Big Data and Artificial Intelligence Deployment for Climate-Smart Agriculture Modelling of the Lake Chad Basin.

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Abstract

Lake Chad and its river basins are sources of water and sustainable lively hood of the growing population of the area. The dwindling water resources of the once thriving Lake Chad region has been attributed climate change phenomenon. These has contributed to the conflict in North-Eastern Nigeria and the neighbouring countries of Chad, Cameroon and Niger republic. In this paper, we used Google Earth Engine, a big data application platform with artificial intelligence to model potential rice-growing land areas within the basin and also characterize the land use and climate change dynamics of the area. The study deployed optical Satellite Remote Sensing using the Synthetic Aperture Radar data sets from the European Copernicus program to derive a climate-smart agricultural model for rice production in the study area. Accuracy assessment with field data for both land use, and land cover characterization and the modelled potential land for rice cultivation was 72% and 75% respectively. Modelled potential land for rice cultivation was 92658 square Kilometre (9,265,800 HA) while the calculated yield for rice is 5,618,686 tons.

Key Words: Big Data, Climate Smart Agriculture, Google Earth Engine, Remote sensing.

Introduction

In this era of digitization for climate-smart agricultural productions, Satellite Remote Sensing offers scalable and unbiased technology for predicting paddy rice production areas and yield. Several Satellite Remote Sensing technologies are available with various spatial and temporal resolutions and have been deployed as a support system for agricultural productions. Similarly, agroecological data such as soil, temperature, humidity, and rainfall are now available at different scales, thereby enabling crop habitat and yield modelling. Agricultural Remote Sensing is one of the backbone technologies for climate Smart Agriculture/precision agriculture [1]. The goal of agricultural remote sensing is to generate spatially varied data for Climate Smart Agricultural operations. Remote Sensing application to Climate Smart Agricultural possesses all the characteristics of big data [1-3].

Emerging technologies like geospatial technologies, the Internet of Things (IoT), big data analysis in conjunction with artificial intelligence (AI) could be used to make management decisions that increase crop production. Big data or data science applications in the field of environmental sciences using artificial intelligence is therefore a new field of study that integrates advances in spatial science with Artificial Intelligence (such as deep learning), and data with high-performance computing [4, 5]. The deployment of Artificial Intelligence with Satellite Remote Sensing is transforming precision agriculture across the world through the power of analytical techniques, modelling and accurate predictions of crop suitability, thus increasing the demand for its use and application to climate-smart agriculture. From in situ field data gatherings, acquisition of Satellite Remote Sensing (SRS) images, pre-processing and processing of satellite images, and analysis and modelling for CSA, all these are characteristics of big data applications and are critical to the success of precision agriculture. The availability of biophysical and climate data coupled with the temporal frequency of satellite image collections and delivery, and a myriad of computational tools capable of processing large volumes of big data have enabled the application and deployment of big data to crop suitability mapping [3]. Satellite Remote Sensing data has been used in several research studies to map rice growing areas, and these studies have been conducted in a variety of locations and with great accuracy [5, 6]. For example, [7, 8] used the time series Synthetic Aperture radar to map rice growing areas in Asia with 83% and 85% accuracies. Similarly. [9] deployed Sentinel radar data and Sentinel 2 Multi pectral images to discriminate rice growing areas in Ethiopia with 71% accuracy.

Nigeria has the largest population in sub–Saharan Africa, the majority of which inhabits the Guinea Sahelian region of Northern Nigeria. The continuous population explosions have pressure on the natural resources of the Sahelian region and the country as a whole. Similar occurrences of the pressure on the natural resources are the same for neighbouring countries of Niger, Chad and Cameroon. Climate change vagaries such as drought, and inadequate rainfall characterise the Guinea Sahelian region of the west African region. The Lake Chad, basin and its tributaries are the major natural resource common to the West African countries. The increase in the livelihood of the inhabitants of the basin region through the exploitation of agricultural potentials has been studied by various authors and organisations.

Nigeria's agricultural environment is evolving as a result of increased government initiatives to encourage private sector participation and improve domestic production [10]. Rice is a staple food in Nigeria, consumed across socioeconomic classes and geopolitical zones. Rice consumption is increasing rapidly in Nigeria owing to factors such as increasing population, increase in income levels, rapid Urbanisation, population growth and the shift in consumer preference towards rice consumption [10]. In natural resource accounting, a country’s information on agricultural production is part of the key accounting system for management and policy purposes. As a result, accurate and timely subnational data on rice acreages, seasonality, and yield are crucial for many nations' national accounting processes, but the current system might not be able to meet information needs for food security and policy [8]. It is of increasing importance to develop efficient methods for mapping paddy rice in the Lake Chad basin. This study, therefore, aims to determine the potential paddy rice growing areas in the Lake Chad basin using Satellite Remote Sensing images.

