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# Calibration and Parameterization of APSIM-Wheat using Earth Observation Data for wheat Simulation in Kenya

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A B S T R A C T

The ability to accurately translate the current condition of the crops into yield foresight expected at the end of the growing season helps the governments and other policymakers around the world to make informed decisions on matters relating to food security and economic planning. While the Agricultural Production Systems Simulator (APSIM-Wheat) is the widely used wheat-yield simulator in the world today, its major challenge is the lack of adequate data for calibration and parameterization of the model in many developing countries. This aspect inhibits the model's performance. This study utilized earth observation data derived from sentinel-2 to calibrate APSIM-wheat (version 7.5 R3008) to compensate for the data inadequacy and improve the model's performance in developing countries. The phenological statistics generated from sentinel-2 were integrated into the model as part of the input parameters. The phenological statistics were based on NDVI, MSI and NPCRI and were used with other crop management data collected at the field level. When the phenological statistics from sentinel-2 were used to calibrate APSIM-Wheat, the improved model outperformed the conventional APSIM-Wheat by 18.65% since the RRMSE improved from 25.99% to 7.34%; RMSE from 1784 Kgha-$^1$ to 501 Kgha-$^1$ and $R^2$ from o.6 to 0.82 respectively.

## 1. Introduction

The accurate interpretation of the current condition of the crops into yield foresight expected at the end of the season helps the governments and other policymakers around the world to make informed decisions on matters relating to food security and economic planning. Many studies on measures to ensure food security are being conducted worldwide following calls for papers from World Bank and Food and Agriculture Organization (Wisser et al., 2018).

Wheat is Kenya's second most important cereal, contributing to food security, poverty reduction, and employment for farmers and others in the value chain (Kamwaga et al., 2016). However, there is inadequate data to parametrize and calibrate the agronomic models for crop simulation. For this reason, even Agricultural Production Systems Simulator (APSIM-Wheat), the most widely used wheat yield simulator globally, does not perform as well as it does in Asia and Australia (Hussain et al., 2018; Asseng et al., 1998 & Gaydon et al., 2017).

The sentinel-2 data, launched in 2015 (ESA, 2015), provided an opportunity for researchers to extract tones of phenological statistics from agricultural crops (Gitelson et al., 2003; Clevers et al., 2017; Harris Geospatial., 2019; Sykas, 2020; ESA, 2015). This research thus used phenological statistics obtained from sentinel-2 to close the parameterization gap of the APSIM-Wheat. The study aims to improve the accuracy of crop yield prediction in Kenya, where it is difficult to get sufficient data for model parameterization. The derived statistics for application are based on NDVI, MSI, and NPCRI.

## 2. Study Area

The area of study is in Kenya's western parts of Narok County (Fig. 1). Wheat is the main crop grown in this area. West Narok has both small and large-scale farms.

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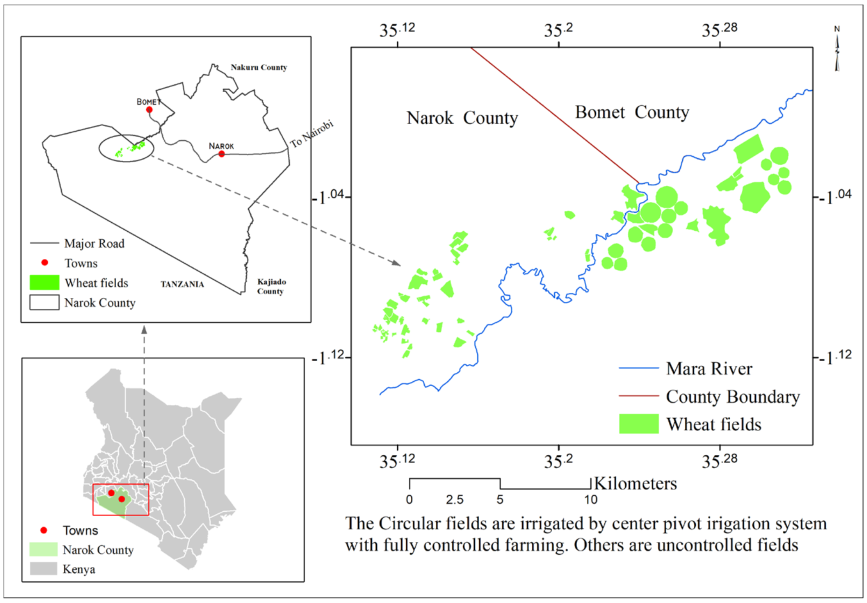


**Figure 1**: Map showing the wheat fields that were used to implement this research in the study area

## 3. Data and Methods

### 3.1 Data

#### 3.1.1 Wheat farm management data

The wheat data used in this study was collected from the 63 wheat farmers in the study area. These farmers were randomly selected based on their willingness to participate. The said data included; irrigation coefficient/factor, wheat seed variety, fertilizer applied and fertilizer type, amount and dates applied, sowing dates, sowing density, observed yields, and the location of wheat farms. The data was captured uniformly and structurally using the geo-enabled digital questionnaire designed from the Survey123 form in the .csv file format.

#### 3.1.2 Weather data

The rainfall, temperature, wind speed, radiation and humidity data in the form of the .csv files and the primary data were used as the input variables to the APSMI-Wheat Module for yield simulation. These datasets were obtained from the nearest Trans African Hydro-Meteorological Observatory station located at -0. 8550752, 35.3945556.

#### 3.1.3 Sentinel-2 data

The sentinel-2 data used in this study were downloaded from https://scihub.copernicus.eu/ between 20/08/2019 and 23/12/2019. A total of 26 Sentinel-2 images were downloaded and processed to extract the phenological statistics of wheat.

