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Review

Advancements in Leaf Area Index Estimation for Maize Using Modeling and Remote Sensing Techniques: A Review

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Abstract: Maize is an important crop used as food, feed, and industrial raw material. Therefore, it is critical to maximize maize yield on available land by using optimal inputs and adapting to challenges posed by climate change. The Leaf Area Index (LAI) is a key parameter that provides significant assistance in forecasting maize yields. This study focuses on modeling the Leaf Area Index for maize. Specifically, it compiles and systematizes the main findings of papers published over the past approximately 10–15 years. Our results are organized and presented based on the five most commonly used models: CERES-Maize, AquaCrop, WOFOST, APSIM, and RZWQM2. The limitations of these models' applicability are also discussed. We present the limitations of these models and compare their minimum climate input requirements. Additionally, we evaluate the performance of the models across different climate zones, explore how the integration of remote sensing data sources can enhance model estimation accuracy, and examine the potential for spatial scalability in maize LAI modeling.

Keywords: leaf area index; model; maize; CERES-Maize; AquaCrop; WOFOST; APSIM; RZWQM2

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1. Introduction

The three fundamental cereal crops in the world are maize, winter wheat, and rice. These crops are essential components of human nutrition [1]. The United Nations estimates that by 2050, the world population could reach 9.7 billion [2]. To meet the nutritional needs of this growing population, agricultural production must provide sufficient, nutrient-rich food. In addition to increasing production volume, ensuring food security is also of critical importance [3].

The global production area for maize (grown for dry grain) is approximately 208 million hectares, encompassing significant regions in the United States of America, Latin America, Asia, and Europe [4]. Farmers must produce the necessary input materials for the food industry, livestock production, and industrial sectors within the already available agricultural land [5,6].

The effects of climate change are already being felt, and these changes significantly impact plant production [7]. These effects include an increase in extreme weather events, such as longer dry periods, which reduce the optimal production window [8,9]. In addition, land degradation, flooding, and the expansion of water-scarce areas are contributing to the decline in arable land available for cereal crops like wheat and maize [10], The deterioration of arable land quality has driven researchers and plant breeders to develop new maize varieties that are more resilient to extreme environmental conditions [11].

Researchers have a variety of models at their disposal for analyzing agricultural problems. In these models, the parameters of maize plants hold varying levels of importance. However, there is no standardized calibration guide for these different models. In the absence of best practices, researchers often select models for specific problems based on their subjective evaluation and experience. The results obtained are typically verified using a statistical method chosen by the researchers [12]. Uncertainties arising from subjectivity can be minimized through the careful calibration of model parameters. The calibration of a given model should be conducted using multiple objective data sources [13]. Models incorporating more detailed input data tend to produce results that more closely approximate measured data [14]. An appropriate routine can significantly improve the accuracy of models. Model versions capable of simulating potential changes with high temporal and regional precision are particularly important in location-specific precision agriculture [15].

The Leaf Area Index (LAI) is a dimensionless scientific parameter that quantifies the total leaf area of a plant or vegetation canopy per unit of ground surface area. It is expressed as the ratio of the total one-sided leaf area to the ground area it covers. The LAI for maize is a critical indicator from both quantitative and qualitative perspectives. Quantitatively, it aids in estimating the assimilation products across different areas. Qualitatively, it serves as an indicator of the effects of various plant diseases and pests. The precise determination of plant dry matter and LAI greatly contributes to accurately estimating maize production. By dividing the growth process into distinct stages, we can gain a clearer understanding of the dynamics of maize development [16].

The LAI value for a plant population depends on various factors, including the variety or hybrid, growth stage, prevailing fertile land conditions, seasonality, and treatment practices. The LAI is a dynamic parameter that changes daily, primarily until the end of the vegetative period for herbaceous plants and during spring and autumn for ligneous plants [17]. The factors influencing LAI and the values calculated using different evaluation methods can vary significantly. In terms of maximum LAI values, deciduous forests typically range between six and eight, whereas annual plants exhibit values between two and four [18–20]. Ni et al., 2001 reported an exceptionally high LAI value of 41.8 in an evergreen, broad-leaved population [21].

There are two main categories for estimating LAI: direct and indirect methods [22,23]. The primary characteristic of the direct method is the direct measurement of the leaf area, while the indirect method involves deriving LAI from parameters that are easier to measure, such as time, load, or technology-related factors [22,24].

Direct methods are the most accurate for determining LAI. One such method involves harvesting the leaf entirely, tracing its shape onto graph paper, and counting the squares within the traced area to calculate the exact leaf area. This method's main advantage is its high degree of accuracy [25,26]. Using certain mathematical functions and an appropriate quantity of data from empirical observations, the dynamics of maize LAI changes can be modeled across phenological phases. However, these methods are extremely time-consuming, making it difficult to measure large agricultural areas with a high number of samples. The accumulation of errors from frequent repeated measurements can lead to accuracy issues that hinder scalability. Direct LAI determination is not suitable for long-term monitoring of the spatial and temporal dynamics of leaf area development, as it is both time- and labor-intensive and has other operational limitations [27].

Adequate accuracy is particularly important when the timing and location of feedback are predefined. Deep learning methods utilizing automatic image processing have been gaining importance in modern agricultural practices, contributing significantly to the automation of the agricultural sector [28]. The wider adoption of agricultural robotics is improving the efficiency of input material usage and enhancing crop safety. While model outputs derived from local data can account for variability within a field to a certain extent, this approach has limitations. As a result, heterogeneity is not fully captured in the model results. To obtain more precise model outcomes, it is necessary to either increase the number of measurement points or utilize remotely sensed data sources. These sources include images from multispectral or hyperspectral cameras mounted on satellites, aircraft, or unmanned aerial vehicles. Incorporating these data sources allows for better representation of heterogeneity in the models.

