remote sensing

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Review

Monitoring and Analyzing Yield Gap in Africa through Soil Attribute Best Management Using Remote Sensing Approaches: A Review

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Abstract: Africa has the largest population growth rate in the world and an agricultural system characterized by the predominance of smallholder farmers. Improving food security in Africa will require a good understanding of farming systems yields as well as reducing yield gaps (i.e., the difference between potential yield and actual farmer yield). To this end, crop yield gap practices in African countries need to be understood to fill this gap while decreasing the environmental impacts of agricultural systems. For instance, the variability of yields has been demonstrated to be strongly controlled by soil fertilizer use, irrigation management, soil attribute, and the climate. Consequently, the quantitative assessment and mapping information of soil attributes such as nitrogen (N), phosphorus (P), potassium (K), soil organic carbon (SOC), moisture content (MC), and soil texture (i.e., clay, sand and silt contents) on the ground are essential to potentially reducing the yield gap. However, to assess, measure, and monitor these soil yield-related parameters in the field, there is a need for rapid, accurate, and inexpensive methods. Recent advances in remote sensing technologies and high computational performances offer a unique opportunity to implement cost-effective spatiotemporal methods for estimating crop yield with important levels of scalability. However, researchers and scientists in Africa are not taking advantage of the opportunity of increasingly available geospatial remote sensing technologies and data for yield studies. The objectives of this report are to (i) conduct a review of scientific literature on the current status of African yield gap analysis research and their variation in regard to soil properties management by using remote sensing techniques; (ii) review and describe optimal yield practices in Africa; and (iii) identify gaps and limitations to higher yields in African smallholder farms and propose possible improvements. Our literature reviewed 80 publications and covered a period of 22 years (1998-2020) over many selected African countries with a potential yield improvement. Our results found that (i) the number of agriculture yield-focused remote sensing studies has gradually increased, with the largest proportion of studies published during the last 15 years; (ii) most studies were conducted exclusively using multispectral Landsat and Sentinel sensors; and (iii) over the past decade, hyperspectral imagery has contributed to a better understanding of yield gap analysis compared to multispectral imagery; (iv) soil nutrients (i.e., NPK) are not the main factor influencing the studied crop productivity in Africa, whereas clay, SOC, and soil pH were the most examined soil properties in prior papers.

Keywords: actual yield; agriculture; data analysis; hyperspectral; multispectral; potential yield

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1. Introduction

Agriculture faces the issue of satisfying growing global food demands by increasing global food production as the world's population grows [1]. Increasing productivity in existing agricultural areas appears to be a viable strategy for meeting current and future food security challenges. This is of even greater importance in Africa, where the agricultural system needs to feed one of the world's highest increasing rates of population, and which is characterized by the predominance of smallholder farmers [2,3]. Furthermore, yields in smallholder cropland systems (i.e., farms covering an area of 1 to 2 ha [4]) are frequently influenced by a variety of interacting and complex factors such as fertilizer application, irrigation management, soil attribute, and climate [5], which can have a significant impact on yield variation. Other factors such as pathogens and weeds can also negatively affect the agricultural productivity and therefore, the yield [6]. To this end, these smallholder agricultural systems are known to be dominant in most African countries, where yields fall short of their potential for ensuring food security.

An important strategy for overcoming the food security challenge is bridging the yield gap [7], especially in developing countries [8]. The yield gap is the difference (i.e., gap) between the actual yield currently being generated by farmers and that which can be achieved (or potential yield) by using the best agronomy practices [7,9]. This can help in the prediction of future crop results for various regions, as well as the identification of factors that contribute to the gap [10]. Overall, there are three levels of yield gap in the literature commonly referred to as yield gap level zero, yield gap level one, and yield gap level three, as described in the methodology section. Most of the research on yield gap analysis has been done on developed countries, whereas yield gap studies on African crops are relatively limited. In most African countries, where agriculture data are frequently incorrect or unavailable at acceptable resolutions (i.e., smallholder family farms), yield gap analyses studies can be inaccurate, particularly where agricultural terrains show a high variability and complexity in terms of croplands and soil properties. Under such conditions, more detailed information about yield gaps is necessary to fully inform research prioritization and investment strategies in Africa countries. Conventional methods available for assessing yield in the field are expensive, time-consuming, and require intensive sampling to characterize spatial variability. More importantly, a geospatially explicit assessment of exploitable gaps is required for the major African food crops.

Given the need for valuable methods to assist with identifying regions with the greatest potential to increase food supply in Africa through yield gap minimization, remote sensing techniques have shown to be particularly valuable in monitoring and analyzing crop yields in recent decades, owing to their ability to process spatial data at large scales and provide outputs that can be modeled [11]. Remote sensing has great potential for improving our understanding of agricultural systems at different scales and analyzing yield gaps. Recent advancements in remote sensing technologies (e.g., hyperspectral, multispectral sensors on drones, and miniature satellites (e.g., Cubesat) have provided a unique opportunity to observe African smallholder systems at high spatiotemporal resolutions [12], allowing for a better assessment of crop yield gaps in those regions. Moreover, a quantitative assessment and mapping of key soil and crop properties such as NPK using remote sensing data turns out to be highly important in reducing yield gap [10]. In addition to NPK, other key soil and crop factors that can affect yield gap are properties related to the soil's reaction, air–water properties, texture, biological activities, organic carbon, and salinity, especially in arid and semi-arid areas. Many studies have focused almost entirely on the assessment of crops' N uptake using remote sensing, assuming the major effect it has on crop biomass and yield, through the identification of the sensitivity of spectral indices [13] or the variation of spectral reflectance to its content in the crop at specific NIR regions of the spectrum [14]. Other studies investigated similar hypotheses with respect to P [15] and K [16]. Recent studies [17] have also worked on scaling the digital soil mapping workflow in Africa using a combination of a legacy regional soil sampling database and a stack of satellite imagery mosaics (i.e., Landsat, Sentinel 2). These studies also derived remote sensing products (i.e., digital terrain model (DTM) derivatives, MODIS climactic products) to make the predictors of a supervised ensemble machine learning (ML) model that aims to quantify a wide variety of soil properties, including the physical (i.e., SOC, soil moisture content (MC), clay, sand, and silt contents) and chemical properties (i.e., NPK) of Africa [18].