### 3.2 Methods

The data in sections 3.1.1, 3.1.2 and 3.1.3 were used to prepare the input file of APSIM-wheat to simulate the wheat yield according to the model (Keating et al.,2003; Zhang et al., 2012).

The APSIM-Wheat model was executed in two instances. In (Fig 2a), the conventional model was executed by parameterizing the model with the study area's local conditions. The second execution instance involved calibration of the model using phenological statistics derived from sentinel-2 as summarized in (Fig 2b)

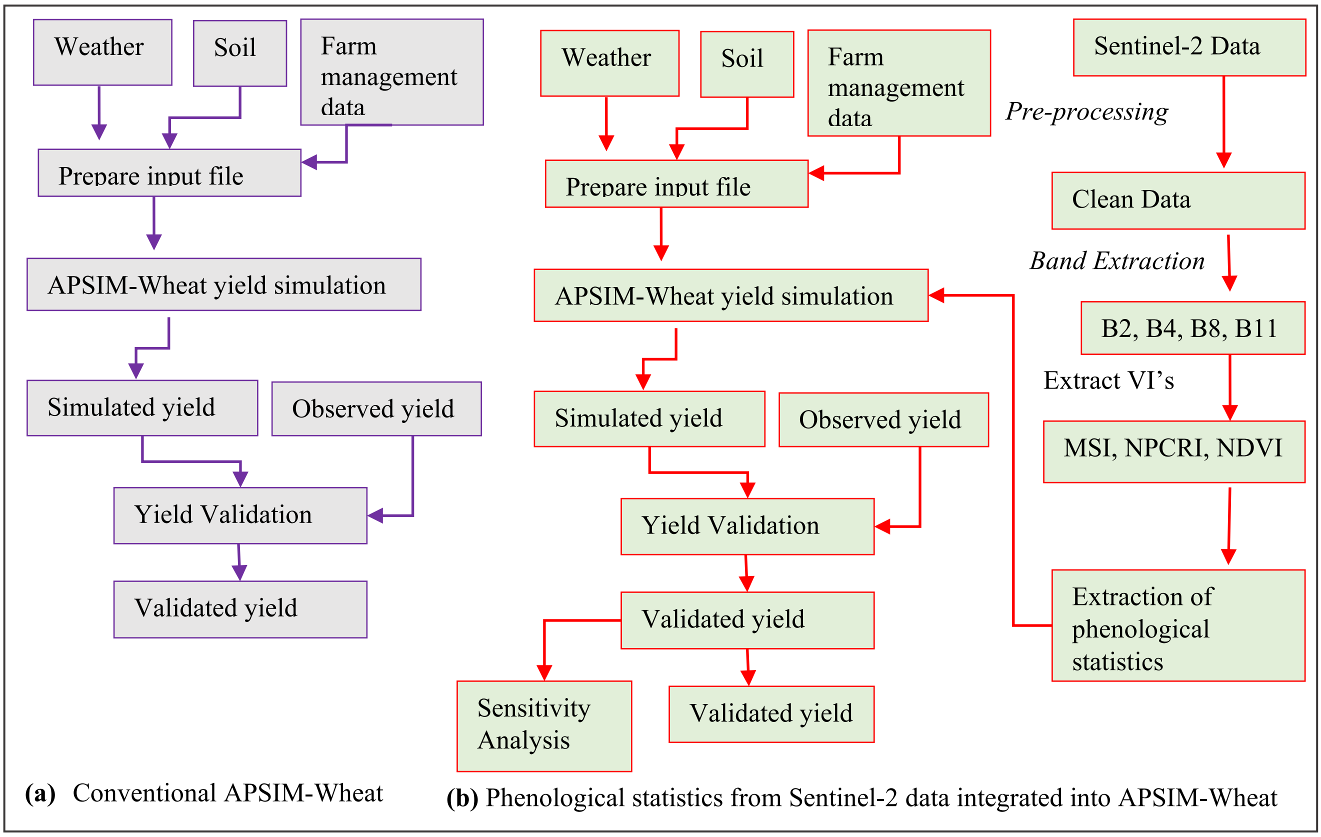


**Figure 2**: Summarized workflow used in research implementation. **2a** shows a summarized procedure that was used to apply the local parameters of the study area in the conventional APSIM- Wheat for wheat yield simulation. **2b** shows the improved model where the phenological parameters from sentinel-2 were used to calibrate the APSIM- Wheat.

### 3.2.1 Data Pre-Processing

The sentinel-2 reflectance was converted from the top of the atmosphere to the top of canopy reflectance. This was necessary because the leaf water content and chlorophyll contents are based on the canopy (Djamai et al., 2018; Zarco-Tejada et al., 2019).

### 3.2.2 Extraction of Vegetation Indices (VIs)

The NDVI in sentinel-2 was computed using the formula (Band 8-Band 4)/ (Band 8+Band 4) according to (Sykas, 2020; ESA,2015). The MSI, on the other hand, was based on the ratio of (Band11)/ (Band 8) according to (Harris Geospatial., 2019; Hunter Jr and Rock, 1989; ESA., 2015). The NPCRI was lastly computed using (Band 4-Band 2)/ (Band 4 + Band 2) as described in (Sykas., 2020; ESA., 2015; Govind et al., 2005).

