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Irrigated winter wheat yield forecast using remotely sensed vegetation indices at field level, in Matobo district of Zimbabwe

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Abstract

Crop monitoring and yield forecasting is a crucial step in addressing food security challenges. This is particularly important for cereals such as maize and wheat which are grown at large scale and constitute the main staple diet for many regions. While, consumption of bread and other wheat products has been on the increase, the national wheat production has been on the decline. Therefore, wheat yield forecasting is vital for providing advance planning on imports to meet the production deficit. This study sought to develop a winter wheat yield forecast model. Observed winter wheat yield data was collected from ARDA farm records for 3 years 2016-2018. Sentinel 2 imagery data was used to extract NDVI values coinciding with the centre-pivots where winter wheat was growing. Maximum NDVI data at anthesis growth stage and observed wheat yield data were regressed to develop a predictive equation. The two datasets were correlated (R2 = 0.8, $p < 0.001$). The developed algorithm was used to predict yields and validated using observed yield data. The root mean squared error was 0.53 tons ha^{-1} when averaged observed yield was 6.8 tons ha^{-1}. Therefore, the algorithm successfully reproduced observed yields indicating that SENTENEL data could be confidently used in winter wheat yield forecasting at field level. Lack of historical observed yield data and satellite imagery from SENTINEL 2 hindered adequate analysis for longer time frames. The model needs to be further tested as more SENTENEL data accumulates.

Keywords: NDVI, Remote sensing, SENTINEL 2**,** Wheat yield, forecasting model.

1. Introduction

Agriculture plays an important role in the supply of cereals. The potential for expansion of agricultural land, however, is limited. Increased production of biofuels, land degradation, volatile grain markets, limited arable land and water resources, and extreme weather events, such as, severe droughts and floods present global agricultural production challenges (FAO, 2017). Accordingly, increasing agricultural production efficiency is an essential way of satisfying the future food demand. As the human population is projected to reach 9 billion by 2050, cereal demand is expected to rise (Vermeulen *et al.*, 2010). The lack of access to food in the past has resulted in hunger, poverty, and conflict. As such, food security remains at the forefront on the international agenda. Consequently, crop production is increasingly demanding reliable, accurate and comprehensive agricultural intelligence. Reliable crop yield forecasts play a significant role in regulating markets and anticipating market imbalances, developing agricultural policies and mitigating food shortages efficiently.

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Reliable forecasting of crop production prior to harvest is a topical problem for many governments in the world particularly in Africa (Chahbi Bellakanji *et al.*, 2018). The governments, agribusiness, traders and farmers alike are in need of such projections. The governments need crop forecast information as a basis for its policy decisions regarding procurement, distribution, buffer storage, import and export, setting prices and marketing of agricultural commodities, while agro-based industries, trading partners and farmers need them to plan their operations properly. In order to meet these needs, most countries, including Zimbabwe issues crop forecasts under the prevalent conventional system. Current methods for estimating crop yields involve collecting field data either through administrative reporting systems or sample crop assessment surveys. The predictions are, however, of a subjective nature as they are based on agricultural officials' eye estimations and personal judgment. The estimates of final crop production based on objective crop valuations are of limited use, since they become available at a later date after harvesting (Bernardi *et al.*, 2016; Greatrex *et al*., 2009). In this regard, an objective methodology for pre-harvest crop forecasting needs to be developed. It involves the development as a forecasting technique of appropriate prediction models that have certain merits over the conventional forecasting process. Such merits include the objectivity of the forecast and its ability to measure the degree of prediction, which attributes cannot be provided by a traditional prediction method.

Data from satellite based remote sensing (RS) provides timely, cost effective, timely and objective information on crop scope, condition, growth and yield in a cost-effective way. As satellite sensor systems technologically advanced, images with higher temporal and finer spatial resolutions have become available. Classifying such multi-temporal information sets is an efficient and precise means of producing crop maps, but techniques that can manage such big and complicated information sets need to be established. In addition, a high temporal overview frequency over geographic areas is often necessary to properly use RS for agricultural production monitoring. This often, however, limits the spatial resolution. RS data is currently being used to estimate crop yields in different parts of the world (Löw & Duveiller, 2014). Vegetation indices derived from RS are considered a potential tool for enhancing simulations of real time crop yield. For example, Wang *et al.* (2017) succeeded in using the Normalised Difference Vegetation Index (NDVI) as a vegetative activity strength indicator represented indirectly by observed chlorophyll activity. Low NDVI values are associated with the absence of vegetation, inactive vegetation or vegetation stressed by drought or diseased vegetation (Páscoa *et al.*, 2018). Routine updated information on crop area and spatial distribution and expected yields are a basic requirement for agriculture surveillance.

