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Remote Sensing for Sugarcane Crop Yield Estimation in Eswatini: Case of Lower Usuthu Smallholder Irrigation Project Sugarcane Farms

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Abstract

Early estimation of sugarcane crop yield is a key requirement for maximising profits in sugarcane production because most operations are based on these estimations. Such operations include planning for the season management of labour, transportation, storage and marketing. This study explored the potential for the use of NDVI to estimate sugarcane crop yield in LUSIP sugarcane farms at Siphofaneni, Eswatini, using Landsat 8 OLI satellite imagery for the years 2013 – 2016. Computed NDVI values were correlated with the respective sugarcane crop yield data sourced from Eswatini Water and Agricultural Development Enterprise (ESWADE), to establish the relationship between them, using regression analysis. The study concluded that the relationship between NDVI and sugarcane crop yield for the whole of LUSIP project at Siphofaneni was strongest for the month of August when considered at overall farms level (R^2 = 0.973), rather than at individual farmer company scale (R^2 = 0.134). Furthermore, it concluded that Landsat imagery was appropriate for sugarcane crop yield estimation in the country, especially in the month of August, even though at large scale than over small, individual project areas.

Keywords

Crop Yield Estimation, Landsat, NDVI, Remote Sensing, Sugarcane

1. Introduction

Crop yield estimation and monitoring have been proven to be of great importance for planning and taking various policy decisions [1-5]. Innovative tools, therefore, are needed in the field of agriculture to help in crop yield estimation and monitoring. Agricultural remote sensing application can be traced back to as early as the 1920s [6], and imagery began to be obtained by Landsat in 1978 [1, 2, 7]. Initially, aerial photography was used before the advancement in satellite imagery [8-10]. Remote sensing is an effective tool for monitoring agricultural practices [2, 3, 11, 12]. Due to a large variety of on-board sensors and an ever increasing number of civilian satellites [13], the spectral and temporal properties of the land surface resulting from human practices can be captured and monitored at different spatial and temporal scales [4, 14, 15]. Remote sensing has provided farmers with a cost effective alternative to agricultural production and monitoring [7].

In the production of sugarcane, remote sensing technology is crucial for the estimation of its yield. Duveiler *et al.* [4], Rahman and Robson [16], Mulyono and Nadirah [7], and Lofton *et al*. [11] highlight the potential of remote sensing for sugarcane crop yield estimation. Landsat imagery has been used globally for sugarcane crop yield estimation and monitoring. Examples include Abbas and Hag [17] who concluded that remote sensing technology had a potential to be used to estimate crop yield and evaluate the impact of environmental conditions to crop production as opposed to physical methods in Sudan. Also, in United States of America, Lofton *et al.* [11] demonstrated how NDVI readings can be used to estimate in-season sugarcane yield production. Mulyono and Nadirah [7] made the same conclusion for Indonesia. Similarly, in South Africa, Mutanga *et al.* [18] concluded that remote sensing plays a significant role in sugarcane management, and that the preceding two months before harvest is the optimum period for yield prediction.

Sugarcane yield prediction can be undertaken using different approaches, such as the use of a sugarcane growth model based on the Normalized Difference Vegetation Index (NDVI) [7, 12, 19, 20], one of the vegetation indices that are derived from visible and near-infrared, and the use of Green Normalized Difference Vegetation Index (GNDVI), Soil Adjusted Vegetation Index (SAVI), and Ratio Vegetative Index (RVI) [19]. NDVI is a measurement of the greenness of a given area, thus, NDVI provides an indication of the trend of intensity of any agricultural activity [20].

Vegetation indices (VIs) that have specific features concerning the range of vegetation cover have been developed. These indices indicate the amount of vegetation cover and/or intensity, as well as distinguish between vegetated and non-vegetated areas [21, 22]. The NDVI stands out among the vegetation indices and is regarded as an all-purpose index. It is simple to calculate, has the best dynamic range and the best sensitivity to changes in vegetation health and cover [1, 2, 15, 23]. Also, the NDVI can be used to provide weekly vegetation maps, monitor vegetation changes and estimate biomass [3, 13, 21].

This highlights how remote sensing has provided farmers and researchers with a cost-effective alternative to the use of primitive field-based method of agricultural monitoring [24], which according to Inman-Bamber [6], is usually time-consuming and costly. This technology gives accurate information on agricultural activities such as different crop identification and classification [1, 20], crop condition/health monitoring, crop growth, crop area and yield estimation [6, 22], mapping of soil characteristics, precision farming [25] and crop status assessment [7]. Both pixel-based and object-based image analysis (OBIA) have been found to and image a high potential for sugarcane yield estimation, predicting sugarcane crop yield with more than 88% and 90% of accuracy, respectively [3, 26, 27]. In most cases, the ability to pin down crop production problems and launch timely intervention strategies leads to higher profitability.

