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Abstract

Cassava production is essential for food security in Sub-Saharan Africa and serves as a major calorie- intake source in Nigeria. Here we use a crop model, LINTUL5, embedded into a modeling framework SIMPLACE to estimate potential cassava yield gaps (Yg) in 30 states of Nigeria. Our study of climate parameter influence on the variability of current and potential yields and Yg shows that cumulative radiation and precipitation were the most significant factors associated with cassava yield variability ($p = 0.01$). The cumulative Yg mean was estimated as 18202 kg·ha⁻¹, with a maximum of 31207 kg ha⁻¹ in Kano state. Across the states, nutrient limitation accounts for 55.3% of the total cassava yield gap, while the remaining 44.7% is attributed to water limitation. The highest untapped water-limited yields were estimated in States, such as Bauchi, Gombe, and Sokoto, characterized by the short rainy season. Conclusively, the current cassava yield levels can be increased by a factor of five through soil fertility enhancement and with irrigation, particularly in semi-arid regions.

Keywords: Nitrogen, Water, Climate, Potential yield, Actual yield

1. Introduction

Cassava (*Manihot esculenta*) is one of the primary food sources in Sub-Saharan Africa (SSA), crucial to food security and the economy under its diverse applications (Rahman and Awerije, 2016; De Souza et al., 2017; Echebiri and Edaba, 2008). Nigeria, the largest cassava root-producing nation globally ^[4], harvests more than 59 Mt of fresh cassava roots annually (FAOSTAT, 2021). Most increases in production in the last 26 years (1994-2019) have been attained by improving cassava varieties and expanding the land area for cassava cultivation (FAOSTAT, 2021; Ugwu, 1996). However, the existing literature suggests that the average cassava root yield from 1965 to 2017 (7000 – 12000 kg·ha⁻¹) was still below its potential productivity (Cock et al., 1979; IITA, 2005). Therefore, since the land estimates for cropland expansion in SSA are also contested (Chamberlain et al., 2014), existing cropland must produce substantially more significant quantities than the current yield levels (de Araújo Visses et al., 2018).

Results from on-station and on-farm research indicate that in some regions, despite having favourable weather conditions, a sizeable exploitable gap exists between current and achievable yields under ideal agronomic management conditions (Ayoola and Makinde, 2007; Bamidele et al., 2008; Eke-Okoro and Njoku, 2012). On the other hand, strong responses have been estimated in the dry matter (DM) yield changes under N, P, and K fertilizers application (2–18, 3–16, and 3–22 t·DM·ha⁻¹, respectively) (Adiele et al., 2020) in different agro-ecological zones of Nigeria. Thus, estimating the yield gaps (Yg) in Nigeria is essential to indicate the most important crop to prioritize, limiting factors for production, and identifying the Yg hotspots. Secondly, these assessments may help set agendas in policy development and research prioritization where current information is scarce.

The Yg of a crop grown in a particular location and cropping system is defined as the difference between the yield under optimum management and the average yield achieved by farmers (Lobell et al., 2019). Yield under optimum control is labelled as potential yield (Yp) under irrigated conditions or water-limited yield (Yw) under rainfed conditions (Van Ittersum et al., 2013; Evans, 1993). Yp is location-specific because of the climate, but in theory, it is independent of soil properties, assuming that the water and nutrients required can be added through management. Thus, Yp is the most relevant benchmark for irrigated systems in locations without significant soil constraints, whereas it is Yw for rainfed crops (Van Ittersum et al., 2013). Hence, Yp and Yw are based on optimum planting dates, planting density, and region-specific crop variety. These factors are crucial to determining the feasible growth duration, particularly in tropical climatic conditions where two or three crops are produced yearly and simultaneously.

