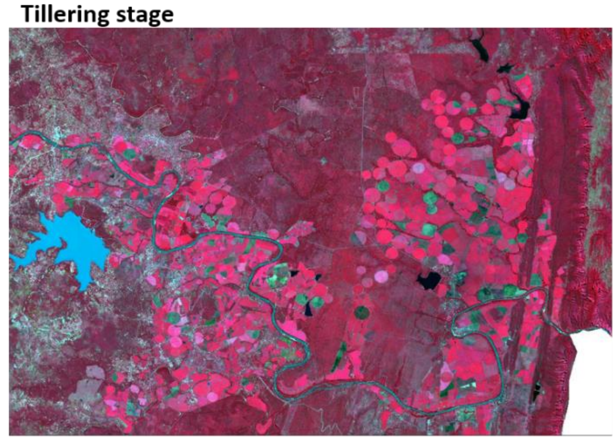
Germination stage



Tillering stage



Elongation stage



Ripening stage

Appendix C: a final feature classification map produced by the support vector machine at rippening stage of the sugarcane growth stage. a good clarification outcome was achived by this model at this later stage of the sugarcane growing timeline