New remote sensing datasets at various spatial and temporal scales from satellite and airborne platforms, and significant advances in computational and data fusion technologies have now enabled unprecedented applications [28, 29]. Likewise, the liberalization of earth observation data by the United States Government [6] and the European Union (EU) through the European Space Agency programme [25, 30] have further facilitated access to large volumes of current and historical data that can be used in the estimation and monitoring of sugarcane crop yield. Furthermore, the continued development of computational technologies including open-source spatial data science tools [31] is supportive of these initiatives. Sugarcane yield estimation is critical for a number of stakeholders, among which includes, planters, growers, industrial producers and policy makers [29]. For example, industrial producers and growers might be interested in avoiding costs through the optimization of harvest campaigns, while policy makers might want to quantify outputs for national statistics, and also address food security issues [29].

However, images from satellites and airborne platforms each bear the risks of frequent poor availability, but also unsuitable survey conditions, mostly due to surface coverage by clouds [32]. Also, the spectral behaviour of sugarcane crop vary rapidly during the vegetation period, which needs several remote sensing readings during the season in order to scout the crops, or at least detailed ground truth information in order to understand the symptoms that you can find in the images [32]. Similarly, changes in the colour of plants can easily be detected by remote sensing, but remote sensing has the general problem that differences in the spectral signature of vegetation has a general shape, which is dependent on chlorophyll absorption and plant species [2, 14, 32].

On the same note, there is no general agreement on the critical spectral regions to use for agriculture and the sensor specifications for a dedicated, orbiting agricultural sensor. Although NDVI has been used for different purposes, there is poor literature on the use of remote sensing to develop a predictive model for sugarcane crop yield in Eswatini. Thus, the aim of the study was to investigate the potential use of remote sensing data for sugarcane crop yield estimation in the country, and in the process explore the appropriateness of Landsat data for sugarcane crop yield estimation in Eswatini.

2. Material and Methods

The study was undertaken in Siphofaneni, eastern part of Eswatini. It is about 50 km from the city of Manzini, and about 68 km away from capital city of Mbabane [33]. It lies between longitudes 31°32'0" E and 31°50'0" E, and latitudes 26°42'0" S and 26°52'0" S, with an altitude of about 164m above sea level, lying on the banks of one of the largest rivers in the country, the Great Usuthu River [33].

Siphofaneni falls within the warmest part of Eswatini, with average summer temperature of 32 °C, a subtropical steppe (low-latitude dry) climate, and a subtropical dry forest biozone dominated by acacia tree species [32]. The dominant crop grown in the area is sugarcane, which is irrigated over an area of about 6500 ha (Figure 1). This is as a result of the poverty alleviation initiative called Lower Usuthu Smallholder Irrigation Project (LUSIP) which assisted the establishment of 54 farmers companies in the project area, with 2 745 shareholders [34].

12 atmospherically corrected analysis ready data (ARD) Landsat 8 OLI images for between the years 2013 and 2016, covering Siphofaneni (Path 168 and Row 79), were acquired from United States Geological Survey (USGS) Earth Explorer [35]. Landsat 8 OLI is an American Earth observation satellite launched on 11^{th} February 2013. It is the eighth satellite in the

Landsat program, with a temporal resolution of 16 days, a spectral resolution of 11 bands, a spatial resolution of 30 m, and a radiometric resolution of 8 bits [36]. In addition, sugarcane crop yield statistics for LUSIP farms for the years 2013 – 2016 were sourced from Eswatini Water and Agricultural Development Enterprise (ESWADE).