During the last 15 years, most yield studies on Africa were conducted exclusively using multispectral imagery (i.e., Landsat and Sentinel), whereas over the past decade, hyperspectral imagery has contributed to a better understanding of yield gap analysis compared to multispectral imagery. To this end, hyperspectral imagery has allowed us to obtain the image of a scene with several spectral bands. For instance, the Hyperspectral Precursor of the Application Mission (PRISMA) has a large number of narrow bands (i.e., 250 bands) that can allow a greater yield gap analysis compared to multispectral imagery, which has fewer spectral bands [19]. In this paper, we conducted a systematic review to assess the current status of African yield gap analysis research and their variation depending on soil properties management using remote sensing techniques between 1998 and 2020.

2. Overview of Yield Gap Analysis Techniques

2.1. Remote Sensing

Remote sensing approaches to estimate crop yield are based on three techniques [20]:

(1) Biomass production and partitioning [21]. In Africa, to our knowledge, there is no publication that has dealt with this first approach, but several studies have been conducted in other non-African countries, for instance, in Mexico [22] and in the Sirsa District of India [23]. (2) Integration of remotely sensed data and crop growth models where crop simulation models can be coupled with satellite measurements. In Ethiopia, Beyene et al. [24] found that integrating MODIS-LAI into WOFOST (i.e., World Food Studies; a simulation model of crop production model [25]) was useful for estimating wheat yields. (3) Empirical models relating to spectral vegetation indices and yield. For instance, the Green Chlorophyll Vegetation Index (i.e., GCVI) was used in a recent study [26] to map corn yield in smallholder farms in Kenya. Other studies employed empirical regression models to assess wheat yield in Tunisia [27]. The authors of this study [27] found that red-edge-based vegetation indices extracted from Sentinel 2 bands have the best correlation with wheat yield data when compared to the widely utilized Normalized Difference Vegetation Index (i.e., NDVI). Another study conducted in Kenya [26] found that maize yield predictions made with the MERIS Terrestrial Chlorophyll Index (i.e., MTCI [28]), which included the red edge band available in RapidEye and Sentinel-2, were superior to those made with other commonly used vegetation indices such as NDVI [29], Enhanced Vegetation Index (EVI) [30], and Wide Dynamic Range Vegetation Index (WDRVI, [31]).

2.2. Modeling

Modeling is another widely technique used for crop yield estimate. Modeling can range from simple climate indices such as Fischer's photothermal coefficient to intermediate models such as AquaCrop and the more complex CERES-type models. For instance, a study was conducted recently in Tanzania [32] that used the Agricultural Production Systems Simulator (i.e., APSIM) model to estimate the yield gap and investigate its variations in rice culture in the Kilombero floodplains region. Here, three yield levels were measured: (i) current yield, (ii) yield with the most recommended management (i.e., attainable yield), and (iii) potential yield. The authors of [32] found that adapted farm management was able to close between 25% and 80% of the exploitable yield gap and concluded that farmers may be unable to close the exploitable yield gap due to variables other than nitrogen fertilizer management. In another study, Tittonel et al. [33] worked on maize culture, predicting maize yields from soil chemical indices using a computer model named the Quantitative Evaluation of the Fertility of Tropical Soils (i.e., QUEFTS). The QUEFTS model is a simple and reliable method that requires little data and was used to assess fertilizer requirements in the tropics [34,35]. The QUEFTS has been calibrated to estimate tropical maize fertilizer requirements and grain output in Kenya [36]. There was no significant correlation between farmers' actual yields and the QUEFTS predictions in the study, indicating that soil nutrients were not the main factor influencing maize yields in the research area. Other yield-reducing factors (i.e., climate and management) that were not taken into consideration by the QUEFTS model could have played a significant role.

2.3. Boundary Functions

Boundary function is another technique that can be used to estimate crop yield. It was first introduced by Webb [37] to evaluate this limiting effect in biophysical systems. The boundary function is based on actual yield comparisons, rather than a single yield benchmark. The attainable yield is stated as a function of one or a few environmental factors, such as actual evapotranspiration. Crop yields can be limited by one or more factors (e.g., water and fertilizer availability) which can be responsible for creating the yield gap. Webb [37] proposed that the boundary indicated the achene number's limiting effect on strawberry weight, and that the measurements lying below the boundary were limited by other factors, such as a water deficit. Since then, the boundary line has become a widely used model for restricting reactions in biological data, with various applications in Africa. Fermont et al. [38] benchmarked cassava production in Uganda and western Kenya in 2009 and found that the discrepancy between actual and attainable yield was due to management and environmental factors. The impact of abiotic, biotic, and related crop management restrictions for cassava production in smallholder farms in the region was assessed using boundary line analysis. When fertilizer was applied, no functional correlations (i.e., boundary lines) could be deduced; however, boundary lines could be recognized under unfertilized circumstances that indicated increased yields with increasing SOC, accessible P, and exchangeable K.

2.4. Studies Combining Remote Sensing-Based Soil Properties Mapping and Advanced Modeling Approaches for Yield Gap Estimation

Accurate and detailed spatial soil information is essential for conducting yield gap analysis. In Africa, where land degradation and a loss in soil fertility have been reported by numerous studies [39,40], such spatial remote sensing-based information is increasingly required by farmers in order to improve land management and thereby reducing yield gap. To this end, many remote sensing-based mapping and advanced machine learning modeling approaches (i.e., multiple linear regression (MLR), random forest regression (RFR) [41] and support vector machine (SVM) [42]) have been used for yield gap estimation.

3. Methodology

In this study we conducted a systematic review, which entails creating a synthesis of the findings of existing original studies. To do so, the Scopus database was used to conduct an online bibliographic search. Papers published between 1998 and 2020 were screened. This 22-year period was used to better understand the evolution of studies with the contribution of remote sensing datasets in characterizing soil properties, as well as the effect of the variation of these soil attributes on yield gap.