### 3.2.3 Extraction of Phenological Statistics from VIs

Phenological statistics for wheat growth were extracted from the vegetation indices in section 3.2.2 using the approach advanced by Li et al. (2019), involving the computation of percentile (P%) of the VIs on the $i^{th}$ day. For convenience, this method begins by multiplying the values of VIs by 100 so that the integer proportions ($VI_{int}$ become usable in the analysis. The pixels (NUMVI) corresponding to each ($VI_{int}$) are then counted.

Using the counted pixels, the approach then calculates the value of P, which indicates the wheat growth statistics according to Lie et al. (2019). The description of the formula is as follows;

$$P_k - t\left(\frac{\sum_{i=0}^{k} NUM_{VI,j}}{NUM_{all}} * 100\right) \qquad \text{Equation 1}$$

Where k ranges from 0 to 100 (which corresponds to VIint); NUMVI is the number of pixels, j ranges from 0 to k; $\mathrm{NUM_{all}}$ is the total number of pixels in the entire VI and is given by the formula below;

$$\mathrm{NUM_{all}} = \sum_{j=0}^{100} \mathrm{NUM_{VI,j}} \qquad \text{Equation 2}$$

The final step in the approach was the conversion of $VI_{int}$ into P using the lookup table to use them to evaluate the wheat growth statistics.
The value of P for the pixel with VI=k/100 indicates the wheat growth statistics. The higher values of P indicate better wheat growth and vice versa, according to Zhang et al. (2018). This is what was used as input variables in APSIM-Wheat to improve the model performance.

### 3.2.4 Model Parameterization and Calibration

APSIM- Wheat was parameterized using the rainfall, temperature, solar radiation, soil texture, soil drainage, soil water content, and organic matter, start and end date of sowing, fertilizer amount and type, crop spacing, pest and weed control measures, and irrigation coefficient data from the study area.

### 3.2.5 Model Validation

The model accuracy was assessed using relative root mean square error (RRMSE). The RRMSE indicator was calculated by dividing the average relative root mean square (RMSE) with the average value of the measured wheat yield according to equations 3 and 4.

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \qquad \text{Equation 3}$$

$$\mathrm{RRMSE} = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2}}{\frac{1}{n}\sum_{i=1}^{n} S_i} * 100 \qquad \text{Equation 4}$$

Where n is the sample size, $S_i$ is the simulated wheat yield and $O_i$ is the recorded wheat yield. The VIs were validated in the field by mapping out the bare soils and removing the VIs that represented them. This ensured that the VIs used were for wheat only.

### 3.2.6 Sensitivity Analysis

Sensitivity analysis was done to assess the changes in the model's performance due to changes in input parameters. This was done using the leave-one-out procedure and estimating the amount of change in the simulated yield to ignore the parameter according to (Holzworth et al., 2014). The procedure was conducted for rainfall and nitrogen parameters because the two were highly variable than the rest.

## 4. Results and Discussion

### 4.1.1 Time Series NDVI Profile

The mean NDVI values for each field were plotted on a time series profile at different growth stages, according to Dong et al. (2019). The results, in Fig. 3, indicates that wheat in the irrigated fields was healthier than those not under irrigation, which showed slow seedling development and indicated steep fluctuations in the NDVI values across the phenological season (0 to 0.4 in the first 20 days of growth). During the same duration, the NDVI values in the irrigated fields rose from 0 to 0.68. In the irrigated fields, sprouting and canopy development occurred after five days instead of eleven days in the unirrigated parts. The reduced vigour in the unirrigated fields is due to little rainfall during the first 20 days of sowing (Fig. 5a), hence lower NDVI values (Masialeti et al.,2010).

The NDVI values rose from 0.68 to 0.84 and remained constant till the 70$^{th}$ day before declining in the irrigated fields. In the unirrigated fields, the values rose slowly from 0.40 to 0.58 during the second stage of phenological development. Health improvement in the unirrigated fields coincided with the heavy rains between October to December (35$^{th}$ day) and spraying done in most fields to control weed and replenish nitrogen.

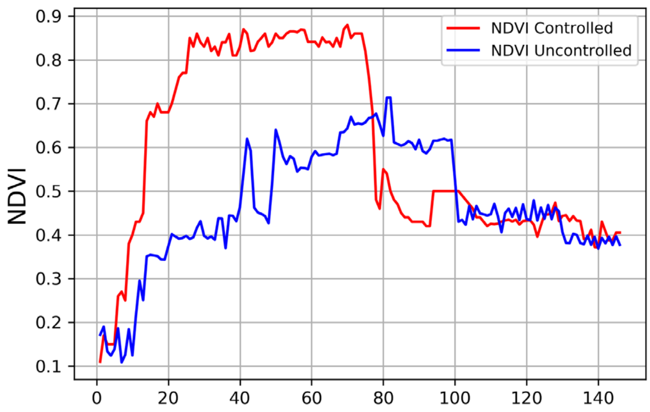


**Figure 3**: The graph shows the time Series NDVI curve for wheat in the controlled and uncontrolled fields from August 20, 2019, to December 23, 2019

During jointing and booting, the NDVI values of wheat rose to reach the highest value of 0.843 and 0.710 in the irrigated and unirrigated fields, respectively, between the 60$^{th}$ and 70$^{th}$ day of growth. At the end of the phenological period, which started in the middle of November, the NDVI values had decreased to 0.38 in both irrigated and unirrigated fields. The values did not come down to zero because of rains received in December, and weeds had started growing again. This agreed with the study by (Jiang et al., 2003; Skakun et al., 2018), which attributed the rise in the values of NDVI to residual water and fertilizer in the soil.