This research will focus on winter wheat yield forecasting in Zimbabwe`s semi-arid regions. Wheat (Triticum aestivum L.) is an important crop in many parts of the world and is the second largest dietary component after maize in Zimbabwe. In addition, wheat is grown in winter in Zimbabwe under irrigation, mainly by commercial farmers. It is therefore, crucial to predict wheat yields as the production of wheat has declined due to climate variability, production costs and other environmental factors.

The estimation of crop yield remains a problem for the majority of developing countries, particularly in countries such as Zimbabwe that are primarily dependent on agriculture for food security (Immitzer *et al.*, 2012). Accurate and timely evaluation of crop yields is an essential step to ensure a sufficient supply of food. Remote sensing, on the other side, provides some possibilities for generating prompt and precise crop output information, enabling crop forecasting across space and time and under multiple agro-climatic circumstance. It offers farmers, government departments, and policy makers in general advance information to plan for either deficit surplus in production. Such predictions warn the decision makers about potential reduction in crop yields and allow timely import and export decision (Svotwa *et al.*, 2014). In Zimbabwe, such studies were carried out mostly at regional level covering large areas using low-resolution imagery, for example tobacco crop yield forecasting in Zimbabwe using high resolution MODIS imagery by Svotwa *et al.*(2014). At the Farm level, though, very little has been done. Therefore, this research attempts to assess the wheat growth using NDVI trends, develop an NDVI wheat yield forecast model and evaluate the developed wheat yield model for ARDA Antelope farm in Matobo district in Zimbabwe using high resolution SENTINEL imagery.

2. Methods and Materials

2.1 Study area description

2.1.1 Geographic location and climate of Matobo and Mat South Province

This study was conducted in Matobo district in Matebeleland South Province of Zimbabwe. The Matobo district receive rainfall ranging from 450 mm to 650 mm per annum(Love *et al.*, 2005). The period of precipitation extends from October to April. The soils in Matobo district can be split into three types: slightly deep, coarse grained kaolinitic sands obtained from granites and Limpopo gneisses, very deep to slightly deep clays and loams created from greenstone belts and very deep basalt sands(Love *et al.*, 2005). These soils have low fertility. The study was located at the ARDA Antelope Farm, (28.4960 N and -21.070 W) (Figure 1). The study farm plots were all under centre pivot irrigation. Red clay soils are the predominant soil type at ARDA antelope. However, some areas of the farm have sandy loam soils, mainly on the on the eastern side of the farm. Currently four pivots sit on the sandy loam soils (Centre pivot 14-17 in figure 3). The remaining 12 are sitting on red clay soils.