The following query strings were used in order to do the search:

i. (TITLE-ABS-KEY ("yield gap") AND TITLE-ABS-KEY (country) AND TITLE-ABS-KEY (yield OR field OR scale OR production OR approach)).

ii. (TITLE-ABS-KEY ("yield gap") AND TITLE-ABS-KEY ("soil properties" OR "soil attributes" OR calcium OR potassium OR ph OR clay OR silt OR sand OR "soil organic carbon" OR " soil texture" OR nutrient* OR cec) AND TITLE-ABS-KEY (yield OR field OR scale OR production OR approach) AND TITLE-ABS-KEY (Ghana));

iii. (TITLE-ABS-KEY (landsat) AND TITLE-ABS-KEY (Morocco OR Senegal OR Tunisia OR "Cote d'Ivoire" OR Kenya OR "South Africa" OR Ethiopia OR Cameroon OR "Burkina Faso" OR Rwanda OR Ghana OR Tanzania) AND TITLE ("soil properties" OR "soil attributes" OR calcium OR potassium OR ph OR clay OR silt OR sand OR "soil organic carbon" OR " soil texture" OR nutrient* OR cec OR production OR yield) AND NOT TITLE-ABS-KEY (erosion) AND NOT TITLE-ABS-KEY (alteration)

AND NOT TITLE-ABS-KEY (moisture) AND NOT TITLE-ABS-KEY (degradation) AND NOT TITLE-ABS-KEY (dune*)).

The first search key was used to find all the documents that relate to yield gap in each selected African country ([i.e., TITLE-ABS-KEY (country)]). To refine our search, we added another box that presents other keywords such as field, scale, and production. The second search key aimed to identify papers that link the yield gap with soil attributes and help us to better understand how variation in these soil attributes can affect production and therefore the yield gap. The third search key was remote sensing included in the study to find the primary craft used for the assessment.

The chosen research was based on the following set of search criteria: (i) they had to be relevant to the topic of the synthetic review; (ii) the papers had to be published in peer-reviewed publications; (iii) the papers had to be published during the selected time period (i.e., 1998–2020) We discarded a large number of studies that did not suit the field of study, as well as remote sensing publications that did not directly address quantifying and mapping yield and soil properties. For the purpose of this study, 15 African countries were selected (Figure 1). These countries included Morocco, Senegal, Tunisia, Ivory Coast, Kenya, South Africa, Ethiopia, Cameroon, Burkina Faso, Tanzania, Rwanda, and Ghana. These African countries (Table 1) were chosen because of the availability of studies specifically designed to answer the study objectives and their potential agricultural yield improvement. To verify the Scopus search and see whether any relevant publications were missing, we used the following word combinations in Google Scholar and ScienceDirect: "yield gap," "soil attributes," and "remote sensing."

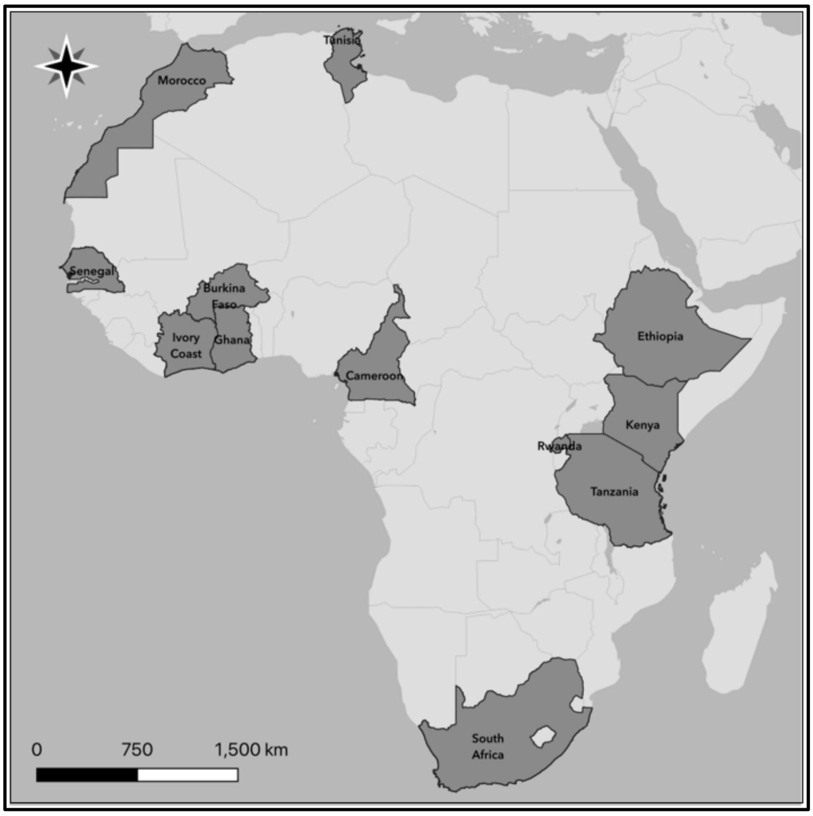

Figure 1. Map showing the 13 African countries investigated (dark grey color) in this study.

Table 1. The table shows the climate of 13 African countries, along with the main crop, average yield, and the percentage of agricultural land related to the country's total area.