Material and methods

The study area

Lake Chad Basin is located in the Sahelian region of Sub Sahara Africa by the ssouthern edge of the Sahara Desert. Adjudged to be one of the largest sedimentary groundwater basins in Africa extending over an area of about 2,381,000 km^2[11-14]. The Lake Chad basin from the Nigerian side has three major rivers forming the basin, they are Hadeja river; the Jamare River and Ngada river. The Hadeja river rises from the plain of Kano and north-eastwards meeting the Jamare River flowing from the Jos Plateau. Both rivers confluence at the Hadeja wetlands before flowing into the Lake Chad. While the Ngada River, situated in the plain of Borno flows directly into Lake Chad. The three rivers form two main basins for agricultural productions within the Nigerian territory. The rainfall of the basin ranges from 1300 millimetres per year in Jos Plateau to less than 500 millimetres in the northeast of the basin [15, 16].

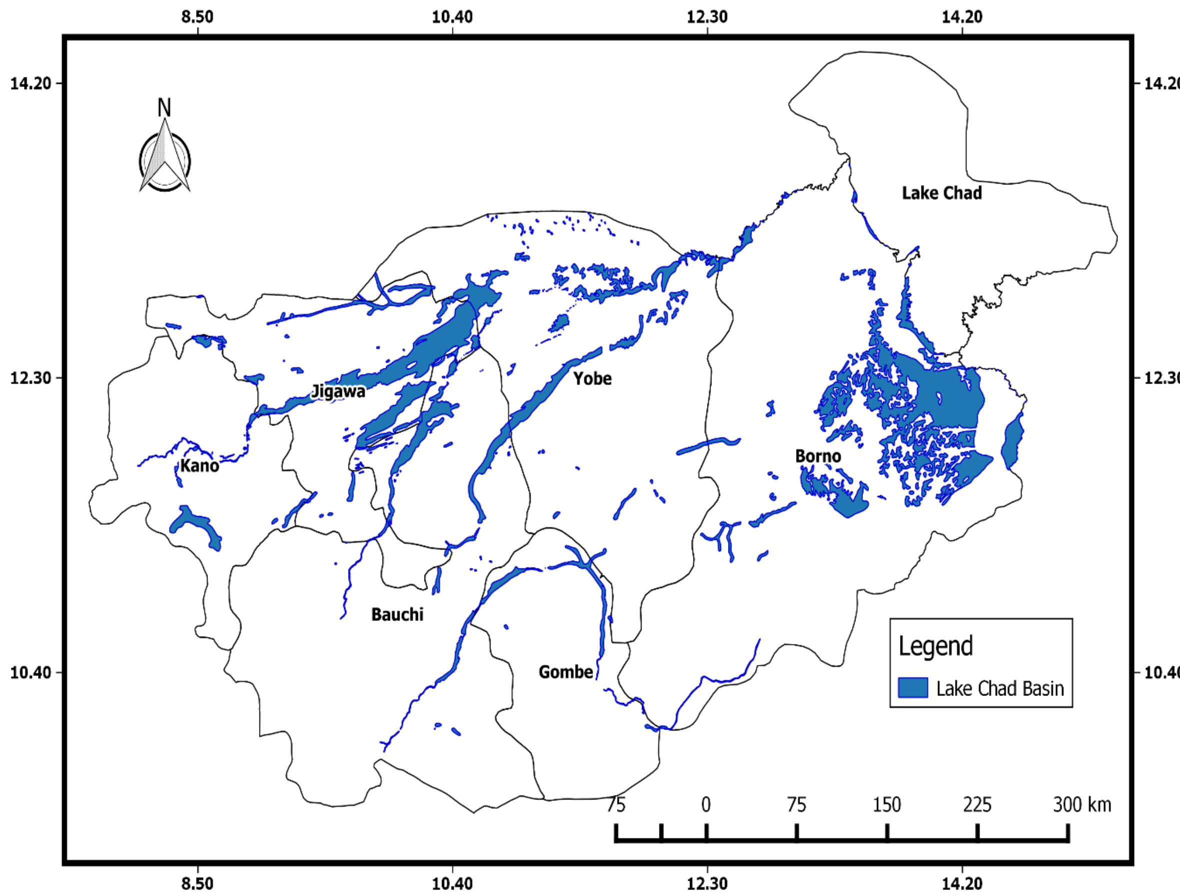

Figure 1: Map of the tributaries of the Lake Chad basin

2.0 Methodology

The methods used in this study are divided into three parts, namely:

2:1 Data collections

Field data on paddy rice farming were collected during the growing seasons of 2019, 2020, and 2021 across the six states of the Lake Chad basin in Nigeria. Data collected were divided into training (70%) and validation (30%) data sets. Both training and validation data were used to train, classify and validate the Sentinel 2A multispectral satellite image in the Google Earth Engine platform.

2:2 Big data and artificial intelligence deployment through the Google Earth Engine platform.

Google Earth Engine (GEE) is the platform for big data deployment for Climate Smart/ Precision Agricultural modelling. GEE is a cloud computing platform for Remote Sensing applications to CSA. As a cloud computing platform, GEE is efficient in storing, accessing, and analysing datasets using powerful servers. The platform provides access to vast arrays of freely available multi-temporal SRS datae, geospatial infrastructures for storage services, and analysis using artificial intelligence and machine packages for big data analysis [17, 18]. Artificial intelligence (AI) methods are a critical enabling technology for automating the interpretation of SRS imageries, therefore the integration of AI methods into GEE represents a promising path toward operationalizing automated RS-based monitoring programs [18, 19].

In this study, the European satellite images, Sentinel-1A Synthetic Aperture Radar (SAR) and Sentinel-2 multispectral sensor (MSI) images were integrated to map the paddy rice field extent of the Lake Chad basin in Google Earth Engine. Sentinel-2A MSI with a spatial resolution of 10 m has 13 bands, with four bands (blue, green, red and NIR). The Sentinel 1-A images used were acquired in the Interferometric Wide Swath (IW) imaging mode with the VV and VH polarizations. A random forest algorithm was applied to identify the optimal node for discriminating rice field and other Land Use Land Covers. The map from the Sentinel-1A image was integrated with Sentinel-2A image products (Normalized Difference Vegetation Index (NDVI) to improve the classification accuracy. Figure 2 below detailing the workflow for the rice modelling with satellite remote sensing in Google Earth Engine with JavaScript.