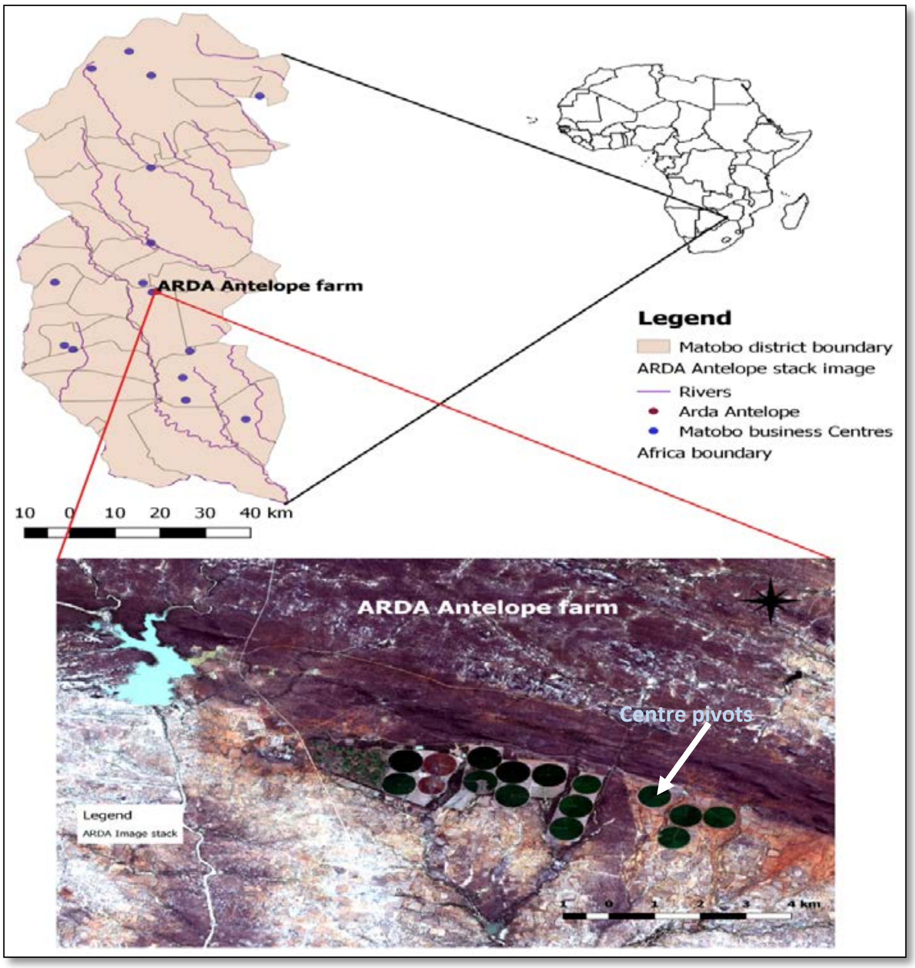

Figure 1: Study Area

Agricultural and Rural Development Authority (ARDA) is a government of Zimbabwe parastal with a main mandate to ensure food security in Zimbabwe. ARDA is therefore authorized to promote its mandate, which is concentrated on achieving economic growth and development driven by agriculture. ARDA Antelope is one of 21 ARDA estates across Zimbabwe. The Estates commercial operations involve production of various crops and livestock. Currently the ARDA Antelope is under a Public–Private Partnership (PPP) Arrangement, since 2014.

2.1.2 Area and Irrigation systems

ARDA antelope has a gross area of about 3000 ha. At present, about 700 ha of land is under irrigation by the Estate and approximately 850 ha is being utilised under the out-grower system. Plans are in place to expand the area under irrigation to a total of 1000 ha. Initially the Estate was making use of flood system on about 150 ha and later changed to sprinkler irrigation system. At present the irrigation system has been changed to centre pivots since the year 2015. The process of Centre pivots installation was done in phases with the first 12 centre pivots functioning since 2016. As shown in figure 2, only 12 pivots have been utilised for winter wheat production in 2016 and 2017. In 2018, 14 centre pivots were utilised for wheat production as shown in figure 2. A total of 16 centre pivots have been set up to date and are all being utilised. The pivots, however vary in sizes from a minimum 30 ha to about 45 ha pivot area.

2.1.3 Cropping programme

In terms of the cropping programme, the Estate produces both in summer and winter under irrigation. In summer Irrigation provides supplementary water in dry spells. Maize is the main summer crop. Soya bean is also produced a secondary summer crop. While in winter wheat is the main crop grown. All cropping is done on commercial basis, with clear guideline on crop management. The planting period for winter wheat is generally from the third week of April to mid-May. Harvesting of winter wheat commences around second to third week of September. Seed select wheat variety was grown on the centre pivot for the study years. Fertiliser, and crop protection was done uniformly for all the centre pivots. For example, rate of fertiliser (both compound D and urea) per unit ha was applied uniformly for all the centre pivots.

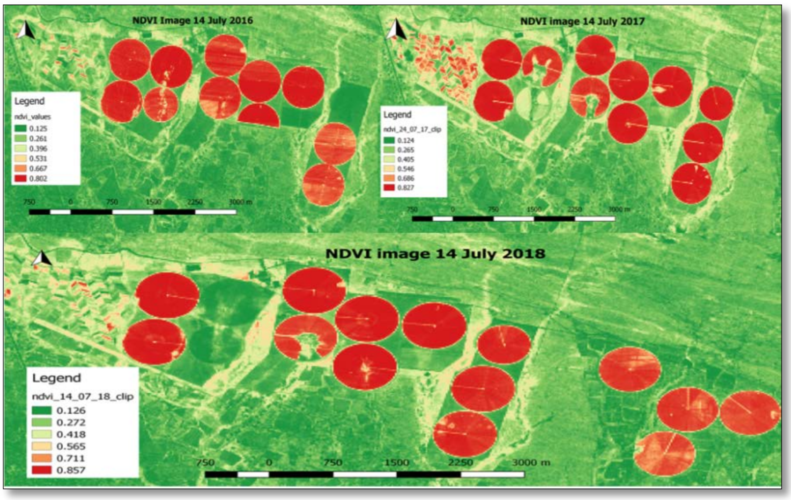

Figure 2: NDVI image for specific dates in July 2016, 2017 and 2018 showing number of Centre pivots utilised for winter wheat production

2.2 Data collection and analysis

2.2.1 Wheat yield data

Seasonal wheat yield data for 3 seasons (2016–2018) were used for this study. The data was only limited to 2016-20018 seasons because SENTINEL satellite images are only available since 2016. The data were obtained from ARDA antelope Farm records. The Farm has 16 centre pivots were wheat production has been practiced. The centre pivots vary in sizes ranging from 35-45 ha. Each centre pivot was taken as a separate study plot for this study. Therefore, the unit of analysis is the centre pivot. For model, development, and model validation the study utilized only 12 centre pivots which were consistently planted for the three seasons. Yield data from two seasons 2016 and 2018 was used for model development whilst yield data for 2017 was used for model testing and validation. The study limitation was the availability of satellite SENTINEL imagery data, which is only available from May 2016.Furthermore the farm has winter wheat records for the same study period only.