Country	Climate *	Main Climate Classification Code ‡	Main Crop **	Average Yield (t/ha)	Agricultural Land % †
Morocco	Temperate, Arid, Cold	Csa, BWh, BSh, BWk, Dsb	Bread wheat	2.3	67
Senegal	Arid, Tropical	BWh, BSh, Aw	Groundnuts	0.8	23
Tunisia	Temperate, Arid	Csa, BSk, BSh, BWh	Durum wheat	3.9	38
Ivory Coast	Tropical	AW	Yams	6	20.5
South Africa	Arid, Temperate	BSh, BSk, BWh, BWk, Cwb	Maize	2.5	79
Ethiopia	Arid, Tropical	BWh, BSh, Aw	Maize	4	34
Kenya	Arid, Tropical	BWh, BSh, Aw	Maize	2	8
Burkina Faso	Arid, Tropical	BWh, BSh, Aw	Sorghum	1	16
Tanzania	Arid, Tropical	BSh, Aw	Maize	1.6	39
Ghana	Tropical	Aw	Cassava	19	62
Rwanda	Tropical, Arid	Aw, BSk	Cassava	20	69
Cameroon	Arid, Tropical	BWh, BSh, Aw, Am	Cassava	15	21

* According to the classification in Beck et al. [43]. † Agricultural land % in 2018 according to the world bank. ** Crop scientific names: Bread wheat = *Triticum aestivum* L.; Groundnuts: *Arachis hypogaea*; Durum wheat = *Triticum turgidum* L. *subsp. Durum (Desf.)*; Yams = *Amorphophallus paeoniifolius*; Maize = *Zea mays* L.; Sorghum = *Sorghum bicolor*; Cassava = *Manihot esculenta*. ‡ After Köppen–Geiger's classification presented in Beck et al.'s Table 2 [43].

It is important to note that our literature review was based on the definition of yield gap indicated earlier in the introduction section and which is summarized in Figure 2. Overall, there are three degrees of yield gap in the literature: Yield Gap 0 (Yg_0), Yield Gap 1 (Yg_1), and Yield Gap 2 (Yg_2) [10,44], as indicated and described in the methodology. To understand each level of yield gap, we had to first define the different variables involved in the definition of these concepts: (i) potential yield (Y_p) is the yield of an adapted crop variety or hybrid when grown under favorable conditions without growth limitations from water and nutrients. The main factors that can impact factors are Y_p, available CO_2, radiation, temperature, and cultivar features; (ii) we refer to potential yield under rain-fed conditions as water-limited yield potential (Y_w); and (iii) attainable yield (Y_{att}) is limited by water and nutrients; and unlike the potential yield, it can be influenced by soil conditions such as texture and topography; and (iv) actual yield (Y_a), which refers to the yield that can be achieved by the farmer under specific management conditions, taking into account the climate and the sustainable use of water.

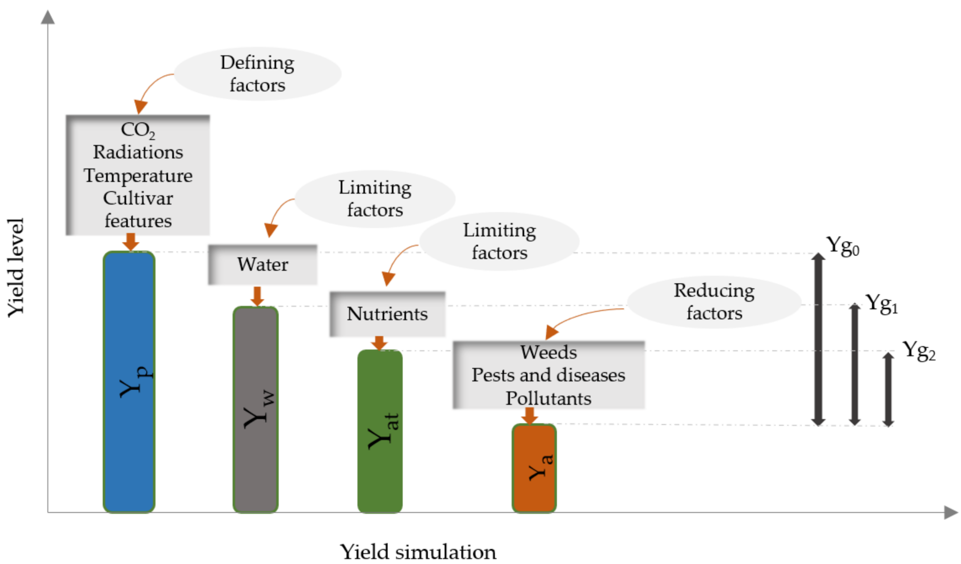

Figure 2. Different production levels yield gap as determined by growth defining, limiting, and reducing factors.

4. Results

In this study, we used 102 papers that highlighted the importance of estimating and analyzing the yield gap as well as the importance of remote sensing as a central technique in monitoring and evaluating crop yields. The number of publications as a function of the date of their publication and countries are shown in Figure 3 and Tables 2 and 3.