The aim of this review is to examine the applicability, limitations, and regional scalability of the presented models through the integration of remote sensing data. We compared the minimum climatic parameters (Maximum Air Temperature, Minimum Air Temperature, and precipitation) required for the successful execution of the models. This manuscript primarily focuses on the modeling of maize LAI. Additionally, it aims to assist researchers in selecting and applying the most suitable LAI models to improve the accuracy of yield predictions.

2. Materials and Methods

Maize and its LAI are the central focus of our study. To ensure the quality of the review, peer-reviewed articles were prioritized during the literature review process.

In the first phase, we defined the keywords and their combinations, including LAI, maize, and modeling. Using these keywords, we conducted searches across multiple databases. We used Scopus, Elsevier, and Google Scholar to gather scientific journal articles, primarily focusing on publications from the last 10–15 years.

In the second phase, we categorized the data based on different models, using them as the primary classification criterion.

In the third phase, where necessary, we created subcategories within the models to further refine the selection of scientific articles related to specific topics. When appropriate, we supplemented the manuscript with older publications during the writing process.

3. Presentation of the Models

The input parameters of the model include climatic factors (e.g., wind, precipitation), agrotechnical parameters, and other agriculture-related variables. Additionally, vegetation indices derived from remote sensing data are incorporated to refine the model's accuracy. After running the model, the calculated values, such as yield, LAI, or plant biomass, are generated as output data. These parameters will be discussed in detail in the following sections. The general structure of a model is illustrated in Figure 1.

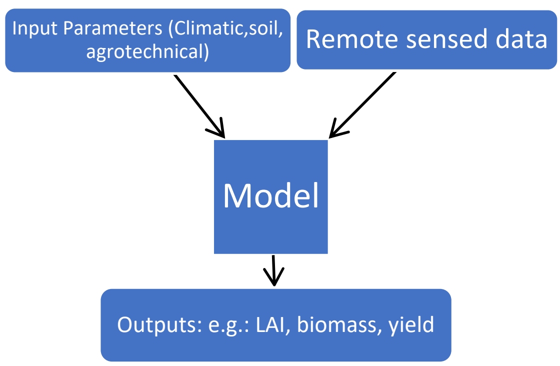

Figure 1. Theoretical Structure of a General Agricultural Model.

3.1. CERES-Maize

The first version of the CERES-Maize (Crop Environment Resource Synthesis-Maize) model was published in 1986 [29]. Over the years, it has been applied across various locations and environments and can be well adapted to agricultural areas with different climates. In the primary corn-growing region of the United States, it has been used for more than 30 years to estimate yield, biomass, and LAI across medium and large areas. Its performance and accuracy are generally considered good [30]. For maize hybrid seed production, the precise timing of male parent row cutting is especially important. Thus, shortly after its development, the basic model was adapted for maize hybrid seed modeling. The resulting CERES-IM model provides adequate accuracy for determining the timing of this intervention and has been in use for more than 20 years [31]. The model is suitable for examining how the plant responds to various irrigation levels and fertilizers. The model's uncertainty changes significantly if seasonal data differ from average conditions. Its outputs indicate which combination of irrigation and fertilizer treatment is most appropriate in a given region [32,33]. In fertilization experiments conducted in North America, it showed adequate accuracy for assessing grain yield, biomass, and LAI. However, its accuracy in water management modeling was not sufficient under both fertilized and unfertilized conditions [34]. Tovihoudji et al. [35] modified the model, making it suitable for modeling microdose fertilization. There was no significant difference between the measured and modeled data for aboveground biomass, LAI, and yield. According to Corbeels et al., [36] when mulch cultivation is implemented, parameters must be adjusted to maintain adequate accuracy. By limiting the rooting depth parameter in the model, accuracy can remain adequate under these cultivation methods.

3.2. AquaCrop

Due to its robustness, the model is well-suited for modeling major herbaceous plants. It requires few input parameters, making it easily adaptable. The core of the model is the relationship between the plant and the water available in the soil, which significantly influences other modeled parameters. LAI is estimated using a coefficient calculated from canopy cover and soil evaporation. The model has been available since 2009 [37]. Ran et al. found that the model's accuracy can be improved by incorporating field data. During the vegetative phase, the model provided adequate predictions for LAI, biomass, and yield, although it was sensitive to water stress. However, during the generative phase, the model tended to either underestimate or overestimate LAI values and became less responsive to water stress. Additionally, it generally overestimated changes in soil water content [38].

3.3. Root Zone Water Quality Model

The RZWQM (Root Zone Water Quality Model) is a complex, process-based simulation model developed to analyze the interactions within the soil, plant, water, and air system, with a particular focus on root zone water quality and agricultural processes. It was developed in 1989 by a research team at the USDA Agricultural Research Service [39]. The primary objective of the model is to study the movement of water, and nutrients between groundwater, and plants, as well as to analyze the effects of irrigation, and fertilization on plant LAI. The model was later enhanced and released as RZWQM2 [40].