Site-specific simulations of Yp or Yw (using crop growth simulation models) are suggested as the most reliable tools for estimating Yp or Yw and Yg of specific crops within a defined cropping system because these models account for the interactions among weather, soils, and management. Therefore, they capture spatial and temporal variations in Yp and Yw, which other methods could not (van Bussel et al., 2015). To increase food production, identifying the regions with untapped production capacity is highly important, and this can be achieved by quantitatively and spatially estimating Yg. This approach requires that we consider the spatial variation in the environment and the production system. As a result, this study (i) evaluates the performance of the LINTUL5 crop model for simulating the growth and development of cassava on the field at the state level in Nigeria, and (ii) identifies geospatial gradients of meteorological factors and the effect of climate on cassava yields and Yg.

2. Materials and methods

2.1. Dataset for model calibration at field scale

For LINTUL5 crop model calibration at the field scale, cassava yields ($\text{kg}\cdot\text{ha}^{-1}$), above-ground biomass ($\text{kg}\cdot\text{ha}^{-1}$), and fertilizer application (N, P, K) of five varieties viz.: TME419, Oko-iyawo, TMS91/02324, TMS96/1632, and TMS98/0505 (from International Institute of Tropical Agriculture, IITA, Ibadan, Nigeria) were collected from Ikenne experimental site in 2015. This site is humid, with rainy and dry seasons spanning April – November and December – March, respectively. The average annual precipitation at Ikenne is 1517 mm, while the average monthly temperature ranges from 23°C in July to 32°C in February. The soil physicochemical properties of the experimental site are summarized in Table 1. The cassava planting and harvesting dates at Ikenne were September 9, 2014, and September 7, 2015, respectively.

Table 1. Physicochemical characteristics of the soil at the Ikenne experimental site.

Characteristics	Ikenne	
Soil depth (cm)	0 – 15	15 – 30
pH(H_2O)	5.7	5.8
OC ($\text{g}\cdot\text{kg}^{-1}$)	12.3	9.3
N ($\text{g}\cdot\text{kg}^{-1}$)	0.98	0.74
P ($\text{mg}\cdot\text{kg}^{-1}$)	3.63	1.57
Exchangeable Cations ($\text{cmol}\cdot\text{kg}^{-1}$)		
Ca	3	2.74
Mg	0.81	0.88
K	0.08	0.16
Na	0.07	0.07
Exchangeable micronutrients ($\text{cmol}\cdot\text{kg}^{-1}$)		
Zn	0.3	0.09
Cu	< 0.01	< 0.01
Mn	0.13	0.14
Fe	0.59	0.81
Particle size distribution ($\text{g}\cdot\text{kg}^{-1}$)		
Gravel content (%)	2-5 %	10-15 %
Sand	730	710
Silt	60	60
Clay	210	230
Textural class	Sandy clay loam	Sandy clay loam

2.2. Data and crop-model setup at states level

2.2.1. Climate and Soil data

The climate data used in this study consists of a daily time series from 1995 to 2019. It includes climate variables required for agricultural modelling (e.g., solar radiation (W/m^2), precipitation (mm), minimum and maximum temperature ($^{\circ}\text{C}$). They were obtained from the ERA5-Land offline land surface re-run of ECMWF's (European Centre for Medium Range Weather Forecasts) latest climate product (ECMWF, 2019). The average precipitation, potential evapotranspiration, solar radiation, minimum temperature, maximum temperature, and the mean temperature during the cassava growing season of 1995 – 2019 in 30 states of Nigeria are shown in Figure S1.

The relevant soil parameters for each soil layer (i.e., sand, silt, clay, gravel content, cation exchange capacity, pH, organic carbon, and bulk density) were extracted from African soil property maps at $1 \text{ km} \times 1 \text{ km}$ resolution (<http://www.isric.org/data/soil-property-maps-africa-1-km>). Other parameters, such as soil water at field capacity, wilting point, saturation point, and Van-Genuchten parameter, were also computed (Rawls et al., 1993). The soil properties for the entire region are depicted in Figure S2.

Figure 1. Nigeria map highlighting the simulation units of 30 states and Ikenne experimental site.