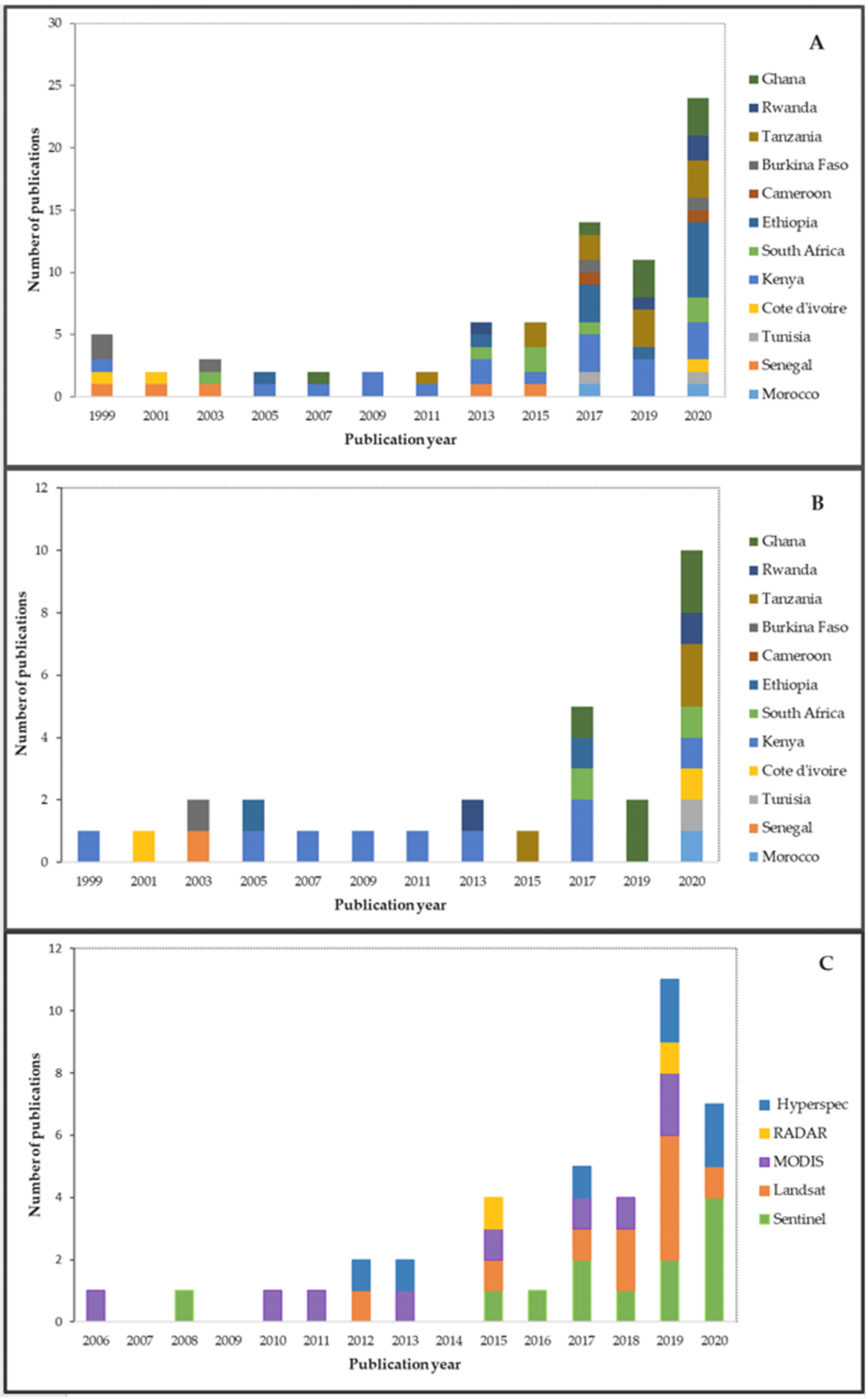

Figure 3. Stacked bar charts show the number of annual publications between 1998 and 2020 in Africa in the Scopus database that have: (**A**) "Yield gap" in their title, abstract, or keywords; (**B**) "Yield gap" and "at least one soil property" in their title, abstract, or keywords. (**C**) The primary platform or sensors used for the yield gap assessment.

Table 2. Summary of papers used in the study for each of the 13 selected countries, sorted by publication year.

Country	Studied Crops	Publication Year	Publication Topic	Reference
Burkina Faso	Sorghum	1999	Effects of soil surface crust on the grain yield of Sorghum in the Sahel	[45]
Ivory Coast	Rice	2001	Cropping intensity effects on upland rice yield and sustainability in West Africa	[46]
Senegal	Rice	2003	Determinants of irrigated rice yield in the Senegal River valley	[47]
Ethiopia	Multiple Crops (MC)	2005	Effects of different methods of land preparation on runoff, soil and nutrient losses	[48]
Senegal	MC	2006	Evaluation of satellitebased primary production modelling in the semi-arid Sahel	[49]
Rwanda	MC	2006	Environmental assessment tools for multi-scale land resources information systems: A case study of Rwanda	[50]
Kenya	Maize	2008	Yield gaps, nutrient use efficiencies and response to fertilizers by maize across heterogeneous smallholder farms of western Kenya	[33]
Kenya	Cassava	2009	Closing the cassava yield gap: An analysis from smallholder farms in East Africa	[38]
Kenya	Banana	2011	Production gradients in smallholder banana (cv. Giant Cavendish) farms in Central Kenya	[51]
Morocco	Cereal	2012	Representing major soil variability at regional scale by constrained Latin Hypercube Sampling of remote sensing data	[52]
Senegal	Vegetables	2012	Sensitivity analysis of the GEMS soil organic carbon model to land cover land use classification uncertainties under different climate scenarios in Senegal	[53]
Sub-Saharan Africa	MC	2012	Determinants of yield differences in small-scale food crop farming systems in Cameroon	[54]
Kenya	Maize	2013	Maize productivity and nutrient use efficiency in Western Kenya as affected by soil type and crop management	[55]
Kenya	Sugarcane	2013	Forecasting regional sugarcane yield based on time integral and spatial aggregation of MODIS NDVI	[56]
Rwanda	Maize	2014	Resource use and food self-sufficiency at farm scale within two agro-ecological zones of Rwanda	[57]
Cameroon	MC	2014	Crop yield gaps in Cameroon	[58]
Cameroon	MC	2014	Explaining low yields and low food production in Cameroon: A farmers' perspective	[59]

Table 2. *Cont.*

Country	Studied Crops	Publication Year	Publication Topic	Reference
Ethiopia	Cereal	2015	Evaluating a satellite-based seasonal evapotranspiration product and identifying its relationship with other satellite-derived products and crop yield: A case study for Ethiopia	[60]
Tanzania	Maize	2015	Agronomic survey to assess crop yield, controlling factors and management implications: a case-study of Babati in northern Tanzania	[61]
Tanzania	Maize	2015	Modeling potential rain-fed maize productivity and yield gaps in the Wami River sub-basin, Tanzania	[62]
Burkina Faso	Wheat	2016	Soil variability and crop yield gaps in two village landscapes of Burkina Faso	[63]
Sub-Saharan Africa	MC	2016	Closing system-wide yield gaps to increase food production and mitigate GHGs among mixed crop-livestock smallholders in Sub-Saharan Africa	[64]
South Africa	Potato	2016	Resource use efficiencies as indicators of ecological sustainability in potato production: A South African case study	[65]
Ethiopia	Cereal	2016	Yield gaps and resource use across farming zones in the central rift valley of Ethiopia	[66]
Southa Africa	Wheat	2017	Soil fertility constraints and yield gaps of irrigation wheat in South Africa	[67]
Kenya	Maize	2017	Occurrence of poorly responsive soils in western Kenya and associated nutrient imbalances in maize (Zea mays L.)	[68]
South Africa	Wheat	2017	Forecasting winter wheat yields using MODIS NDVI data for the Central Free State region	[69]
Tanzania	Rice	2017	Importance of basic cultivation techniques to increase irrigated rice yields in Tanzania	[70]
Tanzania	Maize	2017	Disentangling agronomic and economic yield gaps: An integrated framework and application	[71]
Tanzania	Rice	2018	Increasing paddy yields and improving farm management: results from participatory experiments with good agricultural practices (GAP) in Tanzania	[72]
Burkina Faso	MC	2018	The economic potential of residue management and fertilizer use to address climate change impacts on mixed smallholder farmers in Burkina Faso	[73]

