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# Review of current models and approaches used for maize crop yield forecasting in sub-Saharan Africa and their potential use in early warning systems

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ABSTRACT

Agriculture is the mainstay of many developing economies, and successful production is intricately linked to food security, economic development, and regional stability. Estimates of crop yield for strategic grain crops, such as maize (Zea mays L.) have been used in national food security planning to develop response strategies in years of shortfalls and secure markets in years of surplus. Past studies have shown that despite the potential of models in maize crop yield assessment, they have not been effectively used in understanding seasonal and annual production dynamics. Thus, stakeholders require the availability of accurate and timely data on maize production potential and hence the development and application of crop yield models for maize yield estimation. However, current methods of assessing maize crop yields are based on field assessments, which are expensive, laborious and inaccurate. This mixed methods paper, therefore, aimed to; (i) review information sources for maize crop yield assessments, looking at their strengths, limitations, and potential for application in sub-Saharan Africa, (ii) perform trend and distribution analyses of publications in maize crop yield simulation, and (iii) discuss the challenges in the application of models in agriculture planning in the African agriculture systems. The general aim was to understand these crop yield assessments and the current approaches in maize yield estimation methods, and their potential use in the early warning system. The study narrowed the review to crop growth simulation models and explored the different growth simulation models and their potential integration into real-time monitoring frameworks for grain crop assessments. It was observed in this review, using graphical presentation of trend and distribution analysis of one thousand three hundred and thirty-thre scientific publications, that there is an increase in research interest in crop simulation modelling, with current research being done mostly in developed countries. However, the application of models in maize crop yield assessment is dependent on the availability of data, modelled crop characteristics, model calibration requirements, technical capacity, and model implementation costs. Therefore, it was concluded that using crop yield estimation models integrating remote sensing is an important step in local, national and regional agricultural planning in the sub-region and beyond.

## 1. Introduction

The Food and Agriculture Organisation of the United Nations (FAO) estimates that over 800 million people worldwide are food insecure and undernourished, and of these, close to half are in developing countries (FAO, 2006). The Committee on World Food Security of the United Nations (2005) defines food security as when all people have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life. Due to climate change and variability, the food security situation of many countries in sub-Saharan Africa is being significantly altered, leaving large populations at risk of starvation, and or malnutrition

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(Brown et al., 2012; Lal et al., 2015; Conway et al., 2015). The agricultural sector in sub-Saharan Africa is essential in terms of both employment and livelihoods. However, the sector is faced with many challenges, including recurrent droughts and dry spells, inadequate agricultural technologies, limited capital and poor marketing of produce (Bjornlund, 2009; FAO, 2006). As a result, agricultural development programs such as the Comprehensive African Agricultural Development Programme (CAADP) are integral plans of the African Union to make the sector sustainable.

Although diverse crops are grown across Africa, maize is the most significant grain and staple food for many populations, contributing to over 60% of the calorie intake in Eastern and Southern Africa (Nelson et al., 2009; Smale and Jayne, 2003). This means that when production is lower than requirements, there are dire consequences for society, economies and the entire value chain (Davis et al., 2016, Cairns et al., 2013). Strategic grain crops such as maize become critical agricultural enterprises across nations and regions. The productivity of maize and other agricultural crops is therefore directly related to economic development and performance in most countries in Sub-Saharan Africa (Smale et al., 2013). Employment, migration, and peace are dependent on the performance of the agricultural sector at various scales. Therefore, improving agricultural productivity and profitability are key aspects of achieving many sustainable development goals for many countries across Africa.

. Over the past years, many countries' maize sectors have been facing productivity challenges. Jayne et al. (2010) reported stagnant food crop productivity as one of the crippling factors in smallholder production in Africa when food crop productivity has been rising throughout the rest of the world. This trend is explained by, among many other factors, the low adoption of agricultural technologies and the changing climate that make traditional farming methods risky (FAO, 2007). With increasing population in these countries, inadequate food security, particularly inadequate maize production and supply, has ripple impacts on economic development, migration patterns, and environmental sustainability. All these factors have ripple effects. At field and farm level, many interventions can be prescribed to improve maize production efficiency and productivity even in the face of climate change and variability. However, at a national level, maize production statistics are often collected during or after the maize production season., The information is less useful for disaster planning or early national and regional response mechanisms (Smale and Jayne, 2003).