2.2.2. Crop yield and management data

State-level cassava yield data ($\text{kg}\cdot\text{ha}^{-1}$) from 1995 to 2014 for 30 states (out of the 36 states) in Nigeria were obtained from the IITA, Ibadan, Nigeria. The remaining six states were excluded due to either lack of data and/or lack of consistencies in the available data. Because no significant trend was observed in the crop yield data (e.g.,

due to technological developments) from 1995 to 2014, de-trending was not applied. The cassava sowing period was extracted from the crop calendar database (FAO, 2010).

2.2.3. Crop simulation

Crop Yp and Yw were simulated from 1995 to 2019 using LINTUL5 (Addiscott and Whitmore, 1991) embedded into the modelling framework SIMPLACE (Scientific Impact Assessment and Modelling Platform for Advanced Crop and Ecosystem Management) (Gaiser et al., 2013). The applied LINTUL5 version has been used extensively for cropping systems analysis in SSA (Srivastava et al., 2020, 2019, 2017; Faye et al., 2018; Trawally et al., 2015). The model simulated potential yield and biomass under conditions where the crop growth is driven only by solar radiation and temperature, i.e., without considering water stress, nutrient stress, abiotic stress, diseases, and other factors (Wolf, 2012).

Water stress occurs when the available soil water is between a defined critical point and wilting point or higher than the field capacity (i.e., waterlogged). The critical point is a crop-specific value (Allen et al., 1998) that depends on crop development, soil water tension, and potential transpiration. Water, nutrients (NPK), temperature, and radiation stresses restrict the daily accumulation of biomass, root growth, and yield. To simulate the temporal dynamics of a cropping system, the model was embedded into a general modelling framework, SIMPLACE. Therefore, the SIMPLACE<LINTUL5-SLIM> solution of the modeling platform was used in this study.

The default cassava crop parameter set for LINTUL5 was used as a starting point to establish a new parameter set for the cassava varieties used for this study. A plausible range over which they vary was obtained from the literature (Ezui et al., 2018) for the crop parameters. We established a set containing all the model parameters and evaluated it by comparing the simulated yields and the phenology to the corresponding observations by systematic sampling. The systematic sampling and evaluation were performed for the entire parameter space of all variables before choosing the parameter set with the smallest mean residual error. As a measure of accuracy between the statistical data and simulated values, the mean relative error ($MR = \frac{1}{n} \sum_{i=1}^n (\frac{S_i - O_i}{O_i})$), the mean residual error ($ME = \frac{1}{n} \sum_{i=1}^n (S_i - O_i)$), and root mean square error ($RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (S_i - O_i)^2}$) were used, where n is the sample number, O_i is the observed yield and S_i is the simulated yield. The ME value of zero indicates no systematic bias between simulated and measured values. The MR shows the mean magnitude of the error related to the observed value; the smaller the value, the smaller the difference between simulated and measured values. Whereas, RMSE is the standard deviation of the residuals (prediction errors).

2.2.4. Definition and statistical analysis of spatial and temporal variability

a. Aggregation of weather variables and model outputs:

The crop model was run at 1 km spatial resolution, corresponding to the spatial resolution of the soil input data, for each simulation unit (Figure 1), defined as a combination of soil characteristics, climate, and crop management data. Cassava yields from each state's simulation units were averaged, taking the harvested area of cassava crop into account, sourced from SPAM (Spatial Production Allocation Model) harvest areas dataset (Yu et al., 2010) to obtain a representative value per state per year. To appraise the spatial variability of cassava in all the states, the

coefficient of variation (CV) was calculated for the estimated weather variables (precipitation, potential evapotranspiration, solar radiation, minimum temperature, maximum temperature) within the crop growth period over the simulation period.

b. Yield-gap estimation and statistical analysis:

We define the (Y_p , potential yield) as the yield achieved for the crop in a given state under optimal water and nutrient levels, meaning that the crop experienced no stress. Similarly, the water-limited (rainfed) potential yield (Y_w) is the yield achieved for the crop in a given state under the optimal nutrient level but with no irrigation. The observed (i.e., farmer's yield) average yield (Y_o) is assumed as the water-limited and non-optimal nutrient levels (N, P, and K) since the cropping system in Nigeria is characterized by rainfed and low-input agriculture. Additionally, continuous cassava cultivation on the same piece of land results in intense depletion of soil fertility and consequent reduction in yield quantity (Sarr et al., 2013; Edet et al., 2013).