2.2.2 Remote sensing dataset

The study used Sentinel-2A satellite images. The available Sentinel-2A Level-1C (TOA) products were examined for cloud coverage in the study area. Only cloud-free images were obtained from earth explorer USGS website (https://earthexplorer.usgs.gov/). Overall, 32 cloud free Sentinel-2A scenes of tile T35KPS (Table 1) were acquired over the study area from May to September for 2016 to 2018, a period which coincides with winter wheat cropping season in Zimbabwe.

Table 1: Available cloud-free Sentinel-2 data for the study area in 2016, 2017 and 2018

Year	**Time steps**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**13**	**14**	**15**	**16**	**17**
2016	Date	Jul 19	Jul 29	Aug 08	Aug 18	Aug 28	Sep 07	Sep 27									
2017	Date	May 15	Jun 4	Jun 14	Jul 24	Aug 13	Aug 23	Sep 12	Sep 22								
2018	Date	May 25	Jun 4	Jun 9	Jun 14	Jun 19	Jun 24	Jun 29	Jul 14	Jul 29	Aug 3	Aug 8	Aug 13	Aug 23	Sep 2	Sep 22	Sep 29

NDVI computation

NDVI value can represent the level of yield for each pixel. A regression function of NDVI can therefore explain the yield. Total yield is a product of the model prediction per unit area and the total area. Some literature reviews indicate three kinds of NDVI factors that can be used in yield forecasting: maximum NDVI, average NDVI, and cumulative NDVI (*Study On The Crop Condition Monitoring Methods With Remote Sensing, The International Archives of the Photogrammetry, Remote Sensing And Spatial Information Sciences*, 2008). The cumulative NDVI and a corresponding average NDVI for the same period are correlated because the linear nature of operations. For this study the average NDVIs and the maximum NDVIs were utilized as input data for the winter wheat forecasting model.

A study by Meng and Wu, (2008) showed that maximum NDVI variables are highly correlated to the final yields. In contrast, changes in NDVI values outside the period of wheat production perhaps do not have a positive effect on the yield (Prasad *et al.*, 2006). Wheat yield is mainly determined during the stage of the anthesis (i.e. the highest phonological development phase). Therefore, wheat condition during anthesis phase plays a critical part in determining the yield levels. Wheat anthesis stage occurs around mid-July and early August. At this point, the link between yield and reflectance is powerful. Therefore, NDVIs are a good indicator of wheat yield in the medium- to-late growth period. In view of this background, this study utilized the maximum NDVI for developing the wheat yield forecasting model. While both average NDVI and maximum NDVI were used on tracking the wheat growth.

NDVI was calculated for Sentinel-2A scenes using band 8A (NIR) and band 4 (Red). For each downloaded SENTINEL image, the NDVI formula was as follows:

$$NDVI = (NIR - RED)/(NIR + RED) \tag{1}$$

Where: **NIR** = reflectance in the Near Infrared band
RED = reflectance in the Red band.

NDVI is used extensively to predict plant greenness correctly, i.e. the overall chlorophyll content on crops.

2.2.3 Model development

Linear regression model was developed for the 12 center pivots between the wheat observed yield and the maximum NDVI. The observed yield was taken to be an independent variable and the maximum NDVI was taken to be a dependent variable according to:

$$Yp = a * NDVI + b \qquad (2)$$

Where:
Yp is the predicted yield;
a is the coefficient
and **b** is the constant for winter wheat yield.

The maximum NDVI during the wheat-growth period (NDVImax) for each centre pivot was extracted from the ARDA farm remotely sensed images for the 2016 and 2018 seasons using raster and zonal statistics in a GIS environment. The extracted maximum NDVI was used in developing the model. In order to extract maximum NDVI field sample were digitised for each centre to avoid field edge and ensure data was collected from inside the pivot area. The maximum NDVI is equal to the peak value of the seasonal NDVI profile. Figure 3 shows digitised sample plots for extracting NDVI values. In order to evaluate the models in such a way that the best fitting model was chosen, different models were compared (logarithmic, and exponential). The linear model was found to be optimal for winter wheat yields and NDVI from research carried out in other areas (Huete *et al.*, 2011) , therefore a linear model was chosen for this study.