Past studies have shown that despite the potential of models in maize crop yield assessment, they have not been effectively used in understanding seasonal and annual production dynamics. Thus, stakeholders require the availability of accurate and timely data on maize production potential and hence the development and application of crop yield models for maid yield estimation. However, current methods of assessing maize crop yields are based on field assessments, which are expensive, laborious and inaccurate. Many stakeholders in the maize value chain require the availability of accurate and timely data on maize production potential. This will be useful for timely decision making on required intervention strategies to avert crises, plan for markets and to enable distribution between excess areas and deficit areas. To achieve this, there has been considerable effort in the development and application of crop yield models for maize yield estimation. Therefore, the objectives of this review areis review aims to understand current approaches in maize crop yield estimation methods and their potential for use in early warning systems in sub-Saharan Africa with specific focus on the SADC region. Assessment of the potential of each approach and method for its use in early warning applications took into account its ability to function within: (a) the existing available weather data (b) the available crop characteristic data, and the models' capability or ability to handle such data, (c) whether or not a model has already been calibrated for use, (d) cost and (e) the model's potential for use with remote sensing data and derived products. This mixed method review aims to understand current approaches in maize crop yield estimation methods and their potential for use in early warning systems in sub-Saharan Africa with specific focus on the Southern African Development Community (SADC) region.

## 2. Data and methodology

The assessment of the approaches in maize crop yield estimation methods took into account its ability to function within: (a) the existing available weather data (b) the available crop characteristic data, and the models' capability or ability to handle such data, (c) whether or not a model has already been calibrated for use, (d) cost and (e) the model's potential for use with remote sensing data and derived products.

The keywords used in search of this review's publications included maize crop, crop yield model, yield assessment and yield forecasting. From this search, 1297 research articles, 32 proceedings, 3 book chapters and 1 editorial were used in the review. This study did a graphical presentation of the trend and distribution analysis of publications in crop simulation for maize. Moreso, a trend analysis on the number of publications in maize simulation modelling between the study period of 2008 and 2018. For the same study period, a numerical review of publications on maize crop simulation was effected. The Web of Science database was queried to analyse the number and characteristics of publications. In addition, this study did an analysis on the type of publications that are dominant in maize crop simulation modelling and their regions of origin. An investigation on the expansion and transition of the journals from specialising in agronomy and water management to other strategic sectors was done.

Strengths and challenges in the application of these models in agricultural planning in African Agricultural Systems were highlighted and discussed. In response, recommendations were suggested to provide possible solutions for the highlighted limitations.

## 3. Results and discussions

### 3.1. Review of modelling maize yields for production planning

Crop Simulation Models (CSM) are computerized representations of crop growth, development and yield, simulated through mathematical equations as functions of soil conditions, weather and management practices (Hoogenboom et al., 2004). Crop growth simulation models are important since they provide a means to forecast potential yield for planning purposes and help in identifying yield gaps, which could be useful in developing optimum crop management practices and advising farmers on appropriate management practices. They are essential for policy makers since they can develop productivity-enhancing policies to increase national food security. Researchers use crop models to guide farmers to make crop management decisions such as selection of suitable crops, crop varieties, sowing dates and irrigation scheduling to minimize the risks associated with climate change (Masanganise et al., 2013).

To understand the trends and distribution of publications in crop simulation models for maize, we queried the Web of Science database to analyse the number and characteristics of publications. There is a clear positive trend in the number of publications in maize simulation modelling available in scientific literature as the number almost tripled from 74 in 2008 to 209 in 2018 (Fig. 1). This constant increase in publications shows a rising interest in this topic given the food security needs and the advancement of methods to perform crop simulation models. The breadth of journals publishing on crop simulation models also expanded from mainly agronomy and water management journals in 2008 to modelling, software engineering and applied food security and policy studies that are using these models by 2018. The analysis by type of publications shows that research articles are the most dominant type of publications on maize crop simulation modelling (95%) followed by proceedings and reviews at a distant number (Fig. 1).

The analysis of the publications by region shows that the dominant research articles on maize crop simulation modelling are coming from

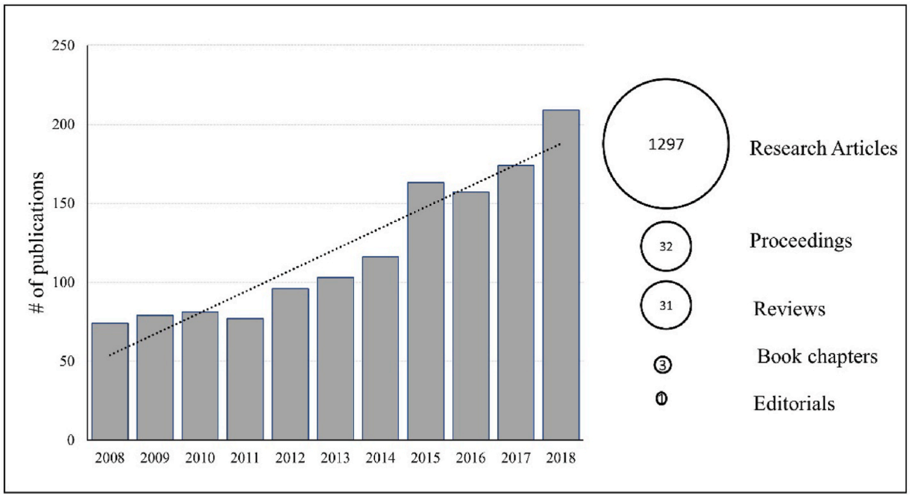


**Fig. 1.** Distribution of maize crop simulation publications and their types between 2008 and 2018 from Web of Science (as of May 6, 2019).