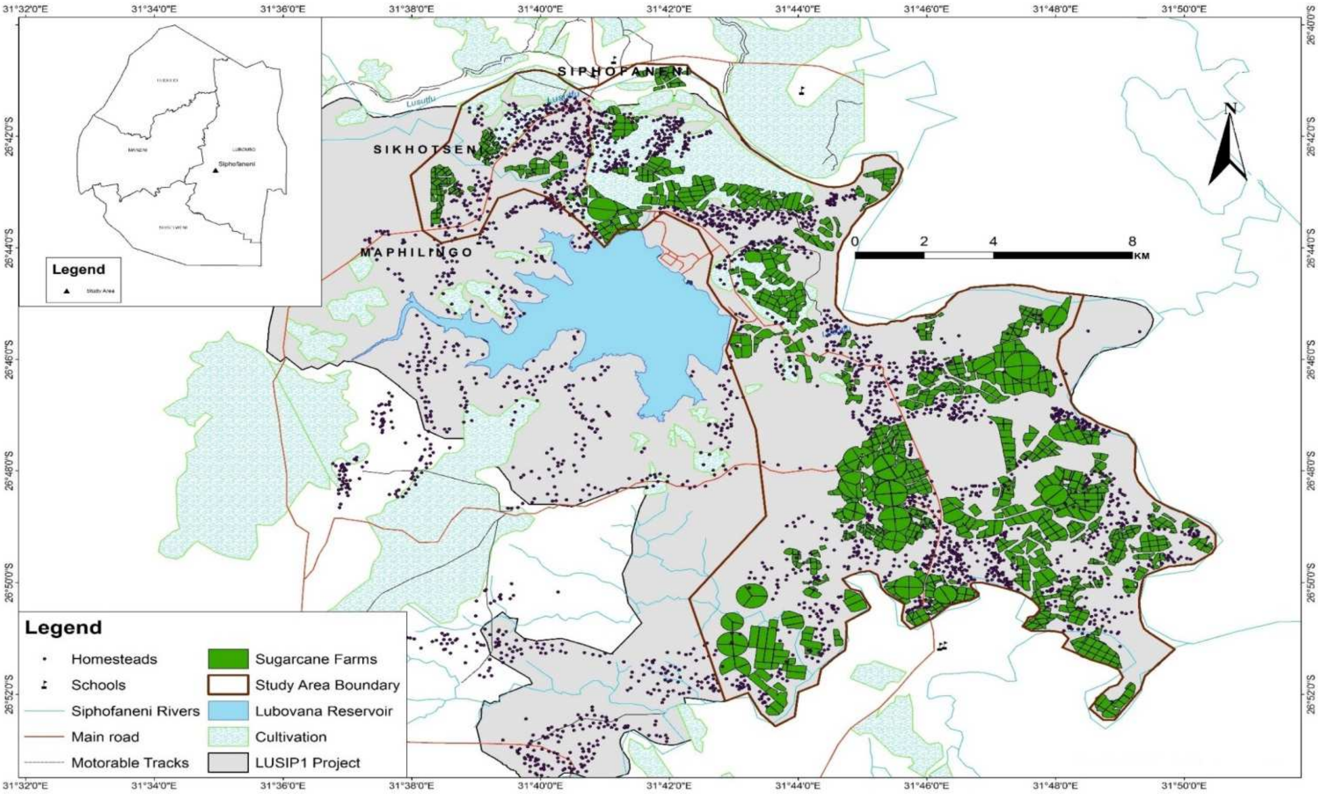


Figure 1. *LUSIP 1 project area in Siphofaneni, Eswatini.*

Figure 2. *Clipped true colour image of Siphofaneni study area.*

The time frame of the study was influenced by data availability both from ESWADE and USGS Earth Explorer. Crop yield data records were available only from the year 2011, while there was no appropriate Landsat imagery over the study area for the years 2011 and 2012. The Landsat data was first pre-processed [35, 37, 19], and then clipped to the study area (Figure 2). NDVI values were extracted using the formula: $NDVI = \left(\frac{(NIR-Red)}{(NIR+Red)}\right)$ [38], using ArcGIS 10.5.1 software. Thereafter, the 'merge' tool in ArcGIS was used to merge fields belonging to the same company. Then zonal statistics were derived, which were used to determine the average NDVI values for each farmers company.

Sugarcane crop yields and the extracted average NDVI values were then subjected to multivariate polynomials regression analysis in Microsoft Excel to produce scatter plots. This was undertaken at four levels; crop yield and NDVI values per company per month, crop yield and NDVI values per company per year, crop yield and NDVI values for the whole of the LUSIP project per month, as well as crop yield and NDVI values for the whole LUSIP project for each year under study.

3. Results

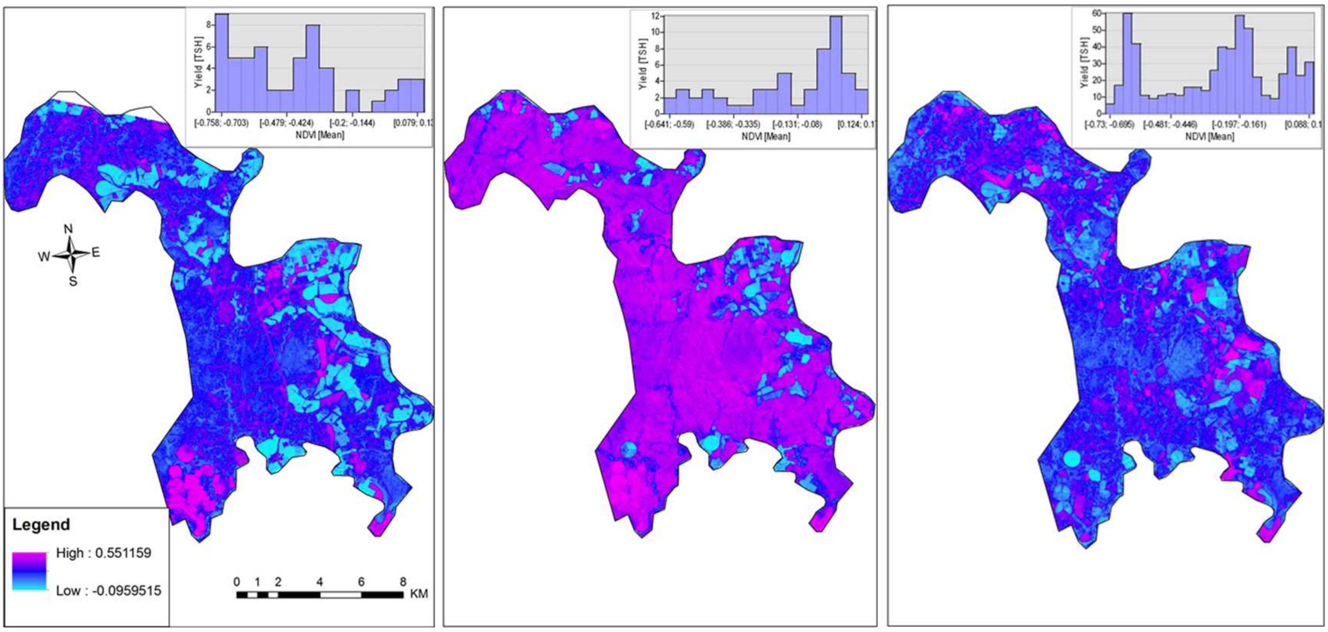
3.1. NDVI Products for LUSIP Sugarcane Farms