3.4. Agricultural Production Systems sIMulator

The APSIM (Agricultural Production Systems sIMulator) is a process-based agricultural simulation model developed in 1996 to study various cropping systems and environmental impacts. The model was developed in collaboration with the Commonwealth Scientific and Industrial Research Organization (CSIRO), the University of Queensland, and other universities. Its primary goal is to examine the effects of climate change, irrigation, fertilization, and other management interventions on crop yield and the environment [41].

3.5. WOrld FOod STudies

The WOFOST (WOrld FOod STudies) model was primarily developed to simulate crop growth and yield under various environmental conditions and farming practices. Its development began in 1989 through collaboration between Wageningen University and the Netherlands Environmental Assessment Agency (PBL). The model's main objective is to simulate the effects of environmental factors (such as weather, water availability, and nutrient supply) on crop yield [42]. Due to its high adaptability, the model can be easily customized for specific agricultural regions [43]. Thanks to this flexibility, the model is well-suited for assessing the impact of increasingly frequent drought periods on maize yield and LAI in the future [44,45].

3.6. Other Models

In this section, we provide a brief overview of models that remain suitable for modeling the maize LAI, along with the approaches these models use to simulate the development of the corn plant.

The HYDRUS-1D software 4.17 primarily focuses on modeling the dynamics of maize root water uptake. First released in 1998 [46], it accounts for evaporation and examines the plant's water absorption in the soil at multiple levels. This model also helps identify specific agricultural issues, such as the formation of the plow sole layer [47].

The STICS (Simulateur multidisciplinaire pour les cultures standard) model provides an opportunity to analyze water, carbon (C), and nitrogen (N) balances in maize. The model has been under development since 1998 and simulates daily changes in LAI under field conditions [48]. The model is adaptable, enabling regional scalability. This capability allows for effective comparisons of performance across different regions [49].

The SALUS (System Approach to Land Use Sustainability) program aims to continuously model crop production, soil, water, and nutrient dynamics under varying agronomic conditions. Since its development in 2006, the model's adaptability has enabled its application across diverse agricultural systems [50].

The JULES-Crop (Joint UK Land Environment Simulator-Crop) is an ecosystem and crop production model designed to study crop growth, yield, and their interactions with the environment. It was developed in 2015 as an extension of the JULES model specifically for simulating agricultural production systems [51].

The GECROS (Genotype-by-Environment Interaction on CROp growth Simulator) model, introduced in 2005, was primarily developed for simulating plant growth and yield, with a particular emphasis on examining interactions between genotype and environment [52].

The EPIC-PHASE model is an extension of the EPIC (Environmental Policy Integrated Climate) model, which was originally developed to analyze resource management and environmental impacts. The PHASE component complements the model by providing a more precise examination of plant phenology and agrotechnical interventions. It was first applied in 1996 to optimize maize growth and irrigation strategies [53].

The CropSyst model was developed to simulate crop growth, yield, water, and nutrient requirements, as well as the long-term impacts of agricultural practices on these factors. The model was developed by researchers at Washington State University in 1994 [54].

The Agro-IBIS model is a specialized submodel of the IBIS (Integrated Biosphere Simulator) ecosystem model, focusing on agricultural systems and their climatic interactions. Agro-IBIS is designed to simulate crop growth, LAI, as well as soil and atmospheric processes in agricultural areas. The model's first version was released in 2000 [55].

We also examined the CROPWAT model, which is less widely used than the five models mentioned above, so there is limited information available regarding its performance and usability.

4. Comparison of Input Parameters

4.1. Climatic Input Parameters of Models

The applicability of models largely depends on the availability of input data and the measured parameters provided by monitoring systems, such as meteorological stations. Meteorological stations typically measure variables like temperature, precipitation, solar radiation, humidity, and wind speed, which are crucial for parameterizing LAI models. These measurements provide a foundation for estimating evapotranspiration, photosynthetic activity, and biomass accumulation, all of which influence LAI. Table 1 lists and compares the climate-related input parameters utilized in each model.

Table 1. Key climatic input requirement of the Models.

Parameter/Model	CERES-Maize	WOFOST	AquaCrop	APSIM	RZWQM2
T Max	X	X	X	X	X
T Min	X	X	X	X	X
Global radiation	X	X	-	X	X
Rain	X	X	X	X	X
Wind	X	X	X	X	X *
Relative humidity	X	X	X	X	X
Vapor pressure	-	X	-	-	-
ET_0	-	X	X	-	-
Annual CO_2	-	-	X	-	-
Sun hours	-	-	X	-	-

Note: "X": This parameter is used in the model. "-": This parameter is not used in the model. "ET_0": Reference evapotranspiration. "T Max": Maximum Air Temperature "T Min": Minimum Air Temperature. "X *": In the Root Zone Water Quality Model (RZWQM2), "Wind" refers to wind run [56–61].

Table 1 shows that the use of climate-related input parameters varies across the five most commonly used models in the literature. Only three key parameters (T Max, T Min, and precipitation) were explicitly deemed essential by all the models examined. Below, we discuss the climate-specific input parameters for each model individually.

4.2. Special Minimum Input Parameters in the Models

For the CERES-Maize model, accuracy can be enhanced by incorporating wind and relative humidity (RH) data. In the case of AquaCrop, data on reference evapotranspiration (ET_0) and mean annual CO_2 concentrations are required. Additional input data are also necessary, although these are not climate-related parameters. For the WOFOST model, vapor pressure, evapotranspiration, sunshine hours, and global radiation are also essential inputs.

For the APSIM model, solar radiation data are additionally required alongside the three previously mentioned parameters. The model can also incorporate other parameters primarily related to soil; however, these are not discussed here, as this section focuses solely on climate input parameters.