Europe and North America. These two regions accounted for almost two thirds of all publications (Fig. 2a). Studies conducted in Africa are the least (132) between 2008 and 2018 as they were just 9.5% of all publications, which was similar to those from Australia (9.6%). Of the publications from Africa, Southern Africa accounted for the largest majority with 42 publications followed by East Africa with 37 publications (Fig. 2b). A further analysis of the publications that were produced from Southern Africa shows that two countries, South Africa (18) and Zimbabwe (16), are the dominant sources of research on maize crop simulation modelling, with the two countries accounting for up to 81% of all publications from Southern Africa (Fig. 2c).

There are two important observations from the numerical review of publications on maize crop simulation modelling between 2008 and 2018. First, there is an evident increase in interest in modelling maize production worldwide by many researchers. However, the geographical focus of the majority of the research is being conducted in regions and countries that already have high maize yields (Neumann et al., 2010; Van Oort et al., 2017), and not in countries where the modelling may be needed for improving maize yields. These regional disparities cascade down to continent and sub-regional levels. Secondly, the types of publications on maize simulation modelling is dominated by research publications which are often too technical for local policy synthesis and applications. Given the nature, accessibility limitations and jargon in research articles, crop simulation modelling communication remains the preserve of researchers and not non-technical fields who may benefit the most in terms of such research. There is an evident need to intensify maize yield modelling in Africa where it is needed the most and also find alternative communication pathways for maize simulation modelling results to enhance their impacts on farming systems and increasing food security.

### 3.2. Information sources for maize production assessment

Over many years, maize production failure has hit hard on communities due to the lack of a crop monitoring framework that stakeholders, such as extensionist agents, government planners and donors could use to understand plant growth and development to provide crop production support and early warning systems (Jeuffroy et al., 2014; Smale and Jayne 2003). Several tools have been developed over the years to assess the production and distribution of food resources across areas as part of food security assessments. To satisfy this long-term requirement for maize yield forecasting, many methods have been developed to provide information in advance about potential maize production. These methods can be grouped into (i) physical field assessments, (ii) time trend analysis, (iii) crop growth simulation models and (iv) remote sensing-based methods.

#### 3.2.1. Physical field assessments

Field-based methods are the traditional way of conducting maize yield estimates where trained and experienced field staff sample and

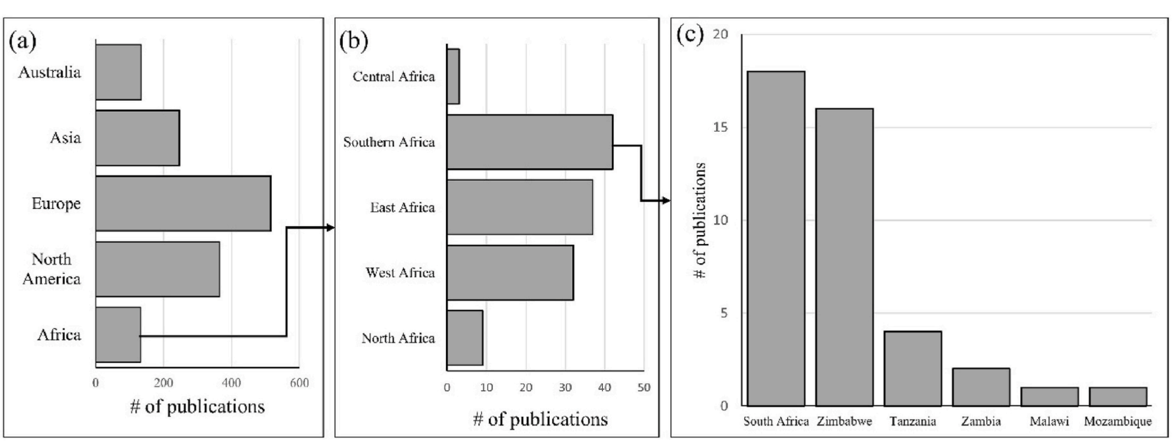


**Fig. 2.** Number of publications on maize crop simulation modelling between 2008 and 2018 from Web of Science for (a) Global, (b) Africa and (c) Southern Africa (as on May 6, 2019).

qualitatively score sampled maize fields to estimate the area under maize and maize quality and therefore derive the expected yield (Fermont and Benson, 2011). This is the commonly used approach in many countries in SADC where ministries use their dense network of field extension officers to report on the quality of the season based on these field reports. It is, therefore, a widely utilized, well-accepted and an official approach of estimating maize yield in many countries. This method is based on field-observed data and relies on verified actual maize fields for the prediction. In addition, with experience, the quality of the forecasts increases as the field officers become more accurate, resulting in better decision making. Field based methods based on estimating crop yield rely on currently established networks to provide maize yield estimates and therefore there are little to no establishment and operational costs. However, these methods also come with many challenges.

