#7681 PREDICTING IN-SEASON SORGHUM YIELD POTENTIAL USING REMOTE SENSING APPROACH: A CASE STUDY OF KANO IN SUDAN SAVANNAH AGRO- ECOLOGICAL ZONE, NIGERIA

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ABSTRACT

Estimating crop yield prior to harvest using remote sensing techniques has proven to be successful. However, accuracy of estimation still varies across crops and landscapes. This study was conducted to examine the applicability of Sentinel-2B for estimating sorghum yield during the 2018 rainy season in three locations (Bebeji, Dawakin Kudu and Rano) within the Sudan Savannah agro-ecological zone of Nigeria. SAMSORG 45 (an early maturing improved sorghum variety) was established in five (5) randomly selected farmer plots in each of the three LGAs. The relationship among different vegetation indices, Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Ratio Vegetation Index (RVI) and grain yield were determined using linear regression analysis. Models at different growth stages were then compared using root mean square error (RMSE), coefficient of variations (CV) and coefficient of determination (R^2) respectively. The results from the statistical analysis showed that NDVI was superior to GNDVI and RVI for grain yield estimation, indicating low RMSE, high R^2 and low CV values at early vegetative (40 days after sowing, DAS), reproductive stage, and entire crop-life cycle. The estimate at 40DAS, reproductive stage, and entire crop-life cycle showed RMSE of 0.04, 0.03, 0.02, R^2 (0.75, 0.77 0.93), CV (13.7%, 27.3%, 39.2%) respectively. In addition, RVI had the best fit for stalk yield estimates, having RMSE (0.06, 0.04, 0.01), R^2 (0.5, 0.83, 0.98) and CV (15.7%, 19.9% 38.5%) at 70DAS, reproductive stage, and entire crop-life cycle respectively. This study therefore concludes that sorghum yield could be accurately predicted in-season with NDVI and RVI for grain and stalk yields using Sentinel-2B.

Keywords: Sorghum, Normalized Difference Vegetation Index (NDVI), green Normalized Difference Vegetation Index (GNDVI), Ratio Vegetation Index (RVI), in-season yield estimate, Sudan Savanna

INTRODUCTION

Sorghum [*Sorghum bicolor (L.) Moench*] is the most important cereal in the Guinea (800–1100 mm rainfall) to Sudan savanna (600–800 mm) zones of West Africa (Akinseye *et al.* 2020) and in the drier Sahel (300-600mm) environments. Its productivity has an important influence on food security, contributing directly to household food availability and as well as influencing incomes due to its industrial demand (Ajeigbe *et al.* 2017). The recent advances in sensors technology and availability of free high-resolution (spatial and temporal) multispectral satellite images afford an opportunity to predict crop yields as well as mapping the spatial distribution in near real-time (Chivasa *et al.* 2017). In particular, crop yield estimation may play a fundamental role in supporting policy formulation and decision-making in agriculture (e.g. management of food shortage) especially in the Savanna region of West Africa that is characterized by high climate variability and food price volatility. Among the possible approaches that may be adopted for yield estimation at large spatial scales include the integration of crop simulation model (Akinseye *et al.* 2020) and satellite data that seems to be one of the most appropriate quantitative analysis methodologies (Moriondo *et al.* 2007). Yield estimation plays an important role in stabilizing prices and can have a direct influence in marketing and logistical issues and determination of pricing policies of food (Lobell *et al.* 2003).

In Nigeria, crop surveys, seed purchase records, land area under cultivation, field visits from extension officers, visual assessment of the crop, etc., are mostly used in estimating yield. These methods are either costly, time consuming, not accurately representing the overall production picture or prone to large errors due to incomplete ground observations, leading to poor crop yield estimation and often not available in good time for early warning purposes. As such, there is the need to develop faster models for early crop yield estimation that can contribute to minimizing yield gap (Printer *et al.* 2003). Satellite data has a wide range of applications in the field of agriculture, which include yield estimation (Claverie *et al*. 2012). In this study, we examine the suitability and applicability of Sentinel-2B for estimating sorghum yield using vegetation indices such as Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI) and Ratio Vegetation Index (RVI).

MATERIALS AND METHODS

The study was carried out during the 2018 cropping season in three selected sites within the Sudan Savanna ecological zone of Nigeria: Bebeji (11.537°N 8.31°E), Dawakin Kudu (11.797°N 8.706°E) and Rano (11.485°N 8.514°E) Local Government Areas of Kano State.. The long-term daily rainfall (1981–2016) for all sites was obtained to establish comparison with the cropping year (2018). The record showed that 2018 total rainfall from May- October (852mm at Bebeji, 757 mm at Dawakin-kudu and 748 mm at Bunkure) was higher in Bebeji and a little below for Dawakin- kudu and Bunkure compared to seasonal (1980 -2015) average of 784 mm for Kano as the reference site. The analysis of monthly rainfall of both stations indicate a distinct mono-modal pattern with the peak amount in August and varied between May and October. Over 50% of the total rainfall was received in the month of July and August, while both minimum and maximum temperatures decrease uniformly throughout the growing season. Furthermore, the Sentinel-2B, level-1C time series images for the year 2018 were sourced and downloaded from Copernicus Open Access Hub (COAH) using the link (https://scihub.copernicus.eu/dhus/#/home). The images used were captured between 25 May and 11 November, 2018 at 10-day interval. The variety of Sorghum used was SAMSORG 45, which is an improved early maturing variety that reaches 50% flowering in 67 days after sowing (DAS) and has a yield potential of 2.4 to 2.8 tons ha^{-1}. Sen2Cor version 2.4 processor was used to generate Level 2A (Bottom-of-atmosphere), while Sentinel application platform SNAP version 5.0 was used to obtain NDVI, GNDVI and RVI values derived for the sorghum plants. The vegetation indices tested were calculated using the formulae presented in Table 1.