Based on the above definitions, YG was estimated as follows:

$$\text{Water-limited yield gap: } YG_w = Y_p - Y_w \quad Eq. (1)$$

$$\text{Actual yield gap: } YG_a = Y_w - Y_o \quad Eq. (2)$$

$$\text{Total yield gap: } YG_t = Y_p - Y_o \quad Eq. (3)$$

Multiple linear regressions were used to explain the relationship between the cassava yield (dependent variable) and the climate variables (independent variables), namely precipitation, minimum and maximum temperature, and solar radiation in the crop growing season (Figure S1). As there were only four explanatory variables, the complete statistical model was applied.

3. Results

3.1. Model calibration and evaluation

Compared to the observed cassava yields, the simulated yield under fertilized conditions was overestimated by 1.0%–7.4% across the five cassava varieties, except for Oko-Iyawo, with a 0.7% yield underestimation (Table 2). Under unfertilized conditions, the simulated yields were overestimated by 1.2%–5% and underestimated by 0.6% for TME419. The above-ground biomass under fertilized conditions was also overestimated by 7.8% except for Oko-Iyawo, with 1.4% under-estimation. Also, under unfertilized conditions, the over-estimation ranged between 0.3% and 5.7%, excluding TME419 where 0.9% under-estimation ensued (Table 2).

The model performed well in capturing the spatial and temporal yield variability. The average simulated yield (average over the 20 study years) across the states was overestimated by 6.9% compared to the observed yields with an RMSE of 478 kg·ha⁻¹ and $R^2 = 0.89$ (Figures 2a and 2b). The simulated yield within the 20 years of simulation (1995-2014) compared to the observed yields was overestimated by 5.5% with an RMSE of 407 kg·ha⁻¹ (Figure 3).

Table 2. Observed and simulated yield dry matter and above-ground biomass (in '000 kg·ha⁻¹), mean error (ME, in '000 kg·ha⁻¹), and mean residual error (in %) under control (unfertilized) and fertilized conditions of the five cassava varieties at Ikenne experimental site, Nigeria.

Varieties		Fertilized				Control			
		Observed (^{'000} kg·ha ⁻¹)	Simulated (^{'000} kg·ha ⁻¹)	ME (^{'000} kg·ha ⁻¹)	MR (%)	Observed (^{'000} kg·ha ⁻¹)	Simulated (^{'000} kg·ha ⁻¹)	ME (^{'000} kg·ha ⁻¹)	MR (%)
TME419	Yield	5.40	5.54	0.14	2.6	3.30	3.28	0.02	-0.6
	Above-ground Biomass	9.20	9.35	0.15	1.6	5.60	5.55	0.05	-0.9
Oko-iyawo	Yield	4.40	4.37	-0.03	-0.7	2.50	2.53	-0.03	1.2
	Above-ground Biomass	7.70	7.59	-0.11	-1.4	4.40	4.44	-0.04	0.9
TMS91/02324	Yield	6.20	6.26	0.06	1.0	3.30	3.46	-0.16	4.8
	Above-ground Biomass	9.30	9.30	0.00	0.0	4.90	5.18	-0.28	5.7
TMS96/1632	Yield	6.40	6.54	0.14	2.2	3.40	3.57	-0.17	5.0
	Above-ground Biomass	9.70	9.74	0.04	0.4	5.20	5.35	-0.15	2.9
TMS98/0505	Yield	7.40	7.95	0.55	7.4	4.30	4.40	-0.10	2.3
	Above-ground Biomass	11.60	12.50	0.90	7.8	6.80	6.82	-0.02	0.3

Figure 2. Simulated (water and nutrient-limited) versus observed (farmer's yield) cassava yield (in '000 kg.ha⁻¹) averaged over 20 years from 1995-2014 (a) and 1:1 graph across the 30 states (b) in Nigeria.