### 4.1.2 Time Series MSI Profile for wheat

At the start of the season, the MSI values rose exponentially to 0.58 in the irrigated fields and from 0.18 to 0.38 in the unirrigated fields within 20 days of sowing. This increase in the irrigated fields was at the same time when the NDVI values rose sharply due to the irrigation, which started immediately after sowing, hence low stress due to water in the controlled fields (Zhao et al., 2020).

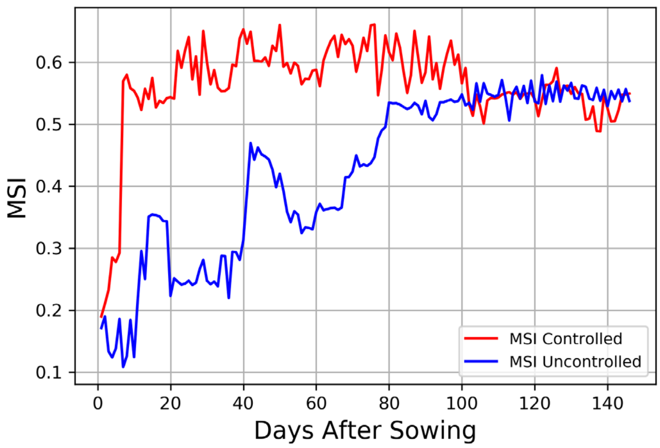


**Figure 4**: Graph of temporal moisture status in wheat from August 20, 2019, to December 23, 2019.

The increase of MSI values in the unirrigated fields fluctuated between 0.30 and 0.53 in the middle of the phenological cycle and finally settled at 0.5 at its end and the start of long rains (Figure 5a). There is a sharp contrast in MSI values from days 45-65 due to the rains that started at this period. The values remained high after 100 days when the wheat was at the maturity stage because of the low demand for water due to reduced photosynthesis (Guo et al., 2013). The correlation between the water stress, rainfall, humidity, wind speed and temperature further showed that the water stress was observed during low rainfall and humidity, high wind speed and temperatures and vice versa (see Figures 5a, 5b, 6a and 6b, respectively).

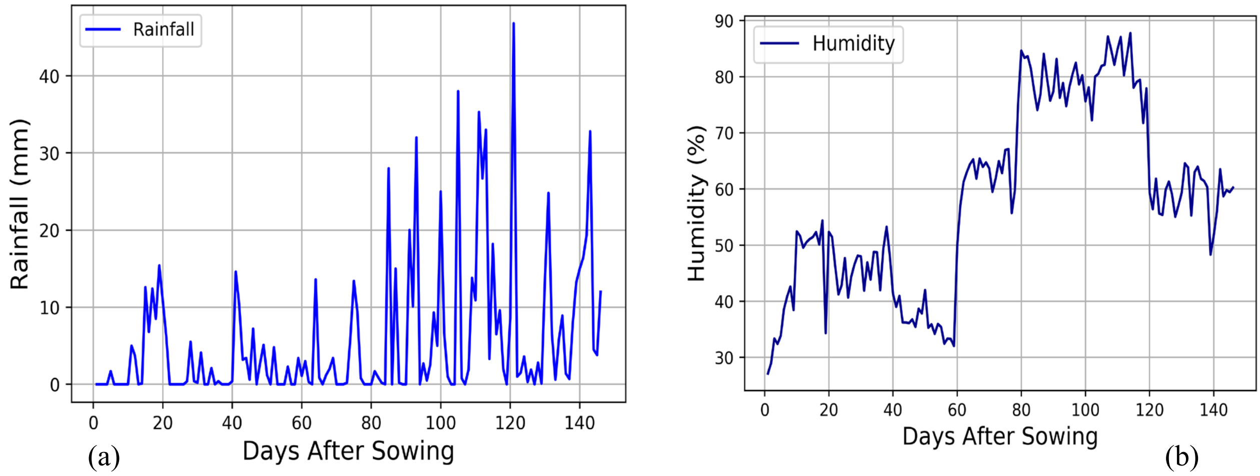


**Figure 5:** The graphs showing **(a)** Rainfall and **(b)** Humidity Variation throughout the phenological cycle in the study area from August 20, 2019, to December 23, 2019

Wind blowing across the crop canopy causes crops to lose water through evapotranspiration (Parkash and Singh, 2020). Therefore, increased wind speed causes massive water loss. Further water loss occurs when temperatures increase with decreasing precipitation. Herein, wind speed and temperature remained almost constant during the phenological period (Figure 6a). The observed crop stress was therefore attributed to precipitation, which had higher variability compared to others(Figure 5a).