Among the greatest setbacks of the field, assessments, is the reliance on subjective judgments by individuals, which give different scores for the same condition (Kuri et al., 2014). They also require extensive field work to produce representative results and this makes it not only grueling and time-consuming, but also very expensive (FAO, 2007). In addition, given the different planting dates in different regions, it is very difficult to harmonize the maize yield estimates based on different crop stages (Funk and Budde 2009). Related to that is that the results from these assessments are not instantaneous as it can take a long time to complete the assessments across large areas. It is also a paradox that the estimate relies on field extension officers employed and expected to increase maize productivity in their areas of jurisdiction. There is, therefore, a general temptation for field officers to overstate the maize yield estimates in order to be considered effective, thereby compromising the results.

### 3.2.2. *Time trend analysis*

Time trend analysis is another method used in estimating maize yields. The method estimates yields using statistical analysis of historical trends and adjusted for other variables such as weather, soils, and markets. The model is parameterized at different spatial and temporal scales and when the relationship between the variables and yield is established, then the yield estimate can be predicted for a season or for many years (Sarker et al., 2012). It is also one of the most commonly used approaches to estimate the yield of maize. The method is also widely used as the FAO's Early Warning System (GIEWS) for yield estimation. In time trend analysis, the field reports on maize yield data are regressed against known influential meteorological parameters such as the start of the rainfall season, total rainfall and mean monthly temperature of the agricultural season to generate a functional model (FAO, 1992a,b; Cabas et al., 2010). An example of time trend analysis was done by Manatsa et al. (2011a,b) where they used long-term rainfall data as input into a crop water balance model to calculate the water requirement satisfaction index (WRSI) for maize in Zimbabwe. Examples of applications of time trend analysis applications in crop yield estimations are shown in Table 1.

Time trend analysis has many advantages in maize yield prediction, especially when compared to field based methods. This approach does not necessarily require extensive field work and is thus cheaper. In addition, the approach can be easily extended and extrapolated beyond the areas where data was available or not available and produce robust results. Since the approach is statistical in nature, there is more confidence in their application as there are established standardized measures of model performance that are used to evaluate the accuracy of the model before use (Unganai and Mason, 2002). Given the recent improvements in computational power, these methods are also faster to implement for decision making.

Time trend analysis however has challenges. The downside of the

**Table 1**
Applications of remote sensing based methods in crop yield estimations.

| Model type | Crop | Type of model | Country | Application | Reference |
|---|---|---|---|---|---|
| Time Trend Analysis | Maize | Non-linear regression | USA | Long terms maize yield prediction | Schlenker and Roberts (2009) |
| | Maize, wheat, rice and soy beans | Non-linear regression | USA | Identify drivers of yield in relation to climate change | Lobell et al. (2011) |
| | Maize and wheat | Non-linear regression | World | Long term maize yield prediction. | Lobell et al. (2013) |
| | Maize | | Kenya | Maize yield prediction | Hansen and Indeje (2004) |
| | Rice, wheat, and maize | Regression and Kendall-tau statistic | China | Maize phenology and yield analysis | Tao et al. (2006) |
| Crop growth simulation models | Winter wheat & spring barley | CERES | Austria | Yield estimation | Eitzinger et al. (2017) |
| | Winter wheat | WOFOST | China | Yield estimation through integration of remote sensing | Huang et al. (2015) |
| | Winter wheat & spring barley | SWAP | Austria | | Eitzinger et al. (2017) |
| | Maize | CERES | Ghana | Climate change impact assessment | MacCarthy et al. (2017) |
| | Maize | AquaCrop | | Yield response relative to water availability | Hsiao et al. (2009) |
| | Maize | Hybrid-Maize | China | Maize yield modelling | Yang et al. (2004) |
| | Maize | PS123 | The Netherlands | Maize gap analysis | Driessen and Konijn (1992) |
| Remote sensing based models | Maize, Sorghum, Peal Millet | Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI) | India | Drought assessment | Dutta et al. (2015) |
| | Maize | Phenologically-tuned MODIS NDVI | Zimbabwe | Yield prediction | Funk and Budde (2009) |
| | Maize | Vegetation indices | USA | Yield prediction | Holzman and Rivas (2016) |
| | Maize | Satellite-Derived Leaf Area Index models | Mexico | Maize yield assessment | Baez-Gonzalez et al. (2005) |
| | Maize | SPOT VGT rainfall dekads | Zimbabwe | Drought assessment | Kuri et al. (2014) |
| | Maize | Vegetation Indices from aerial imagery | USA | Maize yield prediction | Shanahan et al. (2001) |

time trend analysis approach is mainly related to the availability and quality of input data used in the time trend analysis. In many developing countries, such as in sub-Saharan Africa, there is a paucity of data. Most of the available data on yield is at localized scale and in a few cases where this data is available, the quality is often poor. In addition, the approach is dependent on the availability of a dense network of meteorological stations, which are non-existent in many areas, particularly those facing severe food shortages (Unganai and Kogan, 1998, Barret, 1998). This is so because many meteorological stations are located in urban areas and their representativeness of communal areas where much of the agricultural production is done is very much questionable (Bolton and Friedl 2013). In addition, with climate change and variability, the validity of relying on long-term weather data trends to make yield predictions is becoming less reliable. For example, mid-season droughts can significantly reduce yields in a season when the rainfall totals received in a season remain relatively unchanged. Thus using the total rainfall for yield prediction becomes less accurate under these conditions. The strengths, weakness and potential integration of time trend analysis in yield modelling is summarized in Table 2.