Figure 3. Simulated (water and nutrient-limited) versus observed (farmer's yield) cassava yield (in '000 kg.ha⁻¹) for 20 years from 1995-2015 averaged over 30 states in Nigeria.

3.2. Observed, simulated potential (Y_p), and simulated water-limited (Y_w) cassava yield

The cassava's mean Y_p and Y_w were 22390 and 14251 kg·ha⁻¹ in the 30 states from 1995 to 2019. The CV in the simulated potential yields ranged from 2.1% to 4.7%. For water-limited potential yield simulations, the CV varied from 2.9% to 32.2% across the states. In addition, the mean Y_p and mean Y_w ranged from 17479 to 34731 kg·ha⁻¹ and 2944 (Sokoto State) to 19498 kg·ha⁻¹ (Imo State), respectively (Figure 4). However, the observed yields (mean= 4190.5 kg·ha⁻¹) ranged between 892.8 and 6010 kg·ha⁻¹ (Figure 2a). The Y_p increased with latitude, having the highest values of 34731, 33981, and 28118 kg·ha⁻¹ in Kano, Bauchi, and Kaduna, respectively. While, the Y_w increased with the lower latitudes, with the highest yield located in the Southeastern States (such as Imo (19498 kg·ha⁻¹) and Akwa Ibom (18015 kg·ha⁻¹).

Multiple regression analysis (Table 3) shows that the spatial variability in the observed cassava yields across the 30 states correlated significantly with radiation ($p=0.01$) and precipitation ($p<0.01$) within the crop-growth period. The actual yield (simulated) also correlated significantly with radiation ($p=0.01$) and precipitation ($p=0.01$) within the same period ($R^2=0.76$). The Y_w and Y_p significantly correlated with radiation ($p<0.05$), having an R^2 value of 0.84 and 0.91, respectively. Likewise, the simulated estimation of the total yield gap and water-limited yield gap showed a highly significant correlation ($p<0.01$) with the precipitation and radiation amount during the crop-growth period with $R^2=0.95$ and 0.98, respectively. The maximum temperature within the crop-growth period was also significantly correlated with the water-limited yield gap (Table 3). The actual yield gap was not significantly correlated with any of the dependent variables, i.e., radiation, maximum and minimum temperature, and precipitation. Similar results are shown with the nonlinear Random forest algorithm

based on extreme gradient boosting (Table 4).

Figure 4. Spatial analysis of total yield gap, water-limited yield gap, and actual yield gap across the 30 states from 1995 to 2019. Figures A, B, and C pertain to the temporal variability in simulated cassava yield under potential, water-limited, and actual conditions, respectively. The figure at the bottom (last row) illustrates the simulated value average over 20 years of actual yield, water-limited (WL) yield and the potential yield across the 30 states of Nigeria.

3.3. Cassava yield gaps

The difference between the farmers' potential yield and the observed yield represents the exploitable yield gap. This gap is becoming smaller as farmers improve their agronomic management practices, e.g., increasing fertilizer or irrigation use or improved cultivars having higher potential yields. Therefore, the total yield gap can be divided into two parts: yield reduction due to water stress and yield reductions due to other factors such as nutrient stress, diseases, insect pest, and others. On average, for the 30 states, the total yield gap (Y_{G_t}) was 18202 kg.ha⁻¹, about 81.2% of the average simulated potential yield (Y_p). Across the states, Y_{G_t} ranged from 11904 kg.ha⁻¹ in Bayelsa

to a maximum of 31207 kg·ha⁻¹ in the Kano State (Figure 4). The average yield loss due to the suboptimal water availability (YG_w) during the growth period was estimated as 8141 kg·ha⁻¹, about 36.3% of the average simulated potential yield (Y_p) across the states. The yield gaps due to water limitation were prominent at the locations with low cumulative precipitation over the crop growth period, such as in Kano (Figure S1). However, it narrowed down considerably at states with higher rainfall (Figure S1). The average actual yield gap (i.e., YG_a) across the 30 states was estimated as 10061 kg·ha⁻¹ with the highest and lowest (14465 and 2051 kg·ha⁻¹) in Akwa Ibom and the Sokoto States, respectively.