In the RZWQM2 model, the Soil Water Balance Module calculates potential evapotranspiration and then forwards this data to the Plant Growth Module, which supplements the modeled climatic parameters with wind run and RH input values.

To calculate the modeled potential LAI, each model considers additional input parameters, which may be calculated in various submodules. These parameters are presented in Table 2.

Table 2. Comparison of model-specific parameters.

Parameter/Model	CERES-Maize	WOFOST	AquaCrop	APSIM	RZWQM2
Bulk density	X	X	-	X	X
Permanent Wilting Point	X	X	X	-	-
Organic Carbon	X	X	-	X	-
Field Capacity	X	X	X	-	-
Saturation Moisture Content	X	X	X	X	X
Root Grow Factor	X	X	X	X	X
Soil Water Content	-	-	X	-	X
Soil nitrogen	X	X	X	X	X

Note: "X": This parameter is used in the model. "-": This parameter is not used in the model. Source: adapted from [56–61].

Soil parameters are handled in separate modules in some models, while others reduce them to a few key variables. The five most commonly used models account for soil nitrogen content, root growth factor, and soil saturation moisture content.

Volumetric water content is not considered by AquaCrop, while organic carbon is excluded by both AquaCrop and RZWQM2. Permanent wilting point and field capacity are only factored in by CERES-Maize, WOFOST, and AquaCrop. Soil water content is considered only by AquaCrop and RZWQM2. Some models treat soil as a single entity (e.g., WOFOST), whereas others partition soil into multiple layers for more accurate modeling (e.g., CERES-Maize, AquaCrop). These differences demonstrate that, with respect to weather and soil parameters, the models vary in their determination of which factors are most critical for calculating accurate model values.

Some models handle parameters related to agricultural techniques within a separate sub-module, while others incorporate them directly into the main model. A comparison of these parameters is provided in Table 3.

Table 3. Model input parameters related to agrotechnics.

Parameter/Model	CERES-Maize	WOFOST	AquaCrop	APSIM	RZWQM2
Planting Date	X	X	X	X	X
Planting Density	X	-	X	X	X
Seed Variety	X	X	X	X	X
Irrigation Applied	X	X	X	X	X
Harvest Index	X	X	X	X	-

Note: "X": This parameter is used in the model. "-": This parameter is not used in the model. Source: adapted from [56–61].

The parameters Planting Date, Seed Variety, and Irrigation Applied listed in Table 3 are uniformly considered by all five models. However, among these parameters, planting density is not accounted for by the WOFOST model, while the harvest index is not calculated by the RZWQM2 model. There are also parameters that only certain models consider. These parameters are mentioned but not detailed, as the purpose of this article is not to describe the individual models.

The parameters of water capacity, permanent wilting point, and available water are essential for accurate modeling in all four models. APSIM also takes into account pH, organic matter, clay content, and albedo. Differences exist among the models regarding these parameters. AquaCrop considers the current groundwater level and the method of irrigation.

Maize input parameters are considered differently by each model. For example, the AquaCrop model accounts for tasseling and silking stages, maximum canopy cover, and rooting depth, which are not always emphasized as prominently in other models.

The slope angle is only considered by the RZWQM2 model as an input parameter. Furthermore, there are areas where ignoring the angle of slope significantly worsens modeling accuracy.

4.3. Key Considerations for Model Selection and Data Availability

This previous section provides guidance for researchers in selecting the most suitable model based on the available parameters. Before choosing a model, researchers must consider which time-series climatic parameters are available. The minimum required parameters include T Max, T Min, and precipitation. Without these, running any model becomes challenging. To compensate for missing data, it is advisable to use public meteorological data from the closest official weather station to the study area. If such data are unavailable, most models offer an internal database that allows the selection of the most suitable meteorological and auxiliary data for the given location. Additionally, the soil type of the study area must be taken into account, as it is a significant factor influencing model accuracy.

Since different models may yield varying results, it is recommended that multiple models be run for the same area and their outputs be compared. If this is not feasible, researchers should rely on previously published results relevant to the specific location. Whenever possible, empirical data should be used to validate the model's estimated values.

5. Evaluation, Performance, and Improvement of Models

The applicability of models is influenced by numerous factors. The implementation of different parameter combinations in various agricultural environments has led to a significant number of publications. In the following, we present the effectiveness and usability of these models.

5.1. CERES-Maize

5.1.1. Model Performance Under Irrigation Variability

Over time, researchers have examined its response to irrigation from several perspectives. A potential way to enhance the accuracy of modeling with reduced water doses is to introduce a dynamic coefficient into the basic model [62]. Amiri et al. [63] found a strong correlation between LAI and aboveground biomass under both rainy and irrigated conditions. They also observed that the model's accuracy deteriorates in the event of water shortages. Moreover, the model effectively reflected changes in sowing time through corresponding variations in simulated yield. Castrignanó et al. [64] modified the model to make it suitable for testing the effects of saline irrigation water under Mediterranean conditions. Their results showed that the model slightly overestimated evapotranspiration while underestimating LAI and biomass. Nonetheless, the model simulates plant growth well in dry Mediterranean areas with inadequate water management, accurately accounting for the essential soil elements needed by the plant [65,66].