### 3.2.3. *Crop growth simulation models*

Crop growth simulation models is another family of yield estimation methods. These models estimate maize yields based on the known characteristics of the crop grown, the biophysical environment, management practices and other factors (Palosuo et al., 2011). Crop growth simulation models such as CERES, WOFOST, AquaCrop and SWAP capture the most likely production potential of an area by weighing the constraints against the factors promoting production to obtain the most likely production potential (Van den Berg and Driessen, 2002; Goudriaan and Van Laar, 2012). Unlike the time trend analysis approach that relies mostly on historical data, crop growth simulation models are able to provide in-season forecasts by relating crop conditions at particular physiological stages to yield of the crop for each land use system, management regime and other related production factors. There are many crop growth simulation models that have been developed over the years for use in yield modelling. Examples of such models include those that relate to season transpiration reduction to end of season yield reduction. Others link soil moisture condition to the potential yield assuming that soil moisture is the most limiting condition for yield in certain land use systems (Van den Berg et al., 2002). Examples of use of crop growth simulation models in yield estimations are shown in Table 1.

Crop growth simulation models tend to be very accurate for localized applications, when compared other methods, when properly parameterized. They also have fewer data needs and are therefore less complex, meaning that they satisfy the parsimony requirement for models (Hansen et al., 2011). They are also based on field observations making them more empirical and actual data-driven. In addition, they are also able to adjust according to different significant factors that affect maize yields such as crop varieties, soil conditions, water supply, management commitment and other factors (van Ittersum et al., 2003). However, crop growth simulation models are based on experimental data, which significantly differs with actual field conditions for maize production. They also produce an indication of the production potential of a particular land use system but not necessarily the actual production. The strengths, weakness and potential integration of crop simulation models is summarized in Table 2.

### 3.2.4. *Remote sensing-based methods*

Remote sensing based methods are gaining momentum and

**Table 2**
Summary of strengths and weakness of current sources of information in maize yield estimation.

| Method | Strengths for application in maize yield estimation | Weaknesses for application | Potential for use with other methods |
|---|---|---|---|
| Physical Field Assessments | • Well-accepted as the standard<br>• There is already experience in this method as it has been in use for a long time<br>• Based on field-observed data and can be verified<br>• Rely on currently established networks and therefore there are little to no establishment and operational costs. | • Relies on subjective assessments by individuals, which give different scores for the same condition<br>• Require extensive field work to produce representative results<br>• Tedious, time-consuming and expensive.<br>• Results affected by planting dates | • Used mainly as a parameter for evaluating or calibrating other assessment methods.<br>• Little potential for integration with other methods |
| Time trend analysis | • Does not require extensive field work and is therefore cheaper and quicker.<br>• The method can be easily extended and extrapolated beyond the areas where data was available or not available and produce robust results.<br>• The statistical approach is good for ensuring confidence.<br>• It is faster to implement for decision making. | • No quality data is available at required disaggregated level.<br>• The approach is dependent on the availability of a dense network of meteorological stations which are not there in many countries.<br>• The statistical relationships are changing with climate change. | • Can be integrated with remote sensing approach where remote sensing can provide long term data on condition, yield or other parameters<br>• Can be used with field based methods where the field data is used to determine the required statistical relationships. |
| Crop Growth Simulation Models | • Can be very accurate for localized applications.<br>• They have fewer data needs and are therefore less complex.<br>• Based on field observations making them more empirical and actual data-driven.<br>• Can adjust according to different significant factors that affect maize yields. | • Based on experimental data, which significantly differs with actual field conditions for maize production.<br>• Conditions for their development have since changed from now which affects their use<br>• More useful for production potential than the actual production estimation. | • Can be integrated with remote sensing methods as sources of meteorological data required in running the models. |
| Remote Sensing-Based Methods | • Instantaneously provide estimates from large areas covering countries and entire regions, significantly reducing costs of doing such exercises.<br>• Results are timely as indication can be obtained in advance,<br>• Provide both the quantity and quality of the maize yields. | • The learning curve and establishment costs of remote sensing applications are large<br>• Remote sensing estimations are confounded by clouds and non-crop areas. | • Can be integrated with both statistical yield forecasting and crop simulation models. |

acceptance in crop yield estimations. Remote sensing systems capture radiation in different wavelengths reflected/emitted by the earth's surface features, which is recorded by sensors to generate images. Over time, the biophysical understanding, algorithms for data handling, data storage capacity and sensor technology have grown resulting in many applications of remote sensing methods in crop yield estimations (Pinter Jr. et al., 2003). Remote sensing based methods have thus been used to predict crop condition and yields in agriculture through directly assessing crop growth and vigour and indirectly through estimation of plant population and area cropped, plant water status, salinity stress, leaf nutrient status, weed pressure, disease severity, insect attack, and other useful biophysical crop properties related to yields (Boegh et al., 2012).