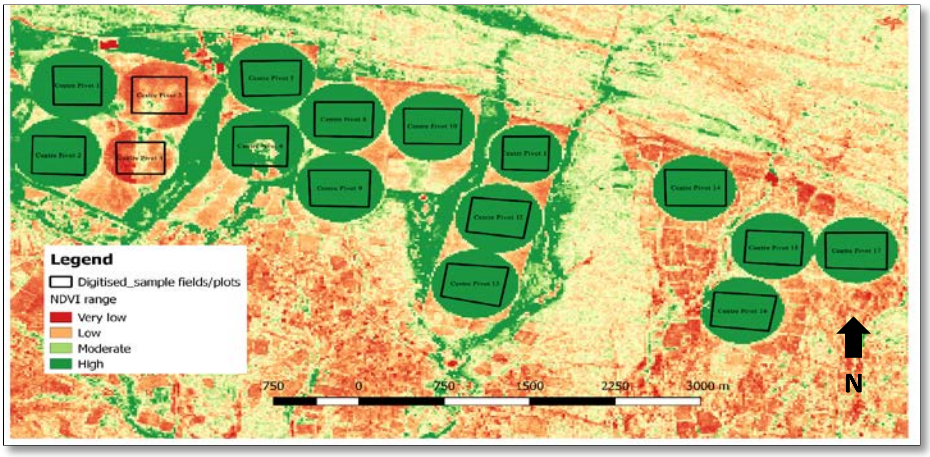

Figure 3: Digitised sample fields for extracting NDVI data

2.2.4 Model evaluation metrics

In order to validate the model efficiency, statistical tests were conducted on 2017 data. The 2017 yield and imagery dataset were not used for model development. The goodness of the model's fitness and the proportion of variance were explained using the coefficient determination. P-values were used to assess the significance of the model. In addition, using the root mean squared error (RMSE), the model was also evaluated for accuracy. Diagnostic plots were used to compare observed yield and predicted output. Furthermore, a quantile-quantile (Q-Q) plot was also used to assess the closeness of the theoretical distributions to the model structure. A strong linear pattern is indicative of a normal distribution of the dataset while outliers can be visually detected. The validation methods also helped to comprehend the fundamental patterns in the data.

2.2.5 Model testing

The observed yield data for 2017 was not used for model development and validation. Therefore, NDVI dataset for the year 2017 was used for model testing on 12 centre pivot plots. The developed model was used to predict the wheat yield for 2017 season. The difference between the forecasted and observed yields was used to calculate the percentage bias for each pivot and the overall error. The percentage bias was used to evaluate of the accuracy of the 2017 forecasted yields. Values less 10 percent bias were taken to indicate good model performance with values close to zero indicating high levels of accuracy. Furthermore, a t- test statistic was also carried out to test the developed wheat forecasting model. This was done to validate and triangulate the results from the percent bias test