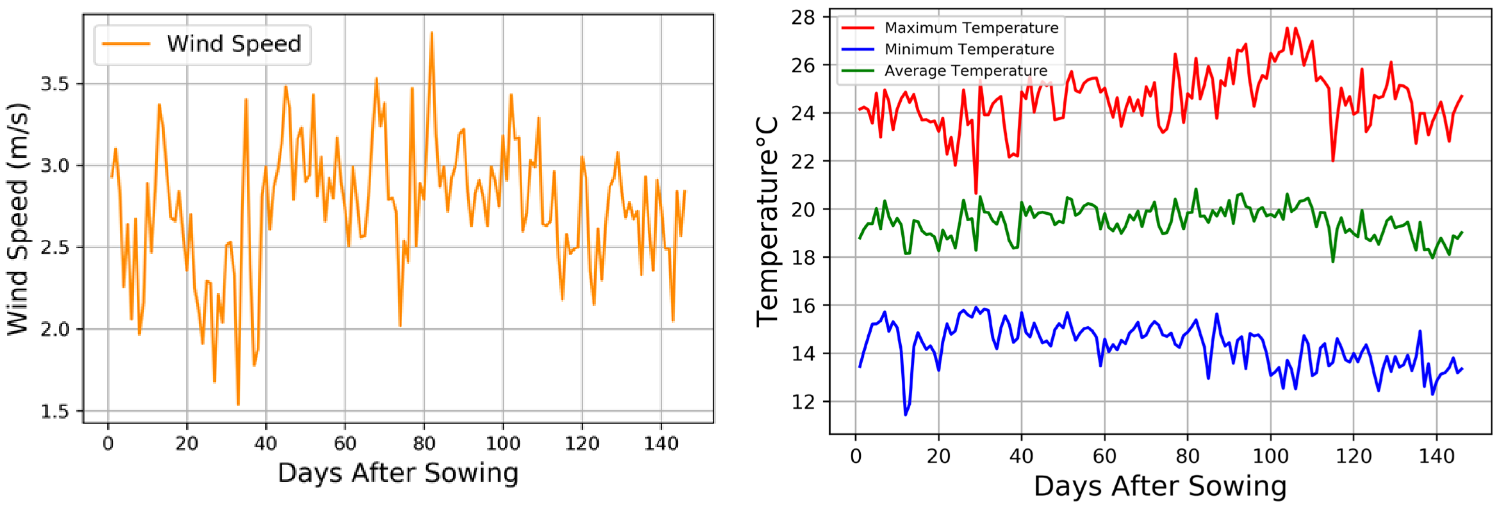


**Figure 6:** Graphs for the time series status of wind speed and temperature in the study area from August 20, 2019, to December 23, 2019. **(a)** Wind speed variation, **(b)** temperature variation

### 4.1.3 Time Series NPCRI Profile

The temporal variation of NPCRI values showed a decreasing trend until around the 80$^{th}$ day of sowing, when the values started to rise again (Figure 7). At the beginning of the phenological season, the NPCRI values for both the controlled and uncontrolled farms were 0, probably because the crops had not developed canopies use by this vegetation index to estimate the chlorophyll (Preza et al., 2019). At around ten days, the values rose to 0.55 and 0.42 for controlled and uncontrolled farms, respectively (Fig 7), due to canopy development and the flourishing of crops from fertilizer applied during sowing, thus raising the NPCRI values (Wang et al.,2019). Crop development increased utilization of available nitrogen, causing NPCRI values to decrease to about 0.33 and 0.31 due to decreased photosynthetic processes (Delloye et al., 2018). After top-dressing, the amount of canopy chlorophyll optimizes because of replenished nitrogen, hence increased NPCRI values (Govind et al., 2005).

At around 40 days after the top dressing, the NPCRI values rose to a maximum of 0.6 and 0.44 in controlled and uncontrolled farms, respectively. Again, the values begin to decrease at the peak level, reaching the lowest point at around the $80^{th}$ day. During this period, the wheat is at the booting and flowering stage, which precedes the grain formation, thus consuming a lot of nitrogen required to facilitate the process (Wang et al., 2019). After this stage, the plant maturity minimizes nitrogen, thus raising values without top dressing (Iqbal., 2008). At the end of the phenological circle, the remaining nitrogen forms soil's residual nitrogen (Gitelson et al., 2003; Cartelat et al., 2005; Govind et al., 2005).

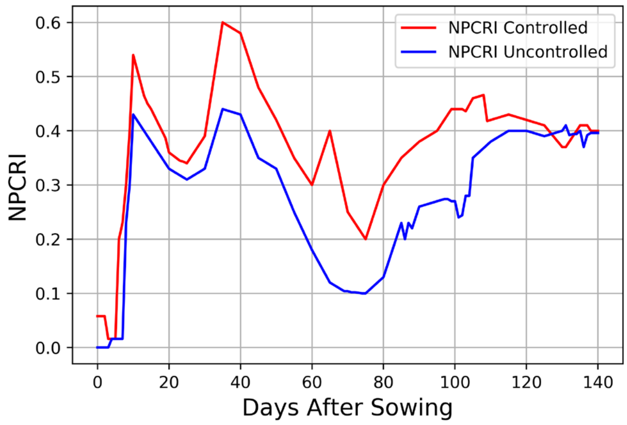


**Figure 7:** The graph is showing the time-series status of NPCRI for wheat both in controlled and uncontrolled farms from August 20, 2019, to December 23, 2019

The findings echoed those of (Cui et al., 2019; Govind et al., 2005), where the highest value of NPCRI was observed between the 50th-60th day after sowing and a few days after top dressing. The two studies also observed the lowest value at around the $118^{th}$ day, the day of full maturity as per the phenological stage. The difference of days in the highest and lowest values between this study and those of (Cui et al., 2019; Govind et al., 2005) is due to different climatic conditions and wheat varieties in question.

**4.2 Model Validation**

The NDVI, MSI and NPCRI values for wheat were validated in the field by identifying and recording the GPS coordinates of the bare ground within the wheat farms. Results helped curate the wheat NDVI, MSI and NPCRI. All the fields that had NDVI, MSI and NPCRI that were equal to or less than the values for bare soil were removed from the list to ensure the information obtained from the VIs only applied to wheat. The MSI condition curve was further validated by comparing it with the rainfall received, and the particular instances of water stress coincided with the specific period of low rainfall. For example, between 0-10 days, 20-40 days, and 50-55 days, there was reduced rainfall, which created stress in unirrigated fields (Fig 5a).