5.1.2. Model Evaluation in Different Climate Regions

In this subsection, we present the results achieved by the model in different climate zones. In Africa's savannah regions, the model has demonstrated highly accurate simulations of LAI, along with yield and grain yield. It is also well suited for evaluating changes in sowing time and yield with considerable precision [67]. The model effectively captures maize growth even in suboptimal, low-yield areas, thereby assisting in selecting optimal agronomic practices and sowing schedules. In these regions, early sowing maximizes both yield and plant biomass, and substituting organic matter positively influences yield under less-than-optimal conditions [68]. Additionally, the model proves highly accurate when modeling extra-early, early, mid-, and late-early maize cultivars under both irrigated and non-irrigated conditions in Nigeria's savannah areas, enabling a more straightforward ranking of maize hybrids [69]. In semi-arid regions, the adverse effects of water shortages can be minimized by ensuring sufficient irrigation during critical growth stages, such as flowering and grain filling. This approach allows for more cost-effective irrigation strategies [70].

In Mediterranean conditions, contradictory results have been reported regarding the model's performance. In sandier Mediterranean areas, the model effectively simulated grain yield, plant evapotranspiration (ET), and soil moisture content. Additionally, it was shown that with 80% ET, maize yield did not significantly decrease. This suggests that in regions with limited irrigation water, yield loss can be minimized by applying a minimal amount of water [71]. According to Mastrorilli et al., in other Mediterranean conditions, the basic model requires adjustments in its calculation functions for LAI, biomass, and grain yield. Modified sub-models that better account for water supply demonstrate improved performance and greater estimation accuracy in these regions [72]. Under Mediterranean semi-arid irrigated conditions, the model's accuracy decreases when mulch tillage is applied. Additionally, its simulation of soil temperature and reduced nitrogen fertilization is not satisfactory [73]. Ben Nouna et al. [74] found that air moisture scarcity is less limiting than groundwater availability for model predictions. In Mediterranean semi-arid conditions with insufficient soil moisture, the model underestimates LAI, biomass, and final yield. Shivani et al. [75] observed that maize biomass increases with non-optimal sowing times, although grain yield decreases. They found a very strong correlation between measured and modeled yield and biomass, while the correlation for LAI was only strong. Rugira's findings highlighted that the model effectively supports determining the optimal sowing time, and the appropriate irrigation volume to maximize yield, identifying critical periods when irrigation is most important [76], By accounting for leaf morphology (growth, and senescence), stand density, and nitrogen's impact on LAI, more accurate model predictions can be achieved [77]. Ren et al. [78] examined the effects of different seeding densities and nitrogen fertilization using the CERES-Maize model. The model successfully identified optimal irrigation and fertilization strategies that maximize LAI, biomass, and yield while minimizing environmental stress. Zhang et al. examined the impact of maize planting density and soil water management on the development of the LAI [79].

Differences in model results may also arise from the empirically measured input data, which can significantly influence the modeled values. To avoid erroneous conclusions, it is advisable to compare the computed values using data from other scientific article sources.

5.2. AquaCrop

According to Giménez, the model showed greater deviations from actual values during flowering and grain filling under water-deficient conditions. In contrast, with sufficient water supply, the differences between measured and estimated values were minimal. However, the model consistently underestimated LAI during periods of water scarcity [80]. The integration of appropriately selected vegetation indices into the AquaCrop model improves the accuracy of maize LAI and biomass production estimations [81].

There is no consensus regarding the use of the model for irrigation planning. On the one hand, Paredes et al. found that with proper calibration, there was only a small difference between measured and modeled plant transpiration data and LAI values. However, they observed that the model tends to overestimate plant evaporation and underestimate soil evaporation. As a result, they do not recommend the model for irrigation planning [82]. On the other hand, Shan et al. applied the model with drip irrigation and soil conditioners on saline soils and reported satisfactory performance. The model provided adequate accuracy in estimating above-ground LAI values and crop yield. However, the difference between measured and modeled data was more significant for soil water content [83,84].

AquaCrop Model Performance Across Climate Zones

In the next subsection, we present the performance of the AquaCrop model in different climate zones. Greaves et al. tested the model under tropical conditions and found that it accurately simulated plant cover, biomass, and yield in areas with both adequate and limited water supply. However, the model's reliability decreased significantly when water became a limiting factor. The authors concluded that the model could be used for irrigation planning with certain limitations [85]. Abedinpour tested the model in semi-arid conditions and determined that its prediction accuracy was reasonably good. The model adequately simulated surface vegetation cover, biomass, plant response to fertilizers, and irrigation water use [86]. Heng et al. [87] evaluated the model under Mediterranean conditions. The model performed well under normal and low water stress conditions. However, during the plant's generative phase under high water stress, its accuracy deteriorated significantly. Despite this, the modeled plant cover values remained fairly accurate. In northwest India, Raja et al. assessed the model and found that predictions for grain yield and plant water use were acceptable. The model also showed satisfactory performance for canopy cover and biomass values, although its accuracy declined as the harvest period approached. They suggested that the model's accuracy could be improved by adjusting the soil evaporation coefficient [88]. Eshete et al. [89] tested the model in Ethiopia and found that the modeled and measured data for canopy cover and plant biomass were consistent. However, the model's uncertainty in predicting evaporation increased under higher water stress conditions. Žydelis et al. [90] observed that yield reductions caused by heat stress were more severe than those caused by water stress. The model effectively tracked yield fluctuations of maize grown in cooler climates.