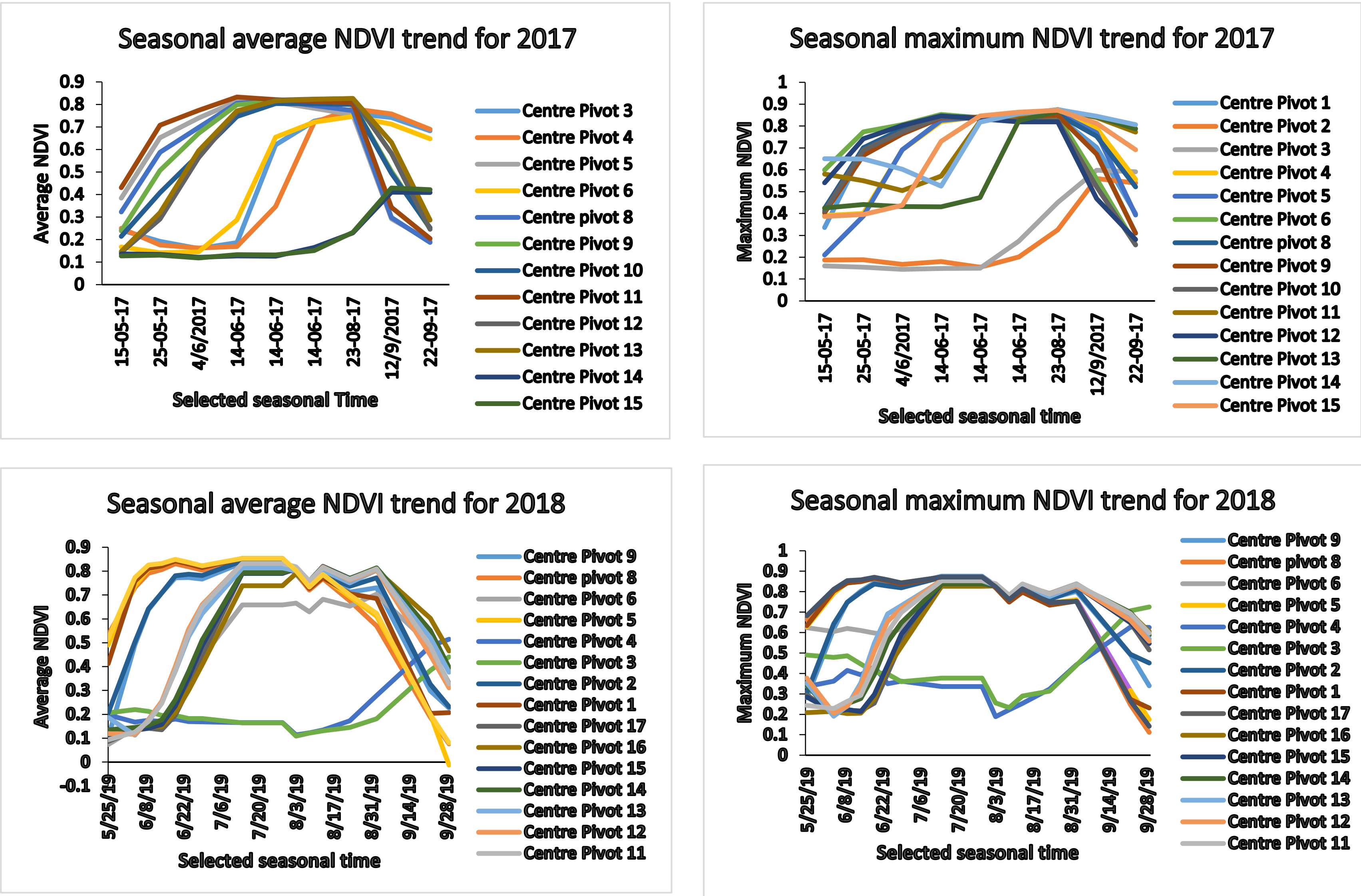

Figure 4: Seasonal average and maximum NDVI trend line for 2017 and 2018

3. Results and Discussion

2.3 NDVI variations across growth stages

The NDVI obtained from the SENTINEL image data showed differences in distribution and size between the different center pivot sample plots (Figure 4). Times-series of maximum and average NDVI values for the different centre pivots for 2017 and 2018 are shown in Figure 4. Each centre pivot had a different NDVI profile for the selected dates in 2017 and 2018. The NDVI values ranged between 0.30 and 0.89. The NDVI values consistently increased with crop growth stages in early season and it reached a maximum by mid-season. The results indicate that NDVI values accurately characterized the generalized wheat crop growth curve. This phenomenon was similar to observations made by Prasad *et al.* (2006) on vegetation with lower amount of green biomass due to either water stress or to normal senescence through the mid-grain filling stage. The mean NDVI value was 0.35 for both 2017 and 2018 seasons in early May. This is because at this growth stage early jointing will be taking place.

With crop growth, the NDVI values progressively increased to a plateau between joining and anthesis growth stages by mid-season. The maximum NDVI values were around 0.89 at mid-season with an average value of 0.87. The NDVI values decreased end of the season which the mid-grain filling stages for winter wheat. This is attributed to leaf senescence and change in colour from green to grey leaves. This results in an increase reflectance of the red band and reduction in reflectance of NIR band. The mean NDVI values in late season were 0.58 under irrigated conditions for all pivots and both 2017 and 2018.

Wheat was not grown on area under centre pivot 2 and 3, therefore the NDVI profiles were generally on the lower side (ranging from 0.2 to 0.5) for 2018 season. The maximum NVI for 2018 season is between the 14th and 29th of July 2018.

2.4 Relationship between wheat yield and NDVI data

The most critical stage in irrigated wheat growth is the anthesis (flowering) according to studies carried out in other regions (Mashaba *et al.*, 2017;Lopresti, Di Bella and Degioanni, 2015). Therefore, this research adopted the anthesis wheat growth stage for model development. The linear relationship between the average yield and average NDVI is represented by equation: **Yield =70.8NDVI$_{max}$ -54.643** (figure 5).