Figures 3, 4, 5 and 6 are the maps showing the NDVI products for the LUSIP sugarcane farms at Siphofaneni. Each product indicates the NDVI range of the sugarcane crop. For the years 2013 – 2016, the lowest NDVI value was -0.0959515 and the highest value was 0.551159.

3.2. Relationship Between NDVI and Sugarcane Crop Yield in the LUSIP Project

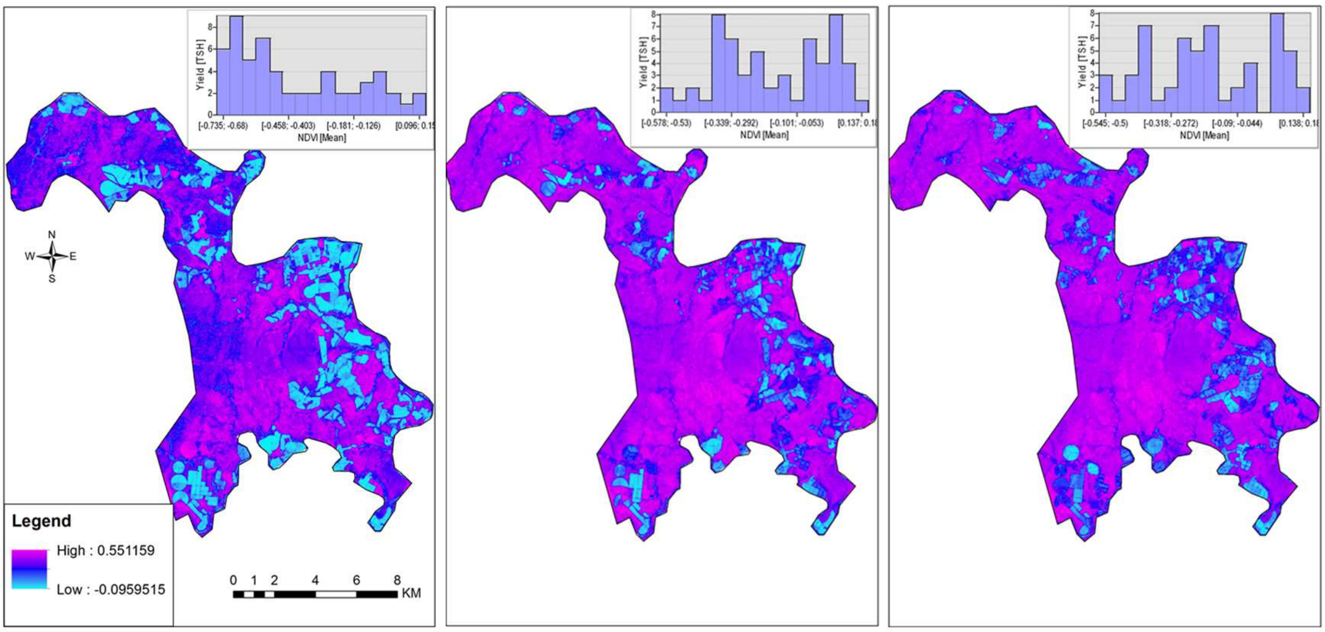
3.2.1. NDVI and Crop Yield Correlation for Each Month in Each Year per Farmers Company

When correlation was sought by each month in each of the years 2013 – 2016, for the year 2013, a correlation of $R^2 = 0$ was found for May, $R^2 = 0.134$ for August, and $R^2 = 0.108$ for November. For the year 2014, the correlation was found to be $R^2 = 0.043$ for May, $R^2 = 0.005$ for August and $R^2 = 0.013$ for October. For the year 2015, the correlation was found to be $R^2 = 0.140$ for May, $R^2 = 0.023$ for August and $R^2 = 0.025$ for November. Lastly, for the year 2016, the correlation was found to be $R^2 = 0.125$ for May, $R^2 = 0.000$ for August and $R^2 = 0.0017$ for October. Figure 7 shows example of plots of the correlation for the respective months in 2016.