4. Discussion

We investigated the relationship between climate variability and simulated yield gaps of cassava in Nigeria. Random forests with extreme gradient boosting was performed for the state-level yields and yield gaps as the dependent variable and precipitation, temperature, and radiation (during the crop growth period) as independent variables. A multivariate linear regression with the same framework revealed that precipitation (negative slope) and radiation (negative slope) significantly explained the spatial variability in simulated actual yield and the observed yield (Table 3). These findings are also corroborated by Akinwumiju et al. (2020), who found that cassava yield-sunshine hour and cassava yield-precipitation relationships are significant, unlike cassava-temperature relationships. However, the negative linear relationship with precipitation could be attributed to the decreasing radiation due to cloud cover changes in the presence of increased rainfall. Additionally, higher precipitation could result in an increased amount of nitrogen leaching from the soil. Water-limited yield and potential yield of cassava were significantly influenced by radiation during the crop growth period.

The observed yield had no significant relation with the temperature values in the crop growing cycle as was revealed by the linear regression. However, the linear regression may not be able to disentangle nonlinear associations. Random forests, which captures the nonlinear relationships as a machine learning methodology highlight that the maximum temperature has the highest importance for observed yield. The linear regression however shows a significant relationship only with the radiation and precipitation amount. From a simplistic mechanistic perspective, we conduct the further inference using linear regression. This phenomenon could be ascribed to the higher radiation with ample precipitation within the crop growth period, which could facilitate higher crop biomass production, hence higher yield (through effects on maintenance respiration) (Akinwumiju et al., 2020; Ramarohetra et al., 2013; Boron et al., 2005; Sultan et al., 2005). Researchers have also reported that under the non-limiting condition of rainfall, attainable yield depends on solar radiation. Thus, it is a limiting factor for potential crop yield, especially in the humid regions of West Africa, due to the dense cloud covers during the rainy season (Srivastava et al., 2017; Sultan et al., 2005; Folberth et al., 2012).

We have plotted potential and water-limited cassava yield against the cumulated precipitation during the crop growth period (Figure 5). We obtained a biphasic pattern for the water-limited cassava yield, consisting of an exponential relationship between 370 and 1750 mm of precipitation and a decreasing plateau for the higher cumulative precipitation amounts. A decreasing trend plateaued around 2250 mm of cumulative precipitation during the crop growth period was obtained with potential cassava yield. However, the same phenomenon was reported in earlier studies in West African countries for maize and pearl millet (Srivastava et al., 2017; Boron et al., 2005).

Figure 5. Relationship between simulated potential yield, water-limited cassava yields, and cumulated precipitation amount (in mm) during the crop growth period.

The model estimated large and variable gaps in cassava yield across the States. The average total yield gap was approximately $18202 \text{ kg}\cdot\text{ha}^{-1}$, with the maximum value of $31207 \text{ kg}\cdot\text{ha}^{-1}$ in Kano State. Also, the average yield gap due to water-limitation was $8141 \text{ kg}\cdot\text{ha}^{-1}$, with the highest value ($24215 \text{ kg}\cdot\text{ha}^{-1}$) in Kano State, a savanna ecological zone characterized by a short rainy season (Akinwumiju et al., 2020). Similarly, cassava's average actual yield gap for the states was $10061 \text{ kg}\cdot\text{ha}^{-1}$, with the highest value ($14465 \text{ kg}\cdot\text{ha}^{-1}$) in Akwa-Ibom State, a region characterized by favourable climatic conditions and well-drained conditions soil (Akinwumiju et al., 2020). Therefore, we suggest that improving crop management through nutrient application and soil water-loss reduction could help to minimize cassava yield gaps. The estimated highest untapped cassava yields (Y_{G_i}) in States (such as Kano, Bauchi, Gombo, and Kebbi) align clearly with a previous study (Akinwumiju et al., 2020). These states are categorized as "suitable" to "very suitable" cultivable areas. Therefore, cassava cultivation would excel adequately; hence profitable cassava production could be successfully undertaken on at least 60 million hectares of land in Nigeria.