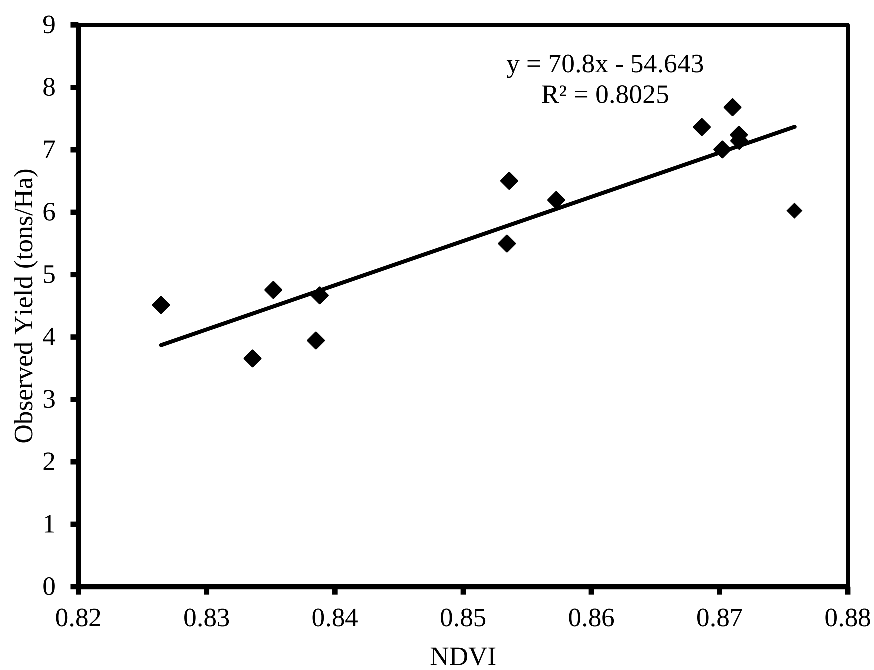

Figure 5: Yield versus maximum NDVI at anthesis stage (end of July 2017)

The ranges of values for the model were 0.8–0.89 during anthesis and mid-grain filling stages. However, other variables such as temperature, moisture content, and soil condition can also be considered in order to improve model accuracy because of lack of consistent data for these variables. A positive correlation (r^2 of 0.80) was noted between maximum NDVI and wheat yield at anthesis stage. These results are consistent to findings by Marti *et al.* (2007) and Royo *et al.* (2003) which have also shown a positive correlation between NDVI and wheat yield at anthesis and mid-grain filling stage. These values fall within the range for winter wheat of 0.2–0.8 indicated by (Sabaghnia et al., 2012).

2.5 Model validation and testing

The model was validated on the basis of the relation between observed and forecasted yield values (Figure 6). The developed model was used to predict the 2017 wheat yields. The observed and model predicted yield for 2017 were compared. The model root mean square error of 0.53 tons/ha was obtained from the comparison. The calculated p and r^2 values were 0.000015 ($p<0.001$) and 0.80 respectively, suggesting a positive relationship between wheat yield and NDVI. These findings are comparable to those recorded in Northern Buenos Aires Province, Argentina by Lopresti, Di Bella and Degioanni, (2015) and at Central Free Sate by Mashaba *et al.*, (2017), who obtained an r^2 value of 0.75 for winter wheat yield. The similarity could be due to the fact that both areas have comparable seasonal cycles and winter production periods. These circumstances are similar to those at ARDA Antelope farm. A random distribution of the residuals was observed, which implies that the linear model corresponds perfectly with wheat yields to NDVI (Figure 6).

In general, the residuals are distributed normally and lie in close proximity to a straight line