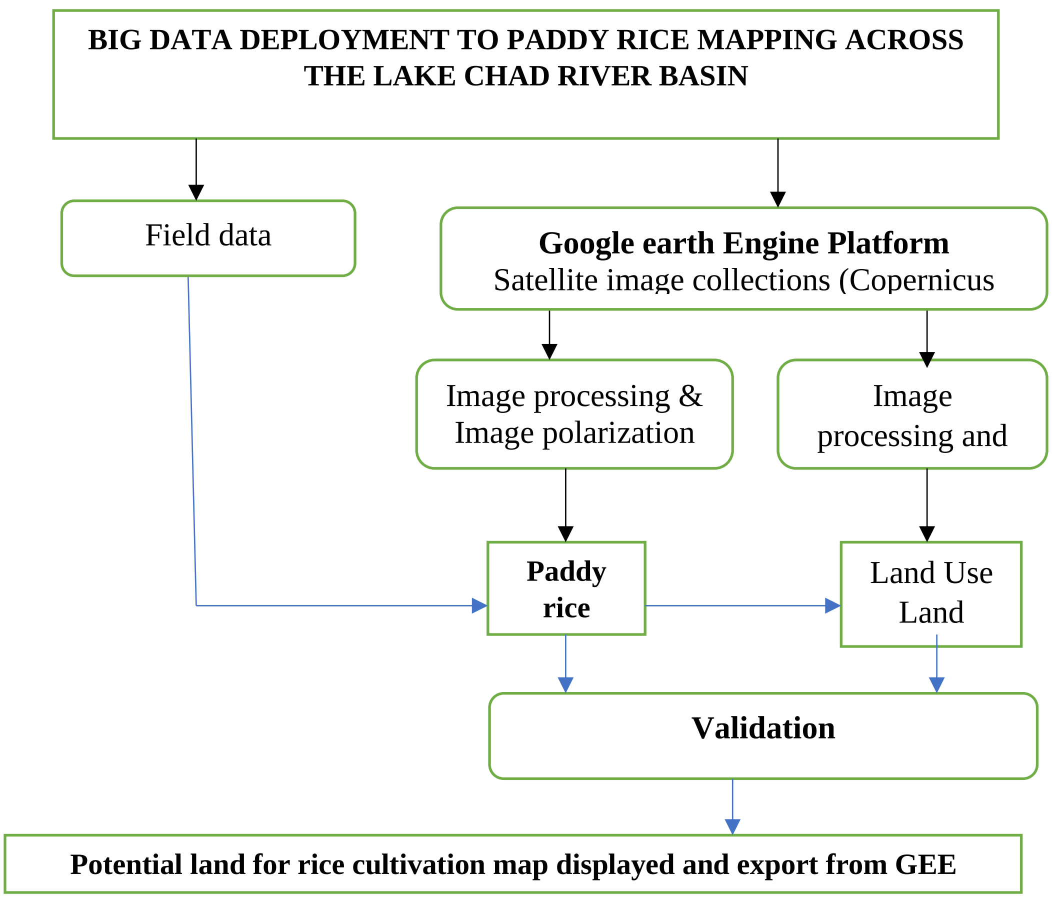

Figure 2: Overview of the pathway to modelling Paddy rice areas with satellite remote sensing in the lake Chad basin.

Results

Accuracy assessment with field data for both land use, and land cover characterization and the modelled potential land for rice cultivation was 80% for rice and 79% for other land classes respectively. Overall accuracies, producer accuracy and kappa coefficient were significantly high (Table:1). Modelled potential land for rice cultivation was 92658 square Kilometre (9,265,800 HA) while the calculated yield for rice is 5,618,686 tons (Table 2).

Table :1. Accuracy assessment of the classified map

	Rice	Other land uses	Total	User accuracy
Rice	3120	325	3455	80.5%
Other land uses	47	6475	6522	79.2%
Total	3167	6800	9967	
Producer accuracy	89.50%	85.2	86.30%	
Overall accuracy			81.50%	
Kappa			84.30%	

Th areas mapped for rice productions for eacg of the basin states as shown in table 2. Modelled potential land for rice cultivation was 92658 square Kilometre (9,265,800 HA) while the calculated yield for rice is 5,618,686 tons.