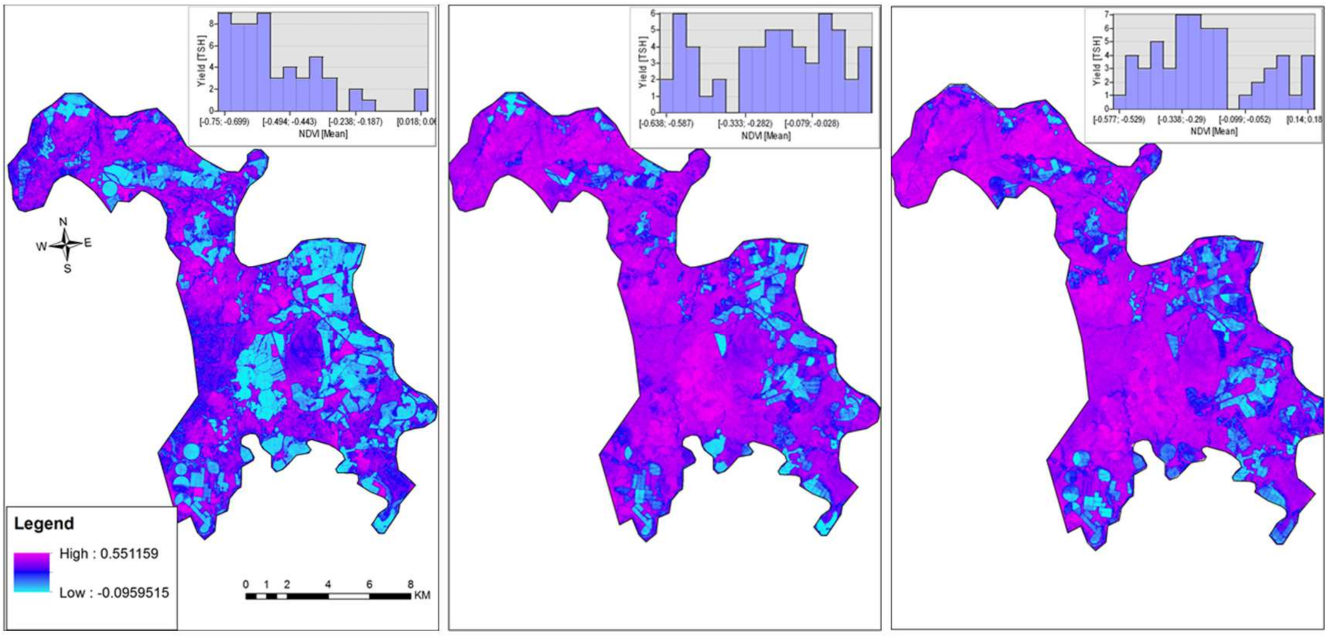
May August October

Figure 3. *NDVI maps for LUSIP project sugarcane farms for 2013.*



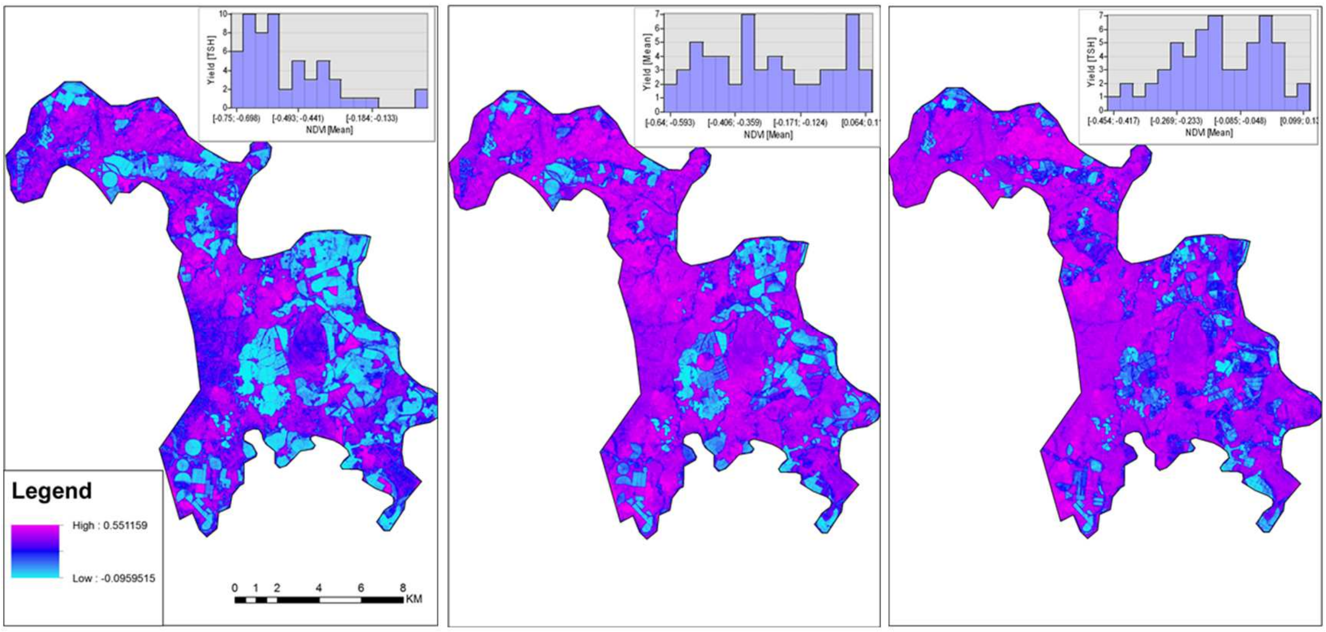
May August October

Figure 4. *NDVI maps for LUSIP project sugarcane farms for 2014.*



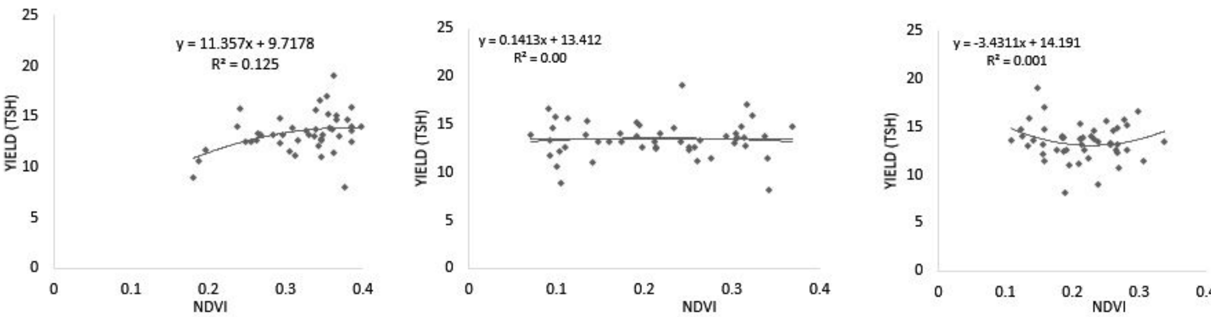
May August November

Figure 5. NDVI maps for LUSIP project sugarcane farms for 2015.



May August October

Figure 6. NDVI maps for LUSIP project sugarcane farms for 2016.



May August October

Figure 7. Correlation between NDVI and crop yield for farmer companies for 2016.

3.2.2. NDVI and Crop Yield Correlation for Each Month Across all Years of Study per Farmers' Company