The current study's estimated cassava yield gap, based on water limitation (i.e., with optimal fertilization and water as the major growth-limiting factors), was consistent and within the reported yield gaps range reported elsewhere. For example, Adiele et al. (2020) reported reducing the cassava yield gaps by 230% under optimum fertilizer application in Edo, Cross River, and the Benue States in Nigeria. Another study (Fermont et al., 2009) estimated a water-limited cassava yield gap (i.e., closing the yield gaps) by improving the soil fertility in Kenya and Uganda (East Africa) ranged from an average difference of $6700 \text{ kg}\cdot\text{ha}^{-1}$ to a maximum of $7900 \text{ kg}\cdot\text{ha}^{-1}$ concerning the attainable yield.

Our study across 30 states estimated that nutrient management accounts for 55.3% of the total cassava yield gap, while the remaining 44.7% is attributed to water limitation. The highest untapped water-limited yields were estimated in States, such as Bauchi, Gombe, and Sokoto, characterized by the short rainy season, therefore posing

a threat to the widely practised rainfed agriculture in Nigeria (Mbanasor et al., 2015; Ogunrinde et al., 2019). However, farmers could use abundant renewable water resources to compensate for soil moisture deficits, particularly in regions with a short rainy season. This scenario could be achieved by retaining a large percentage of the annual runoff for irrigation purposes during the dry season (Akinwumiju et al., 2020). Thus, cassava production should be targeted by suitable land allocation where viable irrigation infrastructure is available, particularly in the northern part of Nigeria. Moreover, the nutrient-related constraints accounting for >55% of the untapped cassava potential yield demands effective on-farm management and soil fertility enhancement (organic and inorganic fertilizer application), already practiced in some SSA countries (Aliyu et al., 2019; Ezui et al., 2015; Edet et al., 2013). Compared to other SSA countries (such as Niger, Ghana, and Cameroon), increased cassava yield has been attributed to effective on-farm management, fertile land allocation, and fertilizer application, where required (Ezui et al., 2017; Kaweewong et al., 2013; Adjei-Nsiah et al., 2007). Whereas in Nigeria, the reverse is the case. Here, local cassava varieties and nutrient-depleted soils are attributed to its cultivation, and the major cassava production belt lacks the required on-farm management practices. Therefore, access to the irrigation facilities (especially in regions with short rainy seasons, semi-arid regions) and newly improved cassava varieties is imperative to improve the current cassava yield and production fertilizer application.

Our results showed that most northern states are better equipped to become leading cassava producers in Nigeria under adequate crop management practices involving irrigation and soil fertility enhancement. We reached this deduction because the northern states usually receive the highest radiation from their characteristic reduced cloud cover, even at the peak of the rainy season. Another reason is that cassava production cost is lower in the north than in the south, courtesy of available extensive, less competitive expanse of lands that could be made suitable for cassava cultivation. Furthermore, considering the ongoing increasing rainfall trend in northern Nigeria (Animashaun et al., 2020), more locations might gain a suitability advantage for rainfed cassava production with time.

There were some limitations of the current study, highlighting the necessary improvements for further research. Usually, large-scale assessments are confronted with the trade-off between the advantages of a large spatial study coverage (useful for policymaking) (Ewert et al., 2015) and the disadvantage of low spatial accuracy at the farmer's field level. The lack of detailed model calibration at a finer scale is a popular challenge for large-scale crop modeling (Müller et al., 2017) because location-specific environmental and management data are usually challenging to obtain consistently for large regions (Angulo et al., 2013). Because we also used the average yield values of five cassava varieties to estimate the yield gaps for Nigeria, a future study can be structured by interacting with local experts so that well-adapted cultivars specific to each state could be simulated.