Prospects for yield modelling using remote sensing are high considering the fast research developments in this area. Dutta et al. (2015) successfully applied a normalised NDVI to get the vegetation condition index that indicate changes in maize crop condition related to drought. They concluded that the vegetation condition index was a reliable predictor of maize productivity that can be used in drought early warning. In another study, Funk and Budde (2009) used the national MODIS derived NDVI time series adjusted temporally according to the timing of the rainy season for maize prediction and correlated it with maize yields to produce spatial and temporal variations in maize production. In another study Kuri et al. (2014) successfully developed an approach that uses SPOT VGT derived dry dekads to predict maize yields at national level for drought early warning and yield estimation. Zhang et al. (2005) used the Climate-Variability Impact Index (CVII) derived from the MODIS Leaf Area Index to quantify the percentage of the climatological production either gained or lost due to climatic variability during a given production month over the growing for yield estimation and reported results that are stable over large areas. A summary of remote sensing applications in crop yield estimations are given in Table 1.

Remote sensing-based methods have many advantages compared to other crop yield estimation methods. Remote sensing can instantaneously provide estimates from large areas covering countries and entire regions, significantly reducing costs of doing such exercises. Results from remote sensing are also timely as indication can be obtained in advance, enabling planners and policy makers to efficiently make decisions in advance. In addition, when appropriately analysed, satellite data provides not just estimates of the quantity but of the quality of the yields (Davis et al., 2016; Bolton and Friedl 2013). This is because it is able to integrate the effect of soil type, relief, climate, varieties and other socio-economic factors that influence crop performance at different locations, making results more representative and accurate. However, the learning curve and establishment costs of remote sensing applications are large, making their uptake limited in developing countries. Remote sensing estimations are confounded by clouds and non-crop areas and thus, their success may be limited in many subtropical areas (Bolton and Friedl 2013). The strengths, weakness and potential integration of remote sensing is summarized in Table 2.

### 3.3. *Crop yield modelling in the Southern African Development Community (SADC)*

The SADC region frequently experiences lower than expected staple food production resulting in different magnitude food shortages. As a way to avert these problems, some crop yielding modelling studies have been done ranging from point, local, national and regional scales. The aim of many of these crop yield modelling projects was to provide a framework for crop yield estimation that can be used to influence decision making. Three broad functional type models used in crop yield focasting in the SADC region are discussed in detail under this section. These are the Water Requirement Satisfaction Index (WRSI), The Simple Crop Growth Model and The WOFOST Crop Growth Model.

#### 3.3.1. *Water requirement satisfaction index (WRSI)*

The FAO-SADC Regional Remote Sensing Project (RRSP) prepared crop yield models using the Water Requirements Satisfaction Index (WRSI) model (FAO, 1992). Manatsa et al. (2011a,b) used rainfall estimates as input into a crop water balance model to calculate water requirement satisfaction index (WRSI) and developed maize yield estimation models based on linear regression between the WRSI values with historical yield data. This method is based on a simple water budget approach where rainfall is the only dynamic input used in correlating with field measurements. This may be inadequate as crop production is a dynamic process, which is influenced by several factors such as rainfall, temperature, day length, relative humidity, soil and crop variety. While such models do not require many hours of field work, their use has limited applicability in developing countries as they are based on rainfall data acquired from a sparse network of weather stations (Unganai and Kogan, 1998).

Attempts by RRSP to use cold cloud duration (CCD) for the production of dekadal rainfall maps were not conclusive since the correlation between long CCD hours and rainfall was found to be too low.

Realising the inadequacies of the above approaches, a project definition study financed by the Netherlands Remote Sensing Board was launched in 1993. The objective was to assist FAO-SADC's RRSP in enhancing the contribution of remote sensing techniques to early warning activities in the SADC region (Roebeling and Rosema, 1999). This collaboration recognised the need for METEOSAT and NOAA based data products for integration into the early warning activities (Agromet Crop Monitoring Project - ACMP, 1995). Currently, the crop water requirement satisfaction index is being used for regional drought early warning system (Funk et al., 2015).