The model's accuracy in the two scenarios used in this study was assessed using RMSE, RRMSE and a coefficient of determination ($R^2$). According to (Jamieson, Porter and Wilson, 1991), the performance of the model is excellent when RRMSE<10%; good if 10%<RRMSE<20%; fair if 20%<RRMSE<30%; and poor if RRMSE≥30%. Furthermore, the model performance is good when RMSE is low and ($R^2$) is approaching 1.

**Table 1**: Linear regression analysis for the two instances the model was deployed

| Model | RMSE, Kgha$^{-1}$ | RRMSE, % | Coefficient of Determination ($R^2$) |
|---|---|---|---|
| Conventional APSIM- model | 1784 | 25.99 | 0.6 |
| APSIM Model Calibrated with EO Data | 501 | 7.34 | 0.82 |

The graphical representation of model validation indicates a higher model performance when phenological statistics derived from sentinel-2 were used to calibrate the APSIM wheat to fill the data gaps. The high model performance is indicated by the strong positive correlation between the simulated yields and observed yields in Fig 8

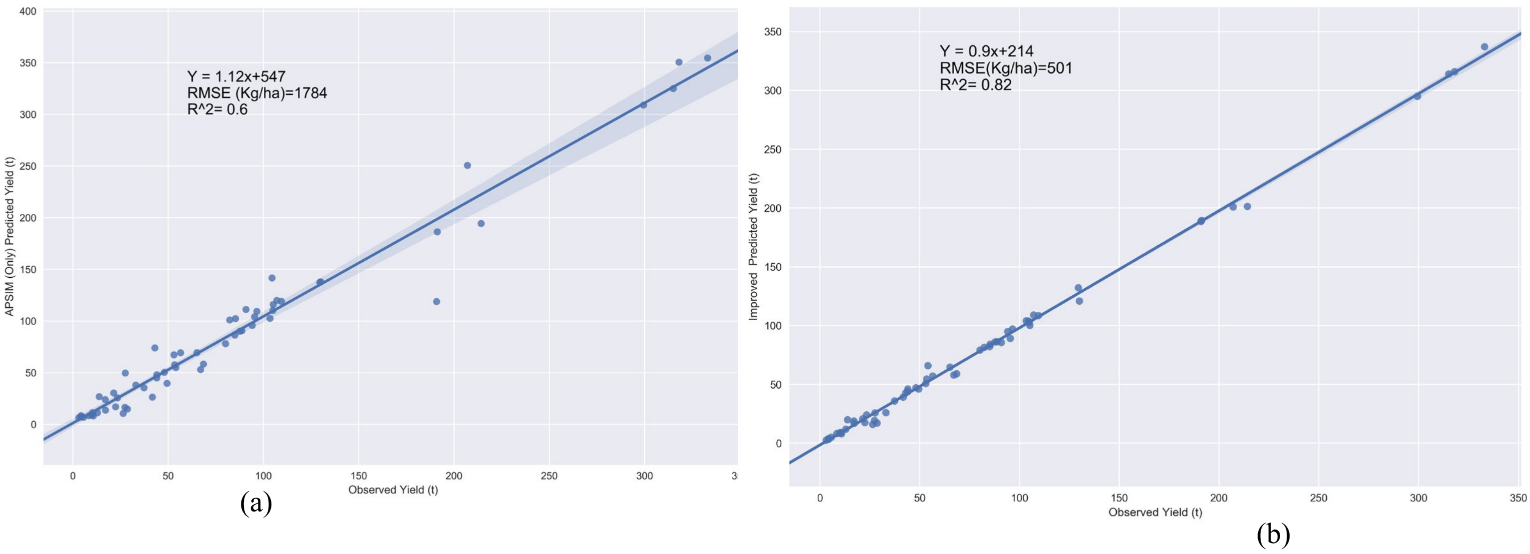


**Figure 8:** The yield predictions by APSIM-Wheat under two circumstances. **(a)** simulated wheat yield using conventional APSIM-Wheat, **(b)** simulated wheat yield when vegetation indices derived from sentinel-2 were incorporated into APSIM-Wheat

### 4.3 Sensitivity Analysis

The sensitivity analysis shows that the improved APSIM-Wheat was more sensitive to precipitation changes than nitrogen since a slight change in the rainfall caused a significant margin in the yield. For example, a slight change in rainfall from 250mm to 300mm results in yield quantity changes from around 750 Kgha-1 to 1500 Kgha-1. After 350mm, the rainfall increase did not increase the yield as it was between 200mm and 340mm. For nitrogen, the saturation point beyond which the additional nitrogen does not result in increased yields is 85 KgNha-1 (Fig 9a). These results agreed with those of (Zhao et al., 2014; Asseng et al., 2013