NDVI and sugarcane crop yield values for the respective months for each farmer company were further averaged across the four years of study (2013 - 2016). The correlation values for May, August and November were found to be 0.039, 0.021 and 0.004, respectively. Figure 8 shows these correlations.

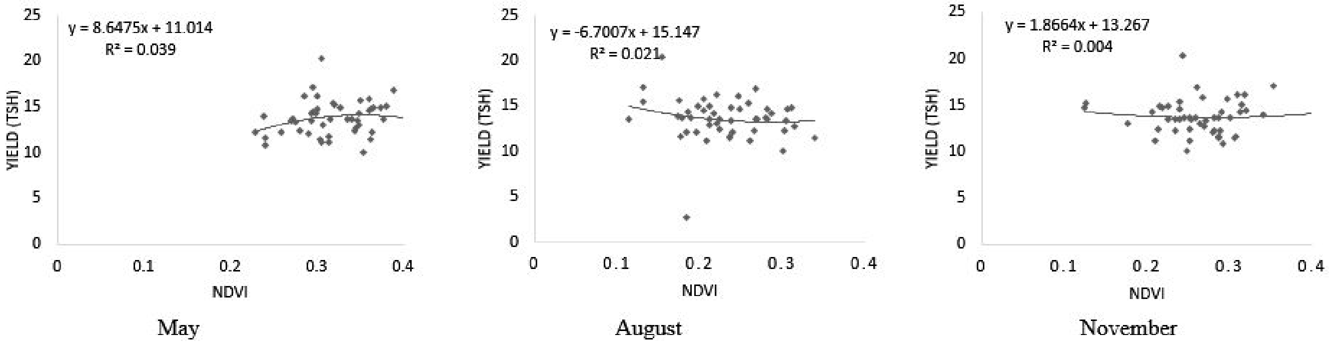


Figure 8. *Correlation between NDVI and sugarcane crop yield for farmer companies per month across four years.*

3.2.3. Average NDVI and Crop Yield Correlation for Each Month in Each Year for the Whole Project Area

NDVI and sugarcane crop yield values were also averaged for the whole of LUSIP project per year, and the correlation values for the years 2013, 2014, 2015 and 2016 were found to be 0.290, 0.970, 0.120 and 0.247 respectively, as shown in Figure 9.