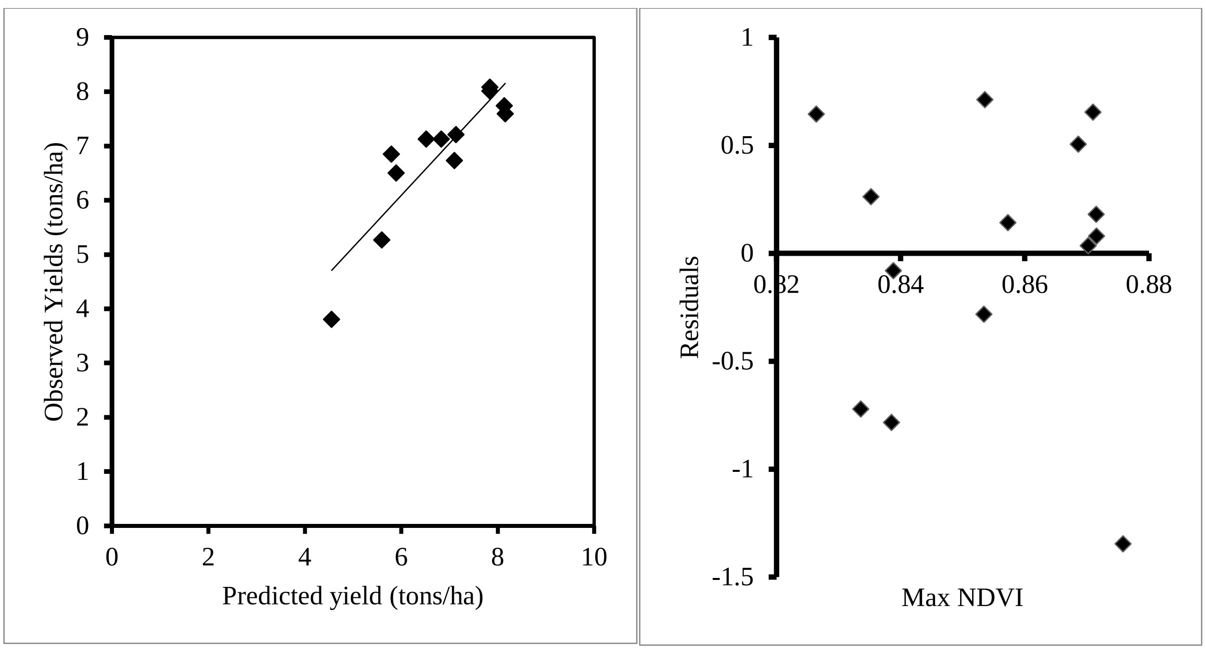

Figure 6: Observed wheat yield as a function of predicted yields and Residual plot of the wheat yield model

The model was also tested using percentage bias between observed and predicted yield (Table 2). The model overestimated yield in centre pivot 10 and understated yield in centre pivot 4 because the percentage bias values are greater 10% as shown in table 2 However, in all other center pivots, the model performed well since the percentage bias are within a ±10% limit.

Table 2: Percentage bias for predicted and observed yield for 2017 season

Zone ID	Max NDVI	Observed wheat yield (tons/ha)	Predicted wheat yield (tons/ha)	Difference in observed and predicted (tons/ha)	% Bias
Centre Pivot 1	0.89	7.60	8.15	-0.56	-7.35
Centre Pivot 2	0.87	6.73	7.10	-0.37	-5.48
Centre Pivot 3	0.85	5.27	5.60	-0.32	-6.16
Centre Pivot 4	0.84	3.81	4.56	-0.75	-19.74
Centre Pivot 5	0.89	7.74	8.13	-0.39	-5.09
Centre Pivot 6	0.86	6.50	5.89	0.61	9.32
Centre pivot 8	0.88	8.01	7.84	0.18	2.19
Centre Pivot 9	0.87	7.21	7.13	0.08	1.07
Centre Pivot 10	0.85	6.85	5.79	1.06	15.41
Centre Pivot 11	0.88	8.08	7.84	0.25	3.05
Centre Pivot 12	0.87	7.13	6.83	0.30	4.25
Centre Pivot 13	0.86	7.12	6.52	0.61	8.55

A non-parametric t- test was carried out to further validate the model predicted yield data (Table 3). An assumption that the sample data had equal variances was made. The null hypothesis (H_o) was that there was no significant mean difference between predicted and observed yield data. The alternative hypothesis was that the means of the two data sets were significantly different. At 5% level of significance (p – value = 0.908), it was found that there was no significant difference between the two means, thus there is no significant difference between observed and predicted yield data.

Table 3:t test statistics to validate the yield prediction model

T-test: two-sample assuming equal variances

	Observed Yields	***Predicted yield***
Mean	6.837582621	6.781329984
Variance	1.491057724	1.305164459
Observations	12	12
Hypothesized Mean Difference	0	
P(T<=t) two-tail	0.908287653	
t Critical two-tail	2.073873068	

4. Conclusion and Recommendations

In this study, 3 conclusions can be drawn:

i. NDVI can be used as a robust proxy/ indicator variation across wheat growth stages.
ii. The model was found to be reasonably accurate and reliable as indicated by no significant difference between means of both predicted and observed yields and a root mean square error of 0.53 tons/ha when averaged observed yield was 6.8 tons/ha.
iii. The paper shows that there is potential to apply remotely sensed wheat forecasting models at local scale for wheat yield prediction.

The study recommends more research and broader testing with more yield datasets for at least five years is necessary as more SENTENEL data accumulates.

5. Acknowledgements

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