Table 1. Vegetation Indices (VIs), their mathematical formulae, the scale of development and parameters estimated (Cammarano *et al.* 2011).

Index	Formula	Scale	Parameter
NDVI (Normalized Difference Vegetation Index)	(NIR-Red)/(NIR+Red)	Canopy	Biomass; Vegetation Fraction
GNDVI (Green Normalized Difference Vegetation Index)	(NIR-Green)/(NIR+Green)	Canopy	Chlorophyll; Vegetation Fraction
RVI (Ratio Vegetation Index)	NIR/Red	Leaf	Biomass

In-season estimated yield (INSEY) was determined using the equation described by Teal *et al.* (2006):

$$INSEY= VI / CGDD$$

where VI is the vegetation index and CGDD is the cumulative growing degree days from the beginning of the season to the day of sensing.
Growing degree days (GDD) were calculated using the equation:

$$GDD = (T_{max} + T_{min}) / 2) - T_b$$

where T_{max} - maximum daily temperature, T_{min} - minimum daily temperature and T_b -base temperature.

In addition, regression analysis was used in determining the relationship between VIs as independent variables and final grain yield as a dependent variable. Finally, coefficient of determination (R^2), adjusted R^2, root mean square error (RMSE) and the variability of the vegetation index measurements expressed as coefficient of variation (CV) in percentage (%) were used as the criteria in selecting the best fit model.

RESULTS AND DISCUSSION

Table 2 shows the multiple regression analysis for the entire crop cycle using INSEY values generated for both grain and stalk yield. The estimates of VIs (NDVI, GNDVI and RVI) for grain and stalk yield varied due to the parameters the VIs measures on the crop. Among the three VIs for grain yield, NDVI indicates the lowest RMSE of 0.019, highest R^2 value of 0.93 and strong R value of 0.96, and CV estimate was 39.2% respectively. Meanwhile for stalk yield, the INSEY estimated revealed that RVI had the lowest RMSE (0.011), highest R^2 value of 0.98 and CV value of 38.5%. The analysis for the entire crop cycle showed that NDVI had the best model fit for grain yield with 93% coefficient of determination, while RVI was found to have the best model fit for stalk yield, estimated 98% accuracy.

Table 2. Multiple regression models for estimating sorghum grain and stalk yields for the entire crop's life cycle.

Yield	VI	CV	RMSE	R^2	Multiple R
	NDVI	39.23	0.019	0.93	0.96
Grain Yield	GNDVI	51.59	0.024	0.89	0.94
	RVI	38.49	0.026	0.87	0.93
	NDVI	39.23	0.025	0.92	0.96
Stalk Yield	GNDVI	51.59	0.034	0.84	0.92
	RVI	38.49	0.011	0.98	0.99

VI= Vegetation Index, CV= coefficient of variation (%), RMSE= Root Mean Square Error and R^2= Coefficient of determination

The results agreed with similar findings reported by Morel *et al.* (2014) that found NDVI has most appropriate estimative measure to crop productivity during entire growing season for wheat crop.

However, Table 3 reveals the estimates of sorghum grain yield at different stages, and the results showed vegetative stage as most suitable model fit for grain yield estimates compared to reproductive and grain filling and physiological maturity stages. NDVI had the lowest RMSE and CV value of 0.03 and 27.3%, highest R^2 of 0.77 and multiple R value of 0.88 respectively. The vegetative stage suggests as the critical growing point differentiation (GPD) of any crop indicating as best fit with 77% yield prediction accuracy. At this stage, the plant is entering into a phase of rapid nutrients and water uptake, and has little tolerance to stress. This can significantly affect the grain yield. This result agreed with findings by Shambel *et al*. (2017) who reported that grain yield prediction in sorghum using spectral measurements should be carried out at a stage of critical nutrient demand.

Table 3. Multiple regression models for estimating sorghum grain yield at different stages of the crop's development.

STAGE	VI	CV	RMSE	R^2	Multiple R
	NDVI	27.26	0.03	0.77	0.88
Vegetative	GNDVI	33.36	0.04	0.76	0.87
	RVI	27.66	0.04	0.63	0.80
	NDVI	16.89	0.04	0.74	0.86
Reproductive	GNDVI	23.57	0.05	0.50	0.70
	RVI	19.91	0.04	0.74	0.86
	NDVI	23.36	0.06	0.40	0.63
Grain Filling and Physiological Maturity	GNDVI	24.12	0.06	0.35	0.59
	RVI	33.30	0.06	0.26	0.51

VI= Vegetation Index, CV= coefficient of variation (%), RMSE= Root Mean Square Error and R^2= Coefficient of determination

CONCLUSIONS

This study concludes that sorghum yield could be accurately predicted in-season with NDVI and RVI for grain and stalk yields using Sentinel-2B.

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