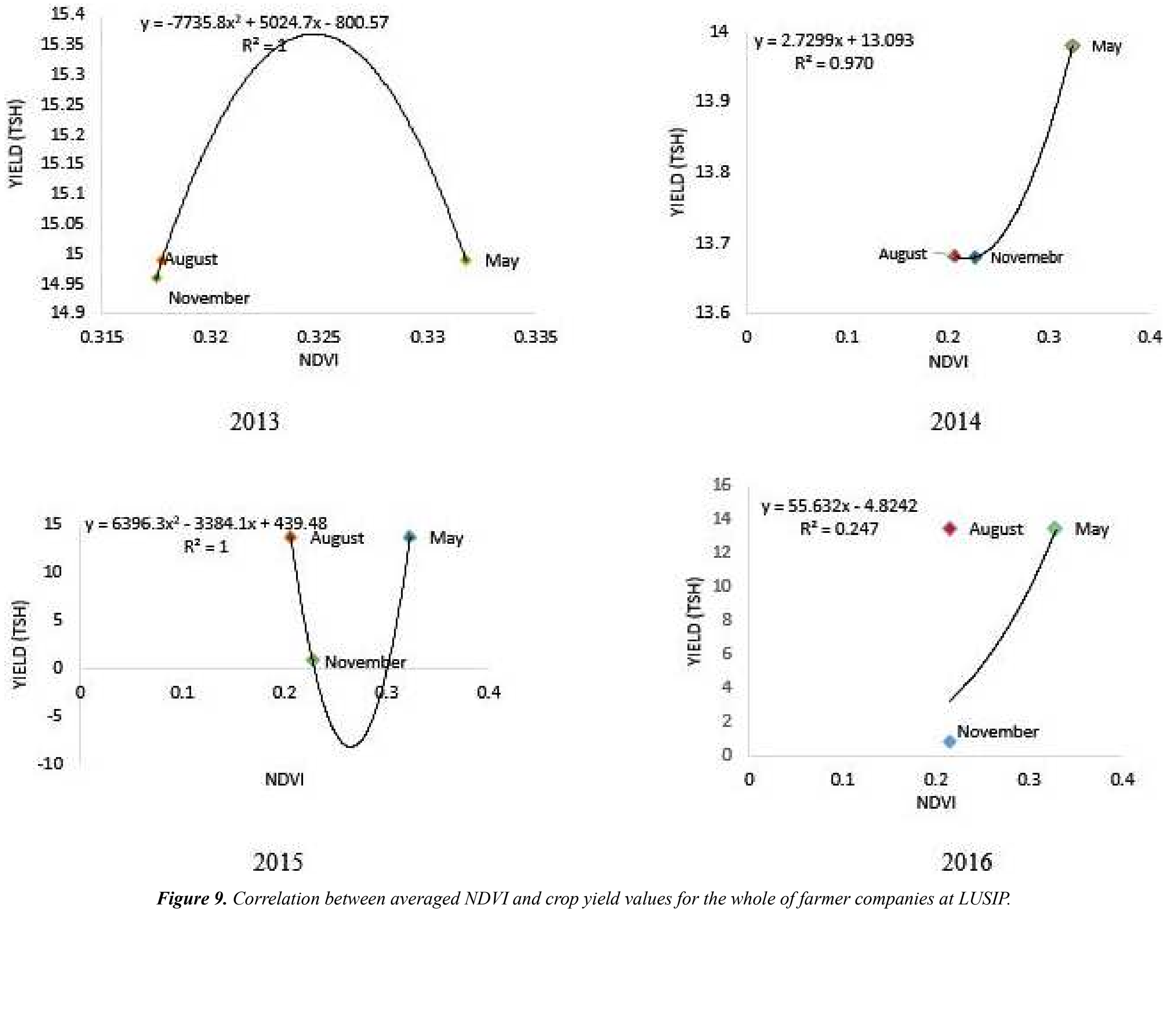


Figure 9. *Correlation between averaged NDVI and crop yield values for the whole of farmer companies at LUSIP.*

3.2.4. Average NDVI and Crop Yield Correlation for Each Month Across the Years for the Whole Project Area

Averaged NDVI and yield values correlation was established for the three respective months across the four years of study, and was found to be 0.534, 0.973 and 0.151 for the months of May, August and November respectively (Figure 10).