#### 3.3.2. *The Simple Crop Growth Model*

The simple crop growth model is a semi-empirical model that links transpiration reduction to yield reduction. The approach is based on the concept of a green cover crop that shades the ground. Crop growth follows a pre-set growth curve reflected by the crop's Leaf Area Index (LAI), which is a function of the growth stage of the particular crop variety used. The approach ignores the quantification of the "net assimilate production" as a major determinant of crop growth. The model does not even quantify production of any marketable product, although yield response factors are considered to permit estimation of seasonal yield reduction due to moisture stress. The response factors are established according to the Stewart approach (Doorenbos and Kassam, 1979), and the extended Stewart approach (Smith, 1992). In both these approaches, the susceptibility to moisture stress is differentiated as a function of crop growth stage. The simple crop growth model does not quantify potential crop production levels. However, the method is an improvement over the WRSI approach, which is entirely based on water budget calculations. It can simulate crop season length and it is driven by METEOSAT derived relative evapo-transpiration data. Attempts to use METEOSAT derived data for drought monitoring are still ongoing (Meteorological Services, Zimbabwe). data.

#### 3.3.3. *Agricultural productions systems simulator (APSIM)*

The Agricultural Production Systems Simulator (APSIM) is a modular modelling framework for the simulation of crop growth and production outcomes based on management, biophysical parameters and weather data (Keating et al., 2003; Holzworth et al., 2014). APSIM has been used for on-farm decision making (Cooper et al., 2008; Asseng et al., 1998), farming systems designed for production or resource management objectives (Hammer et al., 2010; Sultan et al., 2014), assessment of the value of seasonal climate forecasting (Guan et al., 2015), risk assessment for policies, selection of adaptation measures for both crops and pastures (Rurinda et al., 2015). APSIM is a process-based crop model that can be adapted or adjusted for various situations. However, the model is designed for site specific studies and requires a lot of input parameters to be functional. It is also generally not spatially disaggregated which means conclusions and results are limited to specific areas that are being modelled.

#### 3.3.4. The decision support system for agrotechnology transfer (DSSAT)

DSSAT is another process-based model that has been widely used in agricultural applications to understand and simulate crop yields (Dzotsi et al., 2013). DSSAT is a software application program that comprises crop simulation models for over 42 crops and various tools to facilitate setting up and running the crop simulation. Like APSIM, DSSAT has the capacity to simulate growth, development and yield as a function of the soil-plant-atmosphere dynamics. It has been successful because it integrates the effects of soil, crop phenotype, weather and management options and allows users to build scenarios in a virtual environment Brilli et al., (2017); Dias et al., (2016). It has similar applications as APSIM in terms of being used for farming decision support and related management decisions under current and future climate risk assessment (Eitzinger et al., 2017; Ngwiraa et al., 2014; Li et al., 2015). Although by design is a site-based model, it can be implemented spatially by geographically indexing fields (Estes et al., 2013).

### 3.4. Challenges in the application of models in agricultural planning in African agricultural systems

Crop modelling has not gained the popularity it deserves in sub-Saharan Africa despite the advantages it brings to agriculture monitoring systems. Most crop prediction models have been developed and validated using agricultural systems in developed countries. They are virtually untested or poorly tested when it comes to developing countries like Zimbabwe, and hence their usefulness in our local environment is still unproven. In addition to lack of model validation and calibration, there is a challenge of unavailability of historical yield statistics with the right spatial and temporal coverage, which is a key component in yield forecasting. This results in some uncertainities associated with crop models collectively referred to as model error (Hoefsloot et al., 2012). These errors can compromise the accuracy of the yield predictions. However, these errors can be minimized through use of observed data to estimate model parameters. Remote sensing offers several options for reducing these errors especially when observed data is sparsely distributed. Use of indices like NDVI, Leaf Area Index (LAI), evapotranspiration (ET) and soil moisture obtained at adequate temporal and spatial resolutions can improve the quality and precision of yield forecasts when used with these models.

There are now many models that are used in climate change assessment and to explore management issues related to crop production. Advances in technology made possible the development of simple and complex crop simulation models. Therefore, the main point to take into consideration is the availability of information needed to run the model. Crop simulation models need the information of several aspects regarding crop management, soil, and atmosphere. There is a level of complexity in the input data as well, as they range between hourly, daily, and weekly (van Ittersum et al., 2013). However, crop simulation models used for agrotechnology transfer will preferentially run using daily input data. Hunt and Boote (1998) defined a Minimum Data Set (MDS) for operating crop simulation models that are used in agrotechnology transfer. MDS is defined as the minimum amount of input data needed to run a crop simulation models at a given site (Tsuji et al., 2013; Boote et al., 2016).

### 3.5. Crop yield models and climate change

Despite technological advances such as improved crop varieties and irrigation systems, climate is still a key factor in agricultural productivity. Climate change caused by the effects of global warming, has resulted in two major disasters, namely drought and floods. Knowing the impacts of drought or flood on agriculture is essential for taking various relief and rehabilitation measures (Ray et al., 2014). Also, temperature increases in the sub-saharan Africa region where crops are grown near thresholds can be detrimental to rain-fed crop production (Asseng et al., 2015). Crop models are important tools that can be used to unravel the crop responses to climate change and variability. This information can also be used in identifying anad weighing adaptation options that can be implemented to cushion maize production against climate change.