5.3. RZWQM

Over the years, the model has undergone several revisions, with increasing focus on maize response to water availability and nitrogen translocation [61,91]. Contradictions have emerged when incorporating field measurements. According to Ma et al. [92], continuous field measurements provide more reliable input data than laboratory measurements. Additionally, using various parameter combinations (such as crop variety and irrigation treatments) can improve the model's accuracy. However, Sima et al. [93] noted that incorporating field soil moisture data does not always enhance model accuracy. Nonetheless, separately calibrating individual input parameters and carefully considering soil moisture data can improve the model's performance. Furthermore, the model effectively supports the selection of modern irrigation techniques [94].

5.4. APSIM

In situations where input data of sufficient quality and quantity are lacking, the model's detailed structure results in a final output with an acceptable margin of error [95].

APSIM is effective for comparing LAI and biomass parameters among different maize varieties grown on soils with favorable water management. However, its accuracy declines on soils with poor water management, making it unsuitable for such comparisons in those conditions [96].

APSIM Model Accuracy and Performance Enhancements

Chen et al. [97] compared the WHCNS and APSIM models and found that the WHCNS model provides more accurate estimates of crop yield, biomass, and plant water movement in the soil. However, both models inadequately account for soil heterogeneity. Chisanga et al. [98] compared the APSIM model with the CERES model using DSSAT and found no significant differences in their simulated results. Both models exhibit similar sensitivity to input parameters, highlighting the importance of providing accurate and well-cleaned data to achieve reliable results. The basic model effectively measures LAI, plant biomass, and nitrogen uptake dynamics but is less responsive to soil parameters, such as root growth, soil water uptake, and soil temperature [99]. Several researchers have attempted to improve the model's estimation accuracy using various methods. Kivi et al. [100] enhanced the model by incorporating the Ensemble Kalman Filter, significantly improving the estimation of soil moisture leakage. Additionally, this modification enhanced the accuracy of LAI, annual nitrogen turnover, and yield predictions. Machwitz et al. [101] integrated RAPIDEYE data into the model, which improved forecast accuracy and enabled the examination of more extreme growing conditions. This updated model version can now track spatial variability, providing daily resolution for maize biomass production. Peng et al. [102] combined the basic model with the Community Land Model, further improving its performance. This new version enhanced LAI estimation, canopy height prediction, and yield simulation, effectively reducing underestimation and overestimation. The model also accounted for plant phenological changes and environmental abiotic stress factors in greater detail.

5.5. WOFOST

Omar Ali et al. combined the WOFOST model with the Noah Land Surface Model to achieve more accurate estimates of maize LAI and plant-available soil water across three depth levels [103]. Similarly, Li et al. [104] found that integrating the model with the HYDRUS-1D software 4.17 enabled more accurate estimates of LAI and yield. Additionally, incorporating remotely sensed vegetation indices facilitated the regional scaling of the model's predictions without compromising accuracy.

5.6. Further Models to Estimate LAI

The SALUS-Simple model is sensitive to the production location but is less responsive to variations in yield and vintage effects. When 15 or more input parameters are provided, the model's estimation uncertainty can be reduced, allowing for better adaptation to crops other than maize. The model infers biomass and yield by simulating plant cover [105,106].

The central component of the JULES-crop model is the plant's carbon and energy cycles. Its applications range from global-scale analyses to local area comparisons. By adjusting the appropriate parameters, the model's accuracy in estimating LAI as well as carbon and energy turnover can be improved. Cloud cover and soil moisture parameters significantly impact yield estimation accuracy [107].

Ingwersen et al. integrated the GERCOS and NOHA-NP land surface models, extending soil evaporation modeling to the regional level. This integration allows for more accurate monitoring of plant evapotranspiration. By combining models, various climate–plant interaction mechanisms can be explored by incorporating weather parameters to assess early and late cover crops [108].

Applying the EPIC-PHASE and CROPWAT models within the same experimental area enables a more effective comparison of key output parameters (such as LAI, evapotranspiration, and biomass) produced by both models. According to Cavero et al., by adjusting the parameters of the EPIC-PHASE model, LAI inaccuracies caused by water stress can be improved compared to the CROPWAT model [109].

Bellocchi et al. found that the CropSyst model is suitable for comparing parameters related to soil water balance, biomass, and LAI values across different plots. However, it only moderately tracks the effects of the previous year's crop and the release of nitrogen in the soil [110].

According to Amuti et al., the process-based Agro-IBIS model effectively simulates soil water availability, upper soil layer temperature, and LAI. The deviation between measured and estimated data remains within an acceptable range [111].

6. Remote Sensing Data Sources in LAI Estimation

The integration of remote sensing data into maize LAI estimations leads to more accurate, faster, and larger-scale results, while enabling the efficient monitoring of changes in agricultural systems.

These results, however, require researchers to make compromises. For example, vegetation indices derived from multispectral images taken from large distances can have resolution ranging from meters to even a kilometer wide [112,113]. At such scales, smaller variations (below meter-level resolution) are not represented in the imagery, making it more difficult to account for heterogeneity. The following Figure 2 illustrates the relationship between imaging altitude and the data represented by pixels.

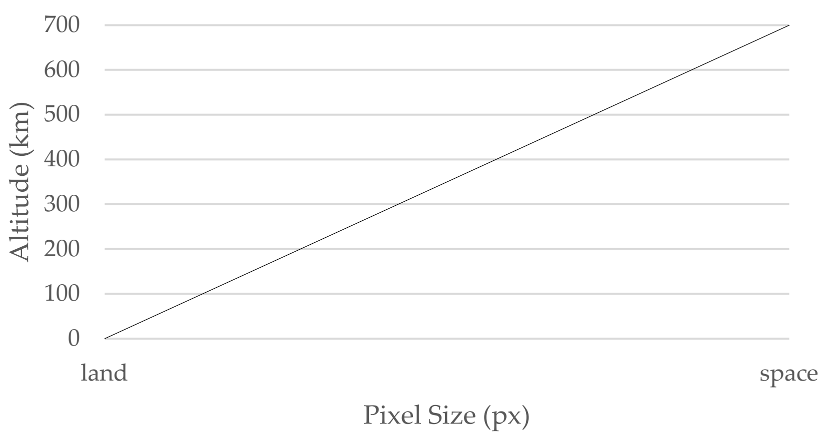

Figure 2. Relationship Between Altitude and Pixel Size.