Table 2. *Cont.*

Country	Studied Crops	Publication Year	Publication Topic	Reference
West Africa	MC	2018	Assessing cropland area in West Africa for agricultural yield analysis	[74]
East Africa	Legume	2018	Prospect for increasing grain legume crop production in East Africa	[75]
East Africa	Maize	2019	Soil data importance in guiding maize intensification and yield gap estimations in East Africa	[76]
Rwanda	Wheat	2019	How to increase the productivity and profitability of smallholder rainfed wheat in the Eastern African highlands? Northern Rwanda as a case study	[77]
Tunisia	Wheat	2019	How far can the uncertainty on a Digital Soil Map be known? A numerical experiment using pseudo values of clay content obtained from Vis-SWIR hyperspectral imagery	[78]
Tanzania	Maize	2019	Is There Such a Thing as Sustainable Agricultural Intensification in Smallholder-Based Farming in Sub-Saharan Africa? Understanding yield differences in relation to gender in Malawi, Tanzania and Zambia	[79]
Rwanda	Maize	2020	Determining and managing maize yield gaps in Rwanda	[80]
Ghana	Cocoa	2020	Variations in yield gaps of smallholder cocoa systems and the main determining factors along a climate gradient in Ghana	[81]
Tanzania	Rice	2020	Rice yield gaps in smallholder systems of the kilombero floodplain in Tanzania	[32]
Tanzania	Maize	2020	Unlocking maize crop productivity through improved management practices in northern Tanzania	[82]
Morocco	Wheat	2020	Explaining yield and gross margin gaps for sustainable intensification of the wheat-based systems in a Mediterranean climate	[83]
Kenya	Maize	2020	Soil and management-related factors contributing to maize yield gaps in western Kenya	[84]
South Africa	Potato	2020	Exploring Variability in Resource Use Efficiencies Among Smallholder Potato Growers in South Africa	[85]
Sub-Saharan Africa	Rice	2020	Decomposing rice yield gaps into efficiency, resource and technology yield gaps in sub-Saharan Africa	[86]
E and S Africa	Rice	2020	Quantifying rice yield gaps and their causes in Eastern and Southern Africa	[87]

MC: multiple crops refers to two or more crops among the following: i.e., potato, cassava, maize; sweet potato, bean, soybean, rice, groundnut, sorghum, cowpea, millet, banana, Colocasia, pea, tef, lentil, and chickpea.

As shown in Figure 3A, Kenya had the largest number of yield gap studies published between 1998 and 2020, with 27 papers, followed by Cote d'Ivoire with a total of 21 papers, and then by Burkina Faso and Ghana, both with 10 publications each. Tunisia had the lowest number of publications, with only 2 in 2017 and 2020. Overall, there has been a significant increase in the number of papers in the last five years (i.e., 2016 to 2020), with a total of 62 papers compared to a total of 80 items in a period of 22 years. Figure 3B shows that the number of papers decreased from 80 to 30 during the same period. This decrease can be explained by narrowing the topic of study, as we have focused our research on the physical and chemical properties of soil, which are considered as key determinants in yield variation. The number of published papers did not remain constant through time, with a considerable increase in 2020 (i.e., 10 papers published).

In terms of remote sensing imagery, (i) MODIS was the first sensor used for yield gap (Figure 3C), although it has a limited spatial resolution (i.e., 250 m); and (ii) about 55% of the conducted research studies during the last 22-year period used multispectral Landsat and Sentinel datasets (Figure 3C). However, only few studies used hyperspectral, LiDAR, and RADAR sensors between 2015 and 2020. These multispectral and hyperspectral studies made it possible to estimate yield of crops in the African continent using remote sensing. The main investigated crops using remote sensing datasets were corn and wheat. Other studies aimed to estimate the physicochemical properties of soil affecting yield such SOC and clay, which are the most studied soil attributes in Africa. To our knowledge, no papers were published between 1998 and 2005, and the first studies were published in 2006.

In term of the crops investigated with regard to yield gap (Table 2), maize was the most studied crop, with five publications, followed by other crops, such as banana and cassava, with one paper each (Figure 4). Overall, between 1998 and 2020, cereals were the most important crop investigated on a continental scale, with maize as the most important crop, followed by wheat and rice (Figure 4). The remaining cultures were researched in relation to the major culture of each country: i.e., cocoa in Ivory Coast, cassava in Kenya, and palm oil in Ghana.

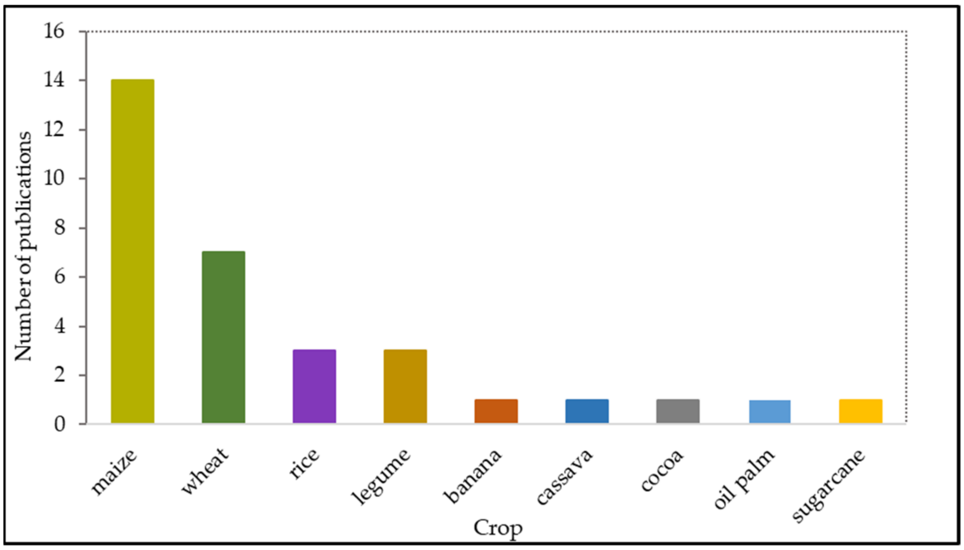

Figure 4. Histogram showing the number of publications in Africa between 1998 and 2020 with regards to the used crops with yield gap.