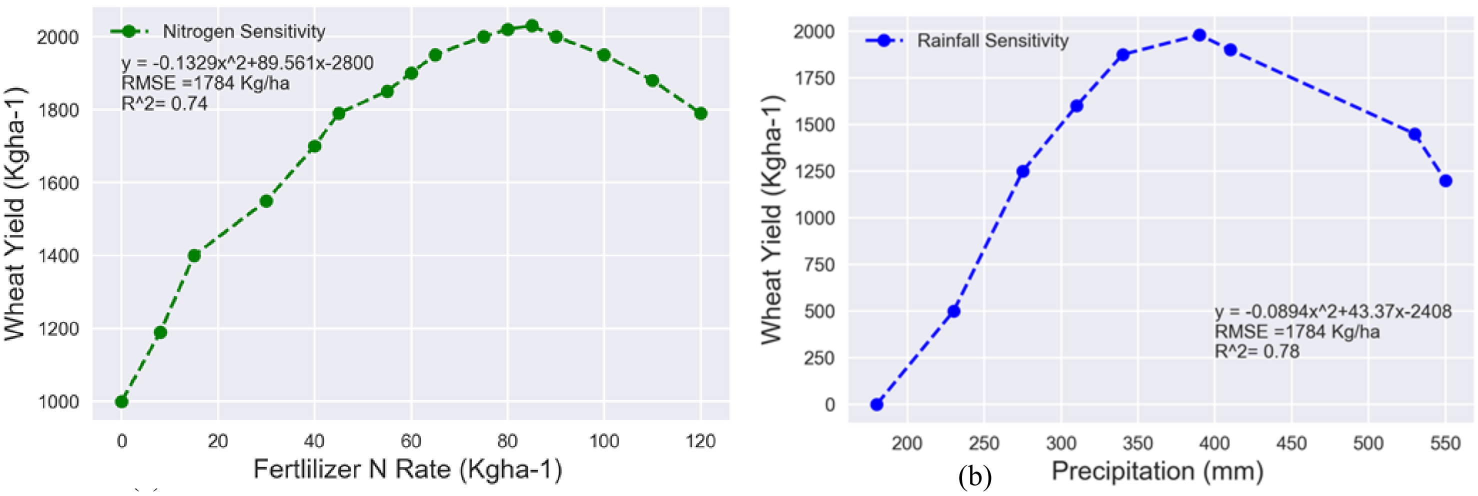


**Figure 9:** Graphs showing the sensitivity of the model to changes in nitrogen and precipitation. (a) Shows how changes in nitrogen levels affect the simulated wheat yields, (b) Shows how changes in precipitation affect the simulated wheat yields.

### 4.4 Conclusion

The inadequacy in data for calibration and parameterization of the model resulted in the low performance of APSIM-wheat (version 7.5 R3008) in the simulation of crop yield. To address this issue, this research developed a new version of the simulator. This new version of the model was developed by incorporating the NDVI, MSI and NPCRI sentinel-2. Phenological Statistics for wheat were generated from NDVI, MSI and NPCRI and used to compensate for the original simulator version's data inadequacy. A test run of this new version demonstrated the improved performance of 18.65%, marked by the drop of RRMSE from 25.99% to 7.34%, $R^2$ from 0.6 to 0.82, and RMSE from 1784 Kgha-1 501 Kgha-1.

This study concludes that nitrogen in wheat is a critical parameter that is required in the estimation of wheat yield and therefore its estimation was a major cause of bigger deviations in yield estimations in APSIM-wheat (version 7.5 R3008). Thus, the study recommends that: In places where the available agronomic field data is not adequate to calibrate APSIM-Wheat Model, the satellite-derived crop nitrogen provides a cheaper alternative of reducing the deviations in the prediction of crop yield. The NDVI and MSI provide insights on the qualitative/quantitative time series analysis of crop water and health status. This information thus helps fill the data inadequacy for improved model performance.

### References

Asseng et al 2013, 'Uncertainty in simulating wheat yields under climate change', *Nature Climate Change*, vol. 3, no. 9, pp. 827–832.

Cartelat, et al 2005, 'Optically assessed contents of leaf polyphenolics and chlorophyll as indicators of nitrogen deficiency in wheat (Triticum aestivum L.)', *Field Crops Research*, vol. 91, no. 1, pp. 35–49.

Clevers, J, Kooistra, L & van den Brande, M 2017, 'Using Sentinel-2 Data for Retrieving LAI and Leaf and Canopy Chlorophyll Content of a Potato Crop', *Remote Sensing*, vol. 9, no. 5, p. 405.

Cui et al 2019, 'Leaf chlorophyll content retrieval of wheat by simulated RapidEye, Sentinel-2 and EnMAP data', *Journal of Integrative Agriculture*, vol. 18, no. 6, pp. 1230–1245.

Delloye, C, Weiss, M & Defourny, P 2018, 'Retrieval of the canopy chlorophyll content from Sentinel-2 spectral bands to estimate nitrogen uptake in intensive winter wheat cropping systems', *Remote Sensing of Environment*, vol. 216, pp. 245–261.

Demotes-Mainard et al 2008, 'Indicators of nitrogen status for ornamental woody plants based on optical measurements of leaf epidermal polyphenol and chlorophyll contents', *Scientia Horticulturae*, vol. 115, no. 4, pp. 377–385.

Djamai, N, Fernandes, R, McNairn, H & Goïta, K 2018, 'Validation of vegetation biophysical parameters derived from Sentinel-2A over an agricultural study site located in Canada (Conference Presentation)', in CM Neale & A Maltese (eds), *Remote Sensing for Agriculture, Ecosystems, and Hydrology XX*.

Dong, C, Zhao, G, Qin, Y & Wan, H 2019, 'Area extraction and spatiotemporal characteristics of winter wheat–summer maize in Shandong Province using NDVI time series', in A Chemura (ed.), *PLOS ONE*, vol. 14, no. 12, p. e0226508.

European Space Agency 2015, *SENTINEL-2 User Handbook Sentinel-2 User Handbook*, ESA, pp. 1–64.

Gaydon et al 2017, 'Evaluation of APSIM model in cropping systems of Asia', *Field Crops Research*, vol. 204, pp. 52–75.

Gitelson, AA, Gritz, Y & Merzlyak, MN 2003, 'Relationships between leaf chlorophyll content and spectral reflectance and algorithms for non-destructive chlorophyll assessment in higher plant leaves', *Journal of Plant Physiology*, vol. 160, no. 3, pp. 271–282.