Production systems were abstracted at the level of a single crop, ignoring possible interactions within crop rotations. If cropping systems were analyzed instead, crop performance in a given simulation unit would result from its performance in different rotations and under different inputs of resources. We did not consider the effect of certain climatic extremes, such as the impact of intense heat during particular development stages, which may lead to total (cereal) crop failure. To overcome this limitation, small-scale studies that incorporate more detailed information (e.g., on-farming environments, management practices, variety distribution, and the socio-economic context of farmers (especially cassava value chain) could be used. They would complement our assessment to provide more detailed recommendations for specific local areas cases minimizing the gaps in cassava yield.

The current study results have provided vital information on how the cassava yield gap could be closed with many attendant economic benefits and food security in Nigeria. Furthermore, the outcome of this study could better enlighten stakeholders and policymakers in Nigeria on the need to harness renewable resources (such as precipitation) and nutrient management while adopting scientific innovations to optimize the vast expanse of lands currently underutilized, especially in the north.

Table 3. Regression coefficients of multiple linear regression of simulated potential, water-limited, actual yield, and observed yield with different climatic variables Maximum temperature (Tmax), Minimum temperature (Tmin), Radiation (Rad), and Precipitation (Ppt). R^2 represents the variance explained by regression models.

Spatial variability Cassava yield N = 30 states	Tmax (°C)		Tmin (°C)		Rad (MJ/m2)		Ppt (mm)		R^2
	coeff.	p-value	coeff.	p-value	coeff.	p-value	coeff.	p-value	
Observed yield	-491.6	0.17	-592.9	0.21	-0.24	0.01	-1.98	<0.01	0.69
Actual yield (simulated)	-451.6	0.1	-125.8	0.7	-0.16	0.01	-1.49	<0.01	0.76
Water-limited yield (simulated)	-1174.1	0.13	-959.1	0.34	-0.47	0.02	-1.89	0.16	0.84
Potential yield (simulated)	150.3	0.82	-1489.3	0.09	0.35	0.04	0.81	0.48	0.91
Total Yield gap (potential yield - observed yield)	642.0	0.2	-896.4	0.2	0.59	<0.01	2.79	<0.01	0.95
Actual Yield gap (water-limited yield - observed yield)	-682.5	0.2	-366.1	0.6	-0.23	0.11	0.09	0.93	0.83
Water-limited Yield gap (potential yield - water-limited yield)	1324.4	<0.01	-530.3	0.31	0.82	<0.01	2.71	<0.01	0.98

Table 4: Feature importance of simulated potential, water-limited, actual yield, and observed yield with different climatic variables Maximum temperature (Tmax), Minimum temperature (Tmin), Radiation (Rad), and Precipitation (Ppt). The feature importance is computed using random forests algorithm with extreme gradient boosting.

	Tmax	Tmin	Rad	Ppt
Observed yield	699	395	182	114
Actual yield (simulated)	603	393	157	120
Water limited yield (simulated)	724	498	295	86
Potential yield (simulated)	576	416	127	109
Total yield gap (potential yield – observed yield)	475	406	172	99
Actual yield gap (water-limited yield – observed yield)	619	349	225	117
Water limited yield gap (potential yield – water limited yield)	521	386	138	132

5. Conclusion

This study was designed to explore cassava yield potential under potential and water-limited conditions in 30 states of Nigeria. We gathered that the simulated growth and development of cassava conform with the corresponding observed values. Thus, the LINTUL5 model can be successfully used to simulate cassava's growth and yield and determine the effects of temperature, precipitation, and other variables on its yield in 30 states of Nigeria. Furthermore, nutrient limitations were found to be more pronounced than the water limitation on cassava yield gaps in 20 states out of 30 states studied in the current study. Radiation and precipitation are the predominant climatic variables that influence cassava yield. The results are based on linear regression and feature importance values from a nonlinear machine learning based method need to be considered in future. There is a high potential to improve the current cassava yield levels, provided farm interventions are made, emphasizing irrigation schemes in the areas characterized by the short rainy season and on nutrient and soil health management.

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