In terms of remote sensing-based soil properties, our review found that the most used mapping and advanced modeling approaches for yield gap estimation in African literature are MLR, RFR, SVM [42], imagery classifications techniques (i.e., supervised and unsupervised), as well as other ML and MLR (Table 3). For instance, Forkuor et al. [42] used high and moderate spatial resolution multi-temporal imagery (i.e., RapidEye and Landsat, respectively) to map the spatial distribution of soil properties (i.e., texture, cation ex-change capacity, SOC, and nitrogen) using different statistical prediction models (i.e., MLR, RFR, SVM, stochastic gradient boosting (SGB)). On the other hand, the application of other advanced methods, such as deep learning (DL), that has drawn attention within the developed remote sensing community over the past few years, is still non-existent, to our knowledge, in yield studies in Africa. For instance, the supervised convolutional neural network, recurrent neural network, unsupervised Auto-Encoders (AE), deep belief network, and generative adversarial network are state-of-the-art DL methods and can be applied for remote sensing imagery yield assessment. However, we think that the large training dataset requirement makes the application of these methods in African studies less advantageous. Compared to conventional shallow structured ML tools, such as neural networks, SVM, and ensemble modelling methods, e.g., RF +LSR+SVP, which have been successfully used in the remote sensing analysis for soil properties characterization in recent years (i.e., [88]).

Table 3. Summary of papers related to remote sensing used in the study, sorted by publication year.

Publication Year	Study Area/Country	Remote Sensing (RS) Data	Study Crop/Soil Properties	RS Data Analysis Techniques	Reference
2012	Senegal	Landsat	SOC	Unsupervised Classification (USC)	[53]
2013	Tunisia	Hyperspectral imagery	Soil properties	Supervised Classification (SC), Random Forest (RF)	[89]
2015	Morocco, Madagascar, Burkina Faso, and South Africa	Landsat	Crops	SVM Decision trees (DT) Gradient boosted trees (GBT), RF	[90]
2016	Cameroon	Sentinel	Maize	Principal component analysis (PCA)	[91]
2017	Kenya	Sentinel	Maize	Simple linear regression model	[26]
2017	Burkina Faso	Landsat	Soil texture, cation exchange capacity (CEC), SOC, and N	MLR, RF, SVM	[42]
2018	Ghana	Landsat	Sugarcane	USC	[92]
2018	Cameroon	Sentinel	Soil properties	Redundancy analysis (RDA)	[40]
2019	Kenya	Landsat	Wheat and maize	Multivariate Decision Tree (MDT)	[93]
2019	Kenya	Landsat	Maize	Neighborhood's function	[94]
2019	Morocco	MODIS	Wheat	Stepwise regression approach	[95]
2019	Tunisia	ASTER multispectral data	Soil clay content	MLR	[96]
2020	South Africa	Landsat	SOC	RF	[97]
2020	Burkina Faso	Sentinel	Tomato, Onion, Green bean	RF	[98]
2020	Tunisia	Sentinel	Durum wheat	Maximum likelihood method	[27]

5. Discussion

This study has dealt with an important topic of reviewing the current state of research regarding analysis of yield gap in Africa as caused mainly by soil attributes and using remote sensing approaches. It is potentially very important for designation of future agricultural research in Africa. Our analysis showed that soil attributes can substantially affect yield variability, and that the need for monitoring and tracking these attributes using remote sensing data are essential for reducing yield gap. For instance, the use of remote sensing was found to be important for the quantification aspects of yield and soil physicochemical properties. Before 1998, the use of remote sensing for yield gap analysis was very limited in Africa; it wasn't until the last two decades that multispectral and hyperspectral satellites took over for yield gap assessment. These trends are consistent with a study by Zhu et al. [99], which found the number of publications started to increase after 1999, when the price of Landsat imagery was reduced from approximately USD 3000 to 600.

Even if the number of publications in recent years has increased, remote sensing studies on yield gap analysis over Africa remains very limited, despite the increased use of freely available and open-access remote sensing imagery [99], i.e., Landsat and Sentinel, compared to other continents. Indeed, Figure 5 shows that the number of publications that used Landsat imagery between 1998 and 2020 was estimated to be 137 in selected Asian countries (i.e., China, India, Indonesia, Iran, Vietnam, Thailand, Philippine, Bangladesh, Myanmar), whereas in the 13 selected African countries, the number of publications does not exceed 46 papers.