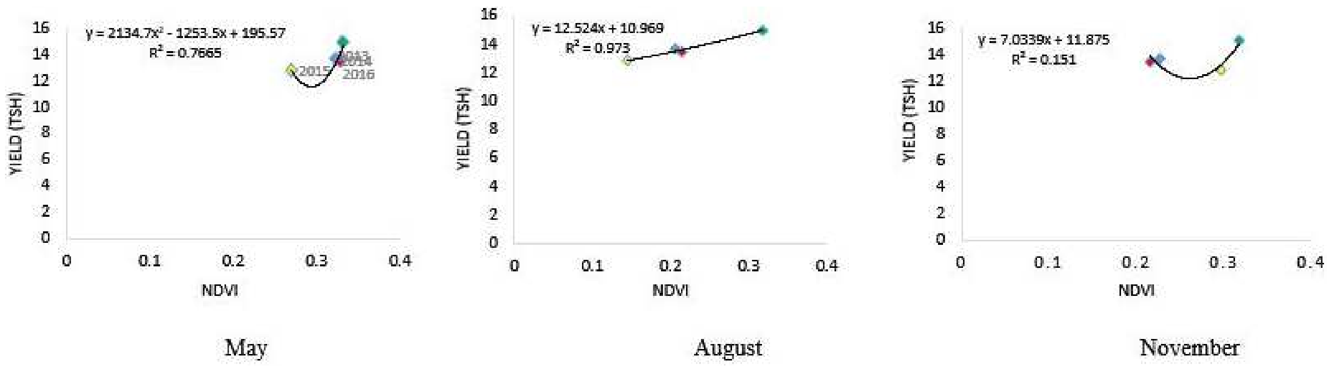


Figure 10. *Correlation between averaged NDVI and crop yield values for the whole LUSIP project across the years by month.*

4. Discussion

4.1. Relationship Between NDVI and Sugarcane Crop Yield in Eswatini

The results of the study indicated that for the three respective months across the four years of study, there were very weak correlations between actual crop yield and NDVI derived from Landsat imagery, at individual farmers' company level. When the relationship was considered at sugarcane farmers company level for each of the respective individual months, a weak correlation was found, with the highest being $R^2 = 0.140$ which was in May 2015. This concurred with other studies such as Caudill [39], who reported no relationship between NDVI and sugarcane crop yield at farm level in South Africa. Likewise, Bastidas-Obando and Carbonell-Gonzalez [40] found no relationship between average NDVI and farmers' yield in Colombia.

Moreover, Mulianga *et al*. [41] and Gunnula *et al.* [42] averaged the yield values and NDVI values for each company across the years of study, and reported a slight improvement on correlation. The same approach yielded a slight improvement in this study, even though not that significant.

Literature, such as Bastidas [40] and Jurecka and Zdenek [43], averaged the yield and NDVI values for each farmer company and concluded that the strength of the correlation increased with the scale under consideration. This was found to be the case when crop yield and NDVI values were averaged across the whole LUSIP project per month as this yielded the strongest correlation of 0.534 for May, 0.973 for August, and 0.151 for November. This was further in line with studies such as [18, 44, 45], which concluded that two months before harvest is the best period for sugarcane crop yield estimation. Dlamini [33] found that in Eswatini, maximum NDVI is reached about two months before harvest begins. Elsewhere, Begue *et al.* [14] reported the strongest correlation of 0.98 two months before harvest period as well. This is consistent with the results of the study as it was noted that the month of August produced the strongest correlation. Similarly, when the crop yield values and NDVI values across the LUSIP project area were averaged across the years, further significant improvement in the correlation was noted. The correlation ranged from 0.120 to 0.970, marking a further notable improvement in the relationship.

4.2. Appropriateness of Landsat Imagery for Sugarcane Crop Yield Estimation in Eswatini

The results showed that NDVI derived from Landsat imagery yielded the strongest correlation in the month of August compared to the months of May and November. Moreover, this correlation improved greatly when large scale areas were considered, compared to localised field level coverage. At individual farm level, the correlation was found to be very weak, and as highlighted, this was a notable conclusion for most similar studies. Therefore, this study concluded that Landsat data is appropriate for sugarcane crop yield estimation in Eswatini at a large scale instead of farm level, ideally in the month of August, a few months before the start of the major harvesting season.

5. Conclusion

Remote sensing has the potential to be used to estimate sugarcane crop yield in Eswatini. For LUSIP sugarcane farms, actual sugarcane crop yields and extracted average NDVI values were subjected to multivariate polynomials regression analysis in Microsoft Excel to produce scatter plots for the years 2013 – 2016. This was undertaken at four levels; crop yield and NDVI values per company per month, crop yield and NDVI values per company per year, crop yield and NDVI values for the whole of the LUSIP project per month, as well as crop yield and NDVI values for the whole LUSIP project for each year. The study found that there was a weak relationship between NDVI and sugarcane crop yield at field level scale, but strongly improved when considered at a larger scale (project area scale). Moreover, August imagery was found to be the best for crop yield estimation as it gave the strongest correlation compared to May and November imagery, owing to that it is a few months before harvesting, as recommended by literature. There is a need, therefore, for further research that will consider other factors affecting sugarcane crop yield, such as fertilization, irrigation, soil type and weed infestation will be crucial for the advancement of knowledge and expertise in the use of satellite imagery for sugarcane crop yield in Eswatini. Moreover, with the introduction of other freely available imagery with better resolution, such as Sentinel 2, there is further an opportunity to explore if such higher resolution imagery yield improved relationship between NDVI and the actual yield. Lastly, with passing years, there will be an accumulation of actual crop yield over years, which will avail an opportunity for more detailed analysis using time series data of this relationship for different sensors.

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