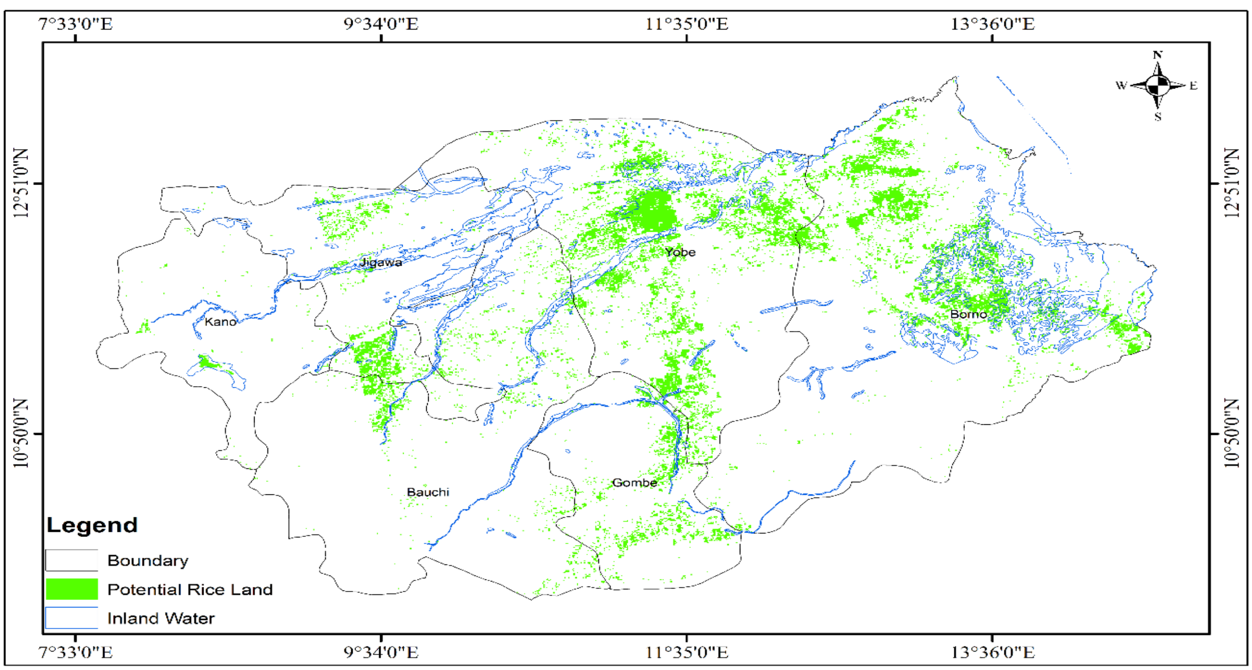

Figure 3: Modelled rice production areas in the seven states of the Lake Chad Basins

Table 2: Potential rice production areas and estimated yield

SN	State	Total land mass	Modelled and validated areas for rice productions	Potential Rice production estimates
1	Bauchi	45,965	6,895	489,545
2	Borno	70,898	10,634	755,014
3	Jigawa	23,154	6,946	493,166
4	Gombe	52,142	4,894	347,474
5	Kano	499,062	38,888	2,761,048
6	Yobe	45,502	15,102	107,210
		Total	92,658	5,613,686

Monitoring Rice Pheneology with Satellite Remote Sensing Spectral Variables

The characteristic of NDVI derived from SRS for assessing the agricultural practices (planting, growth and harvesting period) of rice were analyzed in the study areas. Also, the effectiveness of the NDVI in assessing soil surface statuses during transition periods in relation to the flooding regime was of special interest. The results obtained indicate the occurrence of two annual cycles for rice planting and harvesting in the study area. The rain feed the rice planting season and the flood plain rice planting regime. The ooccurrence of two intra-annual cycles is an indication of the existence of two planting seasons in the study area (Figure 4).

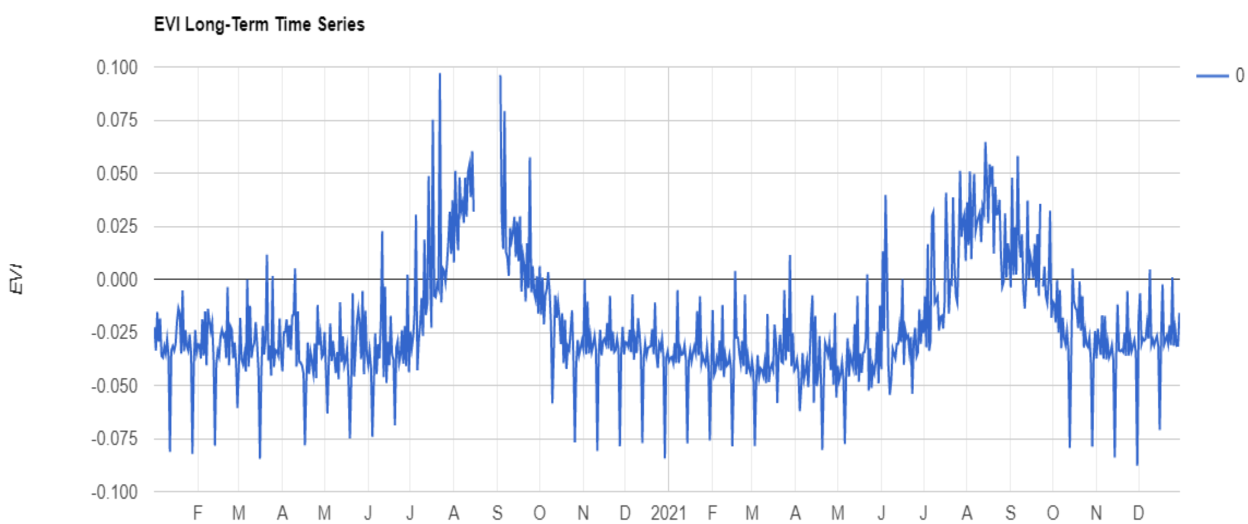

Figure 4: Time Series of Rice Cultivation with EVI

Relationship between Satellite Remote Sensing (SRS) derived spectral indices for rice and other essential variables associated with rice cultivation.

The Normalised Vegetation Indices a satellite remote Sensing spectral indices associated with plant vigour were used as surrogate variables for rice field training data while precipitation and soil components (i:e, soil organic carbon, Soil Bulk density, soil Nitrogen, soil PH and soil carrying capacities) are the basic components required for agricultural productivity. The variables were extracted from Google Earth Engine platforms. The relationships between NDVI and other variables were determined with the aid of a correlation matrix. Results from the correlation matrix indicated a range of positive relationships between NDVI and the soil variables (Figure 5).