Figure 2 illustrates the relationship between altitude and pixel size. This diagram provides a general perspective, showing that a camera with a given resolution captures more detailed imagery (composed of more pixels) from a lower altitude, allowing for better representation of spatial variations in the observed area.

When the same camera is used at a higher altitude, a larger area can be observed with the same resolution, but each pixel will cover a broader surface, reducing its ability to represent local variations accurately.

Additional challenges arise when using satellite imagery because the data are typically available only at periodic intervals—sometimes up to 16 days between consecutive images [112]. Various environmental factors, such as cloud cover, can obstruct data collection, creating gaps that are difficult to fill.

For aircraft- or UAV-based imaging, different weather conditions (e.g., fog, rain, or strong winds) can also hinder or completely prevent image acquisition at a given time. However, these issues can be more easily mitigated by capturing images at alternative times.

Another key issue in early-stage maize LAI estimation is that the small plant size results in significant soil interference in remote sensing data. One approach to addressing this issue is the Reduced Soil Contribution method (CS) [114].

In the following sections, we adopt a top-down approach, first presenting satellite-based LAI observations, followed by aircraft-based measurements, and finally, the results from UAV-based observations.

Satellite-Based Vegetation Indices for Crop Modeling

Satellite-based remotely sensed data are particularly useful for monitoring maize grown under extreme climatic conditions. This approach enables a quick and cost-effective analysis of maize LAI. Additionally, the generated maps can guide the design of ground-based data collection protocols [115].

By selecting the appropriate wavelengths, vegetation indices can facilitate the rapid assessment of specific areas. These indices incorporate infrared wavelengths from different spectral bands. Using multiple indices allows for a better observation of spatial heterogeneity in a given area.

For example:

- NDVI (Normalized Difference Vegetation Index) uses 800,670 nm wavelengths [116].
- MCARI (Modified Chlorophyll Absorption Ratio Index) is based on 700,670 nm wavelengths [116].
- TVI (Triangular Vegetation Index) utilizes 750,670,550 nm wavelengths [116].

Integrating these indices into various crop models enhances and complements ground-based observation data, ultimately improving model accuracy. The following section presents specific examples of how these integrations have been implemented.

Kayad et al. integrated field data and hyperspectral recordings into the PROSAIL model. The resulting NDRE vegetation index provided an acceptable approximation of maize LAI, biomass, and grain yield [117]. Battude et al. [118] enhanced the Simple Algorithm for Yield Estimation (SAFY) model by incorporating high-resolution remotely sensed data, enabling regional estimation of maize LAI and yield without relying on farm-level input data. The generated data demonstrated fairly high accuracy.

The integration of artificial intelligence into crop production models holds significant potential for advancing agricultural modeling and decision making. Artificial intelligence-based models significantly contribute to the optimal selection of hyperspectral wavelengths provided by satellites. Choosing more accurate wavelengths enhances LAI estimation in a fast and cost-effective manner [119]. Castro-Valdecantos demonstrated that using a convolutional neural network (CNN) combined with RGB images yields more accurate LAI estimates compared to using RGB images alone. This approach results in a model that is both cost-effective and time-efficient [120]. According to Liu et al., [121] selecting combined input parameters (such as thermal, multispectral, and RGB camera data) for deep learning neural networks enables rapid and accurate LAI estimation.

The accuracy of regional estimations can be significantly improved with higher-resolution remote sensing imagery. Since the late 1990s, the MODIS (Moderate Resolution Imaging Spectroradiometer) has provided small-scale regional remotely sensed data for various applications, including agriculture [122]. Large-scale regional estimates are particularly important for decision makers in agricultural planning and resource management. Hierarchical data assimilation techniques can further enhance yield predictions by integrating different types of remotely sensed data [123]. In regions facing high food insecurity and unfavorable climatic conditions, plant phenological parameters derived from the SARRA-H model (System for Regional Analysis of Agro-Climatic Risks), combined with remotely sensed vegetation indicators, are especially valuable [124]. Sakamoto et al. [125] successfully reduced the error in remotely sensed data to below 10% by integrating the "Shape-Model Fitting Method". This model allows for higher-resolution crop yield estimation. It more accurately captures the silking stage and spatial variability of maize. However, it may underestimate or overestimate values in peripheral areas.

Integrating the MODIS data into the CERES-Maize model provides sufficient accuracy for daily modeling of maize LAI [126]. Jin et al. [127] combined the Two-layer Canopy Reflectance Model (ACRM), the CERES-Maize model, and MODIS data, enabling rapid regional estimation of LAI. The accuracy of the daily-scale assimilation LAI maps generated through this integration is considered high.

The high-resolution data provided by newer satellites enable more accurate LAI estimations, which are particularly valuable for determining optimal irrigation timing. An example is the Sentinel-2 satellite, whose data can be highly beneficial in such cases. Its high-resolution data, designed for smaller-scale applications, enables precise calculation of water requirements for crops grown on smaller plots [128].