### 3.6. Outlook for modelling maize crop yields

Besides their use in early warning applications, models are analytical tools are useful to extension agents and other stakeholders in food production. In the face of ever increasing input costs, it pays off to screen alternative production recommendations prior to implementation. Crop growth simulation helps to identify the relative stochastic dominance of factors that influence crop production before preparing extension packages. This way, extension officers are able to produce more effective extension messages as they are targeted on specific factors determined to be dominant in crop production. In this way, production is not just increased but costs of ensuring food security and agriculture based livelihoods are reduced. In addition, development of agriculture based insurance packages may also be related to these crop growth and yield simulation models. With these models, it will be easier to know in advance the food situation in a country, which is important in planning to avert potential food shortages.

Given that there are number of growth simulation models developed for SADC, but the region still experiences often severe crop losses and disasters, there are probably many factors that have to be considered in applications of these models in decision making. Firstly, the basket of available models may not be satisfactorily run with much of the available data. This means that even if the models perform well if parametrized well, the potential for them to be satisfactorily parameterized makes them redundant. Thus, they remain good models in shelves or as computer programs that are not being implemented. Secondly, the scale of implementation of these models need to be considered. National and regional scale models are good for influencing policy and direction in agricultural production but may have very little influence in terms of farm level or lower level agricultural decision making. On the other hand, farm or landscape crop yield simulation models may influence farmer decision but with little or no impact for national or regional scale agricultural policy development (Jones and Kiniry, 1986). Thus, satisfying the large scale (national or regional) and the local scale (landscape and farm level) crop modelling requirements is a daunting task.

The reliability and adoption of modelling results in crop production may also be influenced by many socioeconomic factors related to agricultural production. The process through which farmers learn and make decisions needs to be understood to design appropriate model-based messages to farmers, extension agents and other agricultural stakeholders. For example, there is a hierarchy of production in Zimbabwe in which farmers are grouped as either commercial, A2 commercial, A1 communal and communal. These sub-groupings may indicate different capacities but also mindsets as regards to technology adoption. Thus, when crop growth and simulation models produce results, they may need to be tailor made to different sub groups for effective decision making. It has to be clear, therefore, at what level the crop yield forecasting models used so that it is designed to fit the expected audience. This shows that there is need for development of crop simulation models that are not just scientific but appropriate for the sub region. These models will depend on an understanding of the physical and socio-economic current limits to production, the distribution of producers and also mapping of the farmers decision making process.

## 4. Conclusions and recommendations

Outcomes from this review can be split into several sections with respect to the objectives of the study. Firstly, the crop growth simulation models were identified to be of importance since they provide a means to forecast potential yield for planning purposes and help in identifying yield gaps, which could be useful in developing productivity enhancing policies, optimum crop management practices and advising farmers on appropriate management practices. The importance of the crop simulation models was shown by the constant increase in the respective publications which arguably indicate a rising interest in the topic given the food security needs. Moreso, the breadth of journals publishing on crop simulation models also expanded from mainly agronomy and water management journals to modelling, software engineering and applied food security and policy studies. There is need for future studies to concentrate on maize yield modelling in Africa where it is needed the most and also find alternative communication pathways for maize simulation modelling results to enhance their impacts on farming systems and increasing food security.

Among the several tools have been developed over the years to assess the production and distribution of food resources, across areas as part of food security assessments, crop growth simulation models prove to satisfy this long-term requirement for maize yield forecasting better than other methods such as physical field assessments, time trend analysis and remote sensing methods. This is due to their high levels of accuracy since they are based on field observations which makes them more empirical and actual data driven. Although remote sensing-based methods instantaneously provide estimates from large areas covering countries and entire regions, the ability of the crop growth simulation models to adjust to different significant factors that affect maize yields makes it a better choice. However, it is recommended that future studies try and integrate the two methods and assess their performance as the models have the potential to use remote sensed data and derived products. The application of remote sensing products in crop yield modelling should be further explored vis-à-vis the operational requirements of such systems. There are huge opportunities for application of maize crop yield modelling in sub-Saharan Africa to mitigate against the impacts of recurrent droughts and other production limiting factors.

Lastly, this review arguably discovered that crop modelling has not gained the popularity it deserves in sub-Saharan Africa despite the advantages it brings to agriculture monitoring systems. Most crop prediction models have been developed and validated using agricultural systems in developed countries which makes their usefulness in the local environment of developing countries unproven. In addition to lack of model validation and calibration, there is a challenge of unavailability of historical yield statistics with the right spatial and temporal coverage, which is a key component in yield forecasting.

It was concluded from this review that more research is needed to examine the social and biophysical factors that limit maize production and evaluate how these factors can be captured in maize yield models.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pce.2022.103199.

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