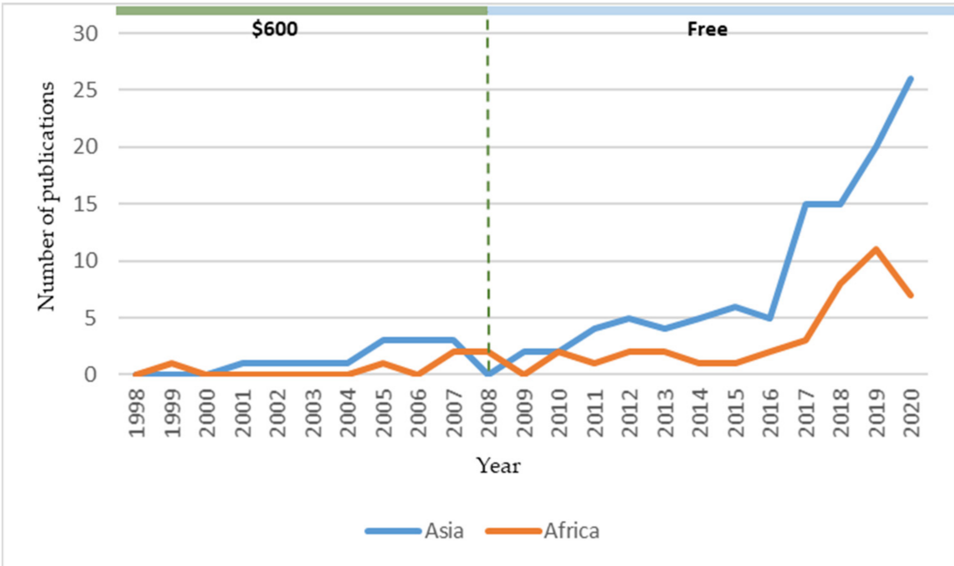

Figure 5. Number of annual publications in the selected Africa and Asian countries from 1998 to 2020 found in the Scopus database with the "Landsat" keyword in their title, abstract, or keywords.

With the recent advances made in the Earth Observation (EO) field, there has been a growing demand for remote sensing data and imagery for agriculture and soil. The use of remote sensing information collected by available sensors on satellite and/or platforms has acquired a very important role across the world in yield estimation, and thereby yield gap analysis. This has been greatly promoted by past and current remote sensing EO instruments, which are able to capture data with higher spatial and spectral resolutions, thus, allowing for the acquisition of a large variety of remotely sensed data and images, such optical, thermal multispectral hyperspectral images, LiDAR, and radar data with medium, high, and very high spatial resolutions. Every day, these EO instruments generate huge amounts of data all over the world and capture a large quantity of images and other remote sensing products. These large amounts of EO data are expected to provide enhanced opportunities to the African scientific community for undertaking EO studies through the use of satellite and other ancillary data. However, researchers and scientists in developed countries are those who are benefiting from the opportunity of the availability of EO data compared to developing countries, particularly in the African continent. Some reasons for the low number of these studies might be explained by several constraints on the uptake and access of EO sensor data in different African countries [100]. These constraints may include insufficient capacity and infrastructure to store and process huge remote sensing datasets (e.g., at petabyte-scale), poor Internet connectivity and bandwidth to access remotely sensed data platforms (i.e., USGS Landsat data), and a limited number of highly trained qualified individuals in remote sensing. Another constraint for most of the African countries is the lack of computing power, infrastructure, and cloud computing that facilitate access to the powerful processing facilities of the Google Earth Engine platform [101]. Such central facilities can process large volumes of geospatial and remotely sensed data. while allowing users to bring algorithms to the large data sets, which minimizes the duplication of storage and processing efforts [101]. For all these reasons, African researchers in the poorest African nations do not have the same opportunities to conduct a high number of yield gap analysis studies as those in more advanced nations. This might also explain why most of the papers reviewed in this study showed that yield gap analysis was mostly performed either by boundary function or by using yield simulation models such as AQUACROP and APSIM.

Besides the free and open multispectral sensors (i.e., Landsat and Sentinnel 2), to our knowledge, papers that used commercial and/or high resolutions sensors (i.e., Quickbird, WorldView, Ikonos, RapidEye) for yield analysis purposes in Africa are very rare compared to developed countries. This absence of studies can be explained by the expensive cost of imagery and access to the specialized software needed and the skills to processes this data, and storage capacity. It is expected that in the coming decade, African scientists will take advantage of the recent advancements in drone multi-sensor remote sensing derived data (e.g., hyperspectral, multispectral, and miniature satellites, such as Cubesat), and thereby produce a high number of publications. For instance, a recent study by Wahab et al. [102] assessed crop yield gaps in Sub-Saharan African smallholder systems using UAV data with an unprecedented spatiotemporal resolutions.

Finally, this review has found that soil nutrients (i.e., NPK) are not the main factor influencing the studied crop productivity in Africa, whereas clay, SOC, and soil pH were the most examined soil properties in prior papers [53,96]. Additional papers that investigated other soil attributes are scarce or non-existent. However, we believe that the absence of high-resolution remote sensing-derived digital soil maps (i.e., fertility maps) can partially explain the misuse of soil properties by African researchers for yield gap analysis studies.

6. Conclusions

In this paper, we conducted a systematic review to assess the status of African yield gap analysis research and their variation depending on soil properties management using remote sensing technics between 1998 and 2020. To do so, we first selected 12 African countries with potential agricultural yield improvement. These countries were Morocco, Senegal, Tunisia, Ivory Coast, Kenya, South Africa, Ethiopia, Cameroon, Burkina Faso, Tanzania, Rwanda, and Ghana. We then discussed the question of how remote sensing studies can help in monitoring soil properties and thus yield gap reduction. At the same time, we categorized past studies to assess how researchers approached assessments of fertilizer, water, and physical and chemical properties of soil. We concluded by providing a set of recommendations to guide future yield gap analysis research.

According to our review, the number of remote sensing studies dealing with yield crop gap has steadily increased over the last two decades, peaking in 2019. The multispectral MODIS and Landsat satellite series dominated early studies. The arrival of additional EO (i.e., Sentinel) and onboard-drone sensors will allow studies to develop more detailed yield estimation and explain factors. However, remote sensing-based soil attribute management in Africa is still underrepresented, and future research should focus on establishing the feasibility of assessing these soil properties as proxy to crop yield. To cope with this scarcity of information and take full advantage of the available remote sensing EO data, the African scientific community will need to participate in the development of an EO African platform which is designed to store and process huge datasets (at petabyte-scale) that covers African countries for analysis and ultimate decision making. In this context, UM6P and the Massachusetts Institute of Technology (MIT) have enabled a new research initiative to help African countries to have such opportunities, which will allow them to take advantage of the EO remote sensing and geospatial tools necessary to process large data sets for African yield applications. We also believe that this project outcome will help promote development applications of deep learning approaches for a variety of remote sensing problems related to yield.

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