Govind, A, M, B, Kumari, J & Govind, A 2005, 'Efficacy of different indices derived from spectral reflectance of wheat for nitrogen stress detection', *Journal of Plant Interactions*, vol. 1, no. 2, pp. 93–105.

Guo, R, Ping, W, Zhi, D, Li, X & Xue, F 2013, 'Effects of Water Stress on Germination and Growth of Wheat, Photosynthetic Efficiency and Accumulation of Metabolites', *Soil Processes and Current Trends in Quality Assessment*.

Harris Geopatial 2019, *Canopy Water Content*, www.l3harrisgeospatial.com, viewed March 22 2021, <https://www.harrisgeospatial.com/docs/CanopyWaterContent.html>.

Holzworth et al 2014, 'APSIM – Evolution towards a new generation of agricultural systems simulation', *Environmental Modelling & Software*, vol. 62, pp. 327–350.

HUNTJR, E & ROCK, B 1989, 'Detection of changes in leaf water content using Near- and Middle-Infrared reflectances', *Remote Sensing of Environment*, vol. 30, no. 1, pp. 43–54.

Hussain, J, Khaliq, T, Ahmad, A & Akhtar, J 2018, 'Performance of four crop model for simulations of wheat phenology, leaf growth, biomass and yield across planting dates', in DA Lightfoot (ed.), *PLOS ONE*, vol. 13, no. 6, p. e0197546.

Iqbal, J, Read, JJ & Thomasson, AJ 2008, 'Site specific N application and remote sensing of cotton crop', *2008 2nd International Conference on Advances in Space Technologies*, pp. 114–117.

Jamieson, PD, Porter, JR & Wilson, DR 1991, 'A test of the computer simulation model ARCWHEAT1 on wheat crops grown in New Zealand', *Field Crops Research*, vol. 27, no. 4, pp. 337–350.

Jiang, D, Wang, N, Yang, X & Wang, J 2003, 'Study on the interaction between NDVI profile and the growing status of crops', *Chinese Geographical Science*, vol. 13, no. 1, pp. 62–65.

Kamwaga et al 2016, *Kenya Wheat Production Handbook*, Kenya Agricultural and Livestock Research Organization, Nairobi, Kenya Agricultural and Livestock Research Organization, Nairobi, viewed March 23 2021, <https://www.kalro.org/sites/default/files/Wheat-Handbook-2016.pdf>.

Keating et al 2003, 'An overview of APSIM, a model designed for farming systems simulation', *European Journal of Agronomy*, vol. 18, no. 3, pp. 267–288, viewed June 8 2020, <https://www.sciencedirect.com/science/article/pii/S1161030102001089?via%3Dihub>.

Li et al 2019, 'Using NDVI percentiles to monitor real-time crop growth', *Computers and Electronics in Agriculture*, vol. 162, pp. 357–363.

Masialeti, I, Egbert, S & Wardlow, BD 2010, 'A Comparative Analysis of Phenological Curves for Major Crops in Kansas', *GIScience & Remote Sensing*, vol. 47, no. 2, pp. 241–259.

Meyer, et al. 2006, 'Relationships between optically assessed polyphenols and chlorophyll contents, and leaf mass per area ratio in woody plants: a signature of the carbon-nitrogen balance within leaves?', *Plant, Cell and Environment*, vol. 29, no. 7, pp. 1338–1348.

Parkash, V & Singh, S 2020, 'A Review on Potential Plant-Based Water Stress Indicators for Vegetable Crops', *Sustainability*, vol. 12, no. 10, p. 3945.

Preza et al 2019, 'Combining Environmental Monitoring and Remote Sensing Technologies to Evaluate Cropping System Nitrogen Dynamics at the Field-Scale', *Frontiers in Sustainable Food Systems*, vol. 3.

Skakun, et al 2018, 'Winter Wheat Yield Assessment Using Landsat 8 and Sentinel-2 Data', *IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium*.

Sykas, D 2020, *Blog*, GIS and Earth Observation University, viewed March 22 2021, <https://www.geo.university/pages/blog?p=spectral-indices-with-multispectral-satellite-data>.

Wang, K, Huggins, DR & Tao, H 2019, 'Rapid mapping of winter wheat yield, protein, and nitrogen uptake using remote and proximal sensing', *International Journal of Applied Earth Observation and Geoinformation*, vol. 82, p. 101921.

Wisser, D, Müller, M, Kavallari, A & Bellú, L 2018, *FAO's long-term projections on the future of food and agriculture: from scenario to modelling*, viewed March 22 2021, <http://www.fao.org/3/CA2250EN/ca2250en.pdf>.

Zarco-Tejada et al 2019, 'Chlorophyll content estimation in an open-canopy conifer forest with Sentinel-2A and hyperspectral imagery in the context of forest decline', *Remote Sensing of Environment*, vol. 223, pp. 320–335.

Zhang, et al 2018, 'Retrieving Leaf and Canopy Water Content of Winter Wheat Using Vegetation Water Indices', *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, vol. 11, no. 1, pp. 112–126.

Zhang et al 2012, 'Evaluation of the APSIM-Wheat model in terms of different cultivars, management regimes and environmental conditions', *Canadian Journal of Plant Science*, vol. 92, no. 5, pp. 937–949.

Zhao et al 2014, 'Sensitivity and uncertainty analysis of the APSIM-wheat model: Interactions between cultivar, environmental, and management parameters', *Ecological Modelling*, vol. 279, pp. 1–11.

Zhao et al 2020, 'Effects of Water Stress on Photosynthesis, Yield, and Water Use Efficiency in Winter Wheat', *Water*, vol. 12, no. 8, p. 2127.