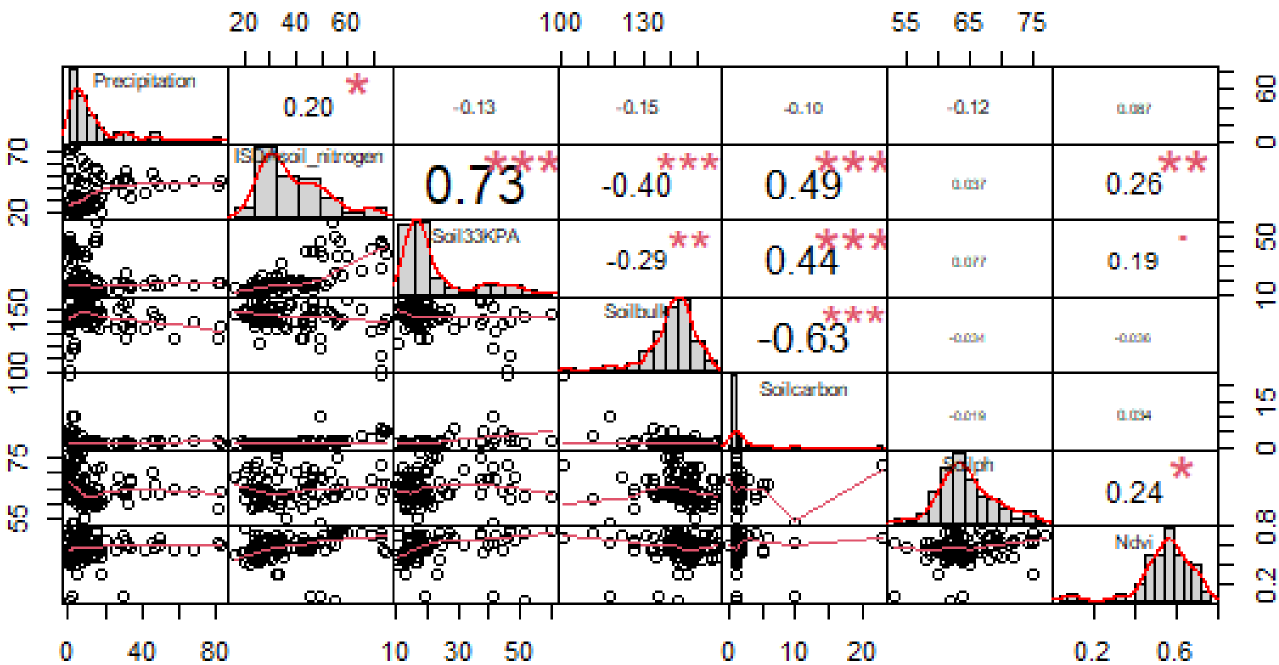

Figure 5: Correlation matrix between NDVI, Precipitation and soil variables.

Discussions and conclusions

By 2050, it is predicted that food production will need to expand by 60–100% to be able to supply the nutritional needs of a population of 9–10 billion people [3]. One of the major ways to achieve this is through the use of AI and Satellite Remote Sensing (SRS) for Climate Smart Agricultural productions. The deployment of Satellite Remote Sensing with other ancillary data has the potential to predict/ determine suitable areas for agricultural production, monitor crop health and forecast yield. Rice has become one of Nigeria's staple foods, although domestic production is low due to subpar technical efficiency, and as a result Nigeria has to resort rice importations to balance for the shortage in local production [10, 20]. Thus making Nigeria the largest importer of rice in Sub-Saharan Africa. Self-sufficiency in rice production has been made a priority policy to minimize importation. The Hadeja-Jamare wetland become the hub of rice production in the region. There are however other areas within the basin that has similar environmental factors for supporting rice production.

Big data and artificial intelligence applications to all area of human endeavour (Agriculture inclusive) have become an essential component of mankind. While its application has been fully integrated into Climate Smart Agriculture in the developed world, the developing world are still lagging in the deployment of Artificial Intelligence to Climate Smart Agriculture. It is imperative therefore to fully integrate big data and AI into the Sub-Saharan Climate Smart strategy to enhance food security.

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