7. Aircraft-Based Remote Sensing Data Collection

If estimates need to be made on a scale smaller than the regional level, satellite imagery may not provide the most suitable solution. For example, while the pixel size of MODIS data is 10 m, a multispectral camera mounted on an aircraft can achieve a pixel size as small as 1 m. This significantly increases accuracy while maintaining spatial scalability. Multispectral camera data collected from aircraft carriers greatly enhances the accuracy of model estimations. The smaller pixel size makes it easier to eliminate soil patches within fields, which can otherwise distort the modeled values for a given area [129]. These data not only improve the performance of crop growth models but also increase the accuracy of various vegetation indices [130]. Beyond agriculture, LAI measurement is also applied in other fields, such as forestry [131]. Although this area is only briefly mentioned here, the use of growth models is equally important in forestry. In certain regions, ground-based sampling is challenging and can be costly. In such cases, LiDAR measurements offer an alternative for data collection. By integrating LiDAR data into growth models, more accurate estimates can be made for specific areas [132].

8. Unmanned Aerial Vehicle

Low- and medium-resolution maps provided by Unmanned Aerial Vehicles (UAVs) significantly contribute to the cost-effective and rapid estimation of maize LAI and biomass. The pixel size of the generated maps represents less than 2 cm [133].

Below are examples of how these solutions have been applied. Using hyperspectral data collected by UAVs, maize LAI can be easily and accurately estimated across multiple growth stages. This approach also allows for the analysis of maize responses to fertilization and irrigation [134]. Vegetation maps generated from hyperspectral data, and Normalized Difference Red Edge (NDRE) images, when combined with a Deep Learning model, enable more precise modeling of LAI data [135]. The WOFOST model, when integrated with vegetation indices derived from hyperspectral data, provides sufficiently accurate LAI estimations across all phenological stages of maize [136–138]. Additionally, the 2-m resolution data provided by UAVs allows for improved approximations. By integrating inverted LAI values and vegetation indices into the SAFY model, the accuracy of the generated data can be effectively evaluated. However, the accuracy of the model decreases under conditions of severe water deficit [139].

Integrating the Random Forest method with vegetation indices into a single system can improve the correlation between measured and estimated LAI values throughout all stages of maize development [140]. By combining Partial Least Squares Regression (PLSR) with the Random Round method, vegetation indices can be determined with greater accuracy. In this model, maize chlorophyll content and plant canopy cover are closely correlated [141,142]. Additionally, combining images from RGB cameras with field measurement data allows for a more detailed analysis of the fertilizer response in different maize hybrids [143].

9. Conclusions

It is essential to examine how maize responds to changes in individual climate parameters, given its vital role in human nutrition. The maize LAI is closely linked to the plant's water use and yield. This study presented the applicability of the most commonly used models across various climate zones. We highlighted that the CERES-Maize model demonstrates good adaptability across different climate zones; however, some researchers have raised concerns about its effectiveness in the Mediterranean region. Due to its robustness, the AquaCrop model can also be effectively used and adapted to various climates. Nevertheless, researchers have noted that while AquaCrop produces accurate LAI values during maize's vegetative phase, its accuracy decreases during the generative phase. Additionally, we provided an overview of models from the past 10–15 years that remain suitable for modeling maize LAI. In the future, researchers must adapt models to account for the increasing frequency of extreme weather events. Additionally, field heterogeneity should play a more significant role in model outputs. One way to improve this is by improving the integration of remote sensing data.

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Abbreviations

LAI	Leaf Area Index
CERES-Maize	Crop Environment Resource Synthesis-Maize
WOFOST	WOrld FOod STudies
APSIM	Agricultural Production Systems sIMulato
RZWQM	Root Zone Water Quality Model
RH	Relative Humidity
T Min	Minimum Air Temperature
T Max	Maximum Air Temperature
SAFY	Simple Algorithm For Yield estimation
MODIS	Moderate Resolution Imaging Spectroradiometer
ET0	Reference evapotranspiration

ET	EvapoTranspiration
IM	Inbred-Maize
WHCNS	soil Water Heat Carbon and N Simulator
DSSAT	Decision Support System for Agrotechnology Transfer
STICS	Simulateur mulTIdisciplinaire pour les Cultures Standard
SALUS	System Approach to Land Use Sustainability
JULES-crop	Joint UK Land Environment Simulator
GERCOS	Genotype-by-Environment interaction on CROp growth Simulator
Noah-MP	Noah-Multiparameterization
EPIC-PHASE	Environmental Policy Integrated Climate
Agro-IBIS	Agro-Integrated BIosphere Simulator
PROSAIL	fusion of PROSPECT (leaf reflectance and transmittance) and SAIL (plant canopy reflectance)
NDRE	Normalized difference red edge
CNN	Convolutional Neural Network
RGB	Red Green Blue
SARRA	System for Regional Analysis of Agro-Climatic Risks
ACRM	Two-layer canopy reflectance model
LiDAR	Light Detection and Ranging
UAV	Unmanned Aerial Vehicle
PLRS	Partial Least Squares Regression
USDA	U.S. Department of Agriculture
ARS	Agricultural Research Service
CSIRO	Commonwealth Scientific and Industrial Research Organisation
CS	Reduced Soil Contribution
NDVI	Normalized Difference Vegetation Index
MCARI	Modified Chlorophyll Absorption Ratio Index
TVI	Triangular Vegetation Index
PBL	Netherlands Environmental Assessment Agency

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