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REVIEW

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Crop models and their use in assessing crop production and food security: A review

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Abstract
Agriculture is directly related to food security as it determines the global food supply. Research in agriculture to predict crop productivity and losses helps avoid high food demand with little supply and price spikes. Here, we review ten crop models and one intercomparison project used for simulating crop growth and productivity under various impacts from soil–crop–atmosphere interactions. The review outlines food security and production assessments using numerical models for maize, wheat, and rice production. A summary of reviewed studies shows the following: (1) model ensembles provide smaller modeling errors compared to single models, (2) single models show better results when coupled with other types of models, (3) the ten reviewed crop models had improvements over the years and can accurately predict crop growth and yield for most of the locations, management conditions, and genotypes tested, (4) APSIM and DSSAT are fast and reliable in assessing broader output variables, (5) AquaCrop is indicated to investigate water footprint, quality and use efficiency in rainfed and irrigated systems, (6) all models assess nitrogen dynamics and use efficiency efficiently, excluding AquaCrop and WOFOST, (7) JULES specifies in evaluating food security vulnerability, (8) ORYZA is the main crop model used to evaluate paddy rice production, (9) grain filling is usually assessed with APSIM, DAISY, and DSSAT, and (10) the ten crop models can be used as tools to evaluate food production, availability, and security.

KEYWORDS
climate change, crop modeling, food availability, food insecurity

1 | INTRODUCTION

Food Security (FS) refers to the ability to access safe food, the economic possibility to afford it (Tarasuk & Mitchell, 2020), and the ability to achieve dietary needs (Coleman-Jensen et al., 2021; FAO, 1996; Zhou, 2020). FS consists of five important related dimensions (FAO, 1996; Zhou, 2020): food availability, which is the most critical aspect; supply sustainability, which secures food in sufficient quantity for the future; food quality and safety, which assures that dietary needs are met from safe food; cultural acceptability, which means that the food meets preferences; and the ability to access food, which involves the ability of the consumer to afford sufficient and diverse foods. The global population determines global food consumption, and the quantity of food produced in agriculture determines the global food supply. Since the agricultural sector involves various products, grain production is one of the few international, continental or regional food supply indicators (Kogan, 2019). Sustainable farm production, infrastructure, and technology improvement with public policies and lower trade costs are also important for FS.

Eight hundred million people globally suffer from food insecurity (FI) (Fahad et al., 2019). Moreover, people in low- and middle-income countries, poor people, young adults, less educated people, women and children, Indigenous People, Black People, Hispanic People, Immigrants, and Quilombola communities (communities of enslaved Afro-Brazilian Descendants) are more prone to suffer from FI (Depa et al., 2018; Maluf, 2021; Morales et al., 2021; Quandt et al., 2006; Tarasuk & Mitchell, 2020). Besides, rural households buy 80% of their food diversity intake from the market (Dean & Sharkey, 2011; Sibhatu & Qaim, 2017). However, this population is often denied assistance because organizations assume they can produce their own food (Minkoff-Zern, 2014).

Historically, global crop producers selected maize, wheat, and rice as the principal staple crops for the most remarkable adaptation in diverse areas and climates, their vast acceptance and consumption by the population, and their nutritional status (FAO, 1995). Together, they provide 60% of global food energy intake (FAO, 1995) as they are used as a staple food by more than half of the world's population (FAO, 2021a; Haile et al., 2017). Maize is the most produced crop in the world (FAO, 2021b). It is a staple food, feeds livestock, and has industrial uses (Ranum et al., 2014). Rice is important for global caloric intake, especially for those below the poverty line (Maclean et al., 2014). Wheat is the second most-produced crop in the world (FAO, 2021b). This crop is high-yielding and easily adapts to diverse climates (de Sousa et al., 2021). Currently, almost one-third of the world's land area is used for agriculture. Over 4 billion hectares were dedicated to agriculture in 2019, of which 1.6 billion were exclusively croplands (FAO, 2021a). Of the total cropland, 1.26 billion hectares are rainfed, while the rest can be considered marginal land that can be farmed because of irrigation (FAO, 2021a), representing 70% of global water use (ICID, 2021). Further, more than 4 billion people live in urban settings (United Nations, 2019) and rely on others to produce their food. Hence, losing the ability to plant and harvest maize, wheat, and rice, whether as a result of the (re)emergence of a disease or pest, political instability, or climate change effects (e.g., flood, drought, storms), is likely to increase morbidity and mortality, particularly amongst the most vulnerable around the world (Harari, 2014; Visser et al., 2018).

When shortfalls in food production are detected early, mitigation solutions can be found before a significant crisis of hunger and famine (Krishnamurthy et al., 2020), avoiding FI impacts on people's mental and physical health (Tarasuk & Mitchell, 2020) and therefore, productivity. An early warning system could be the answer to prepare people and supply chains to (re)adapt to new conditions, predicting food productivity, demands, and nutritional needs by monitoring, collecting, and modeling agricultural and population data (Barrett, 2013). Crop models can accurately predict the crop reality of a site considering field management, weather and soil conditions for various spatial and temporal resolutions (Aggarwal et al., 1994). They are more commonly statistical, dynamic, or multidimensional systems based on the climate, environment, niche, or process (Fodor et al., 2017), focusing on soil-water-plant-atmosphere interactions. They run complete simulations with relatively few field data. As a critical part of food security, food availability is predicted in crop models' simulations by grain yield and biomass outputs. Simulated grain yield outputs are used to optimize management (crop and soil) conditions to achieve optimal productivity and ensure future food security (see, e.g., Fischer et al., 2014; Neupane et al., 2022; Xu, Henry, et al., 2020). Crop models generate a better understanding of future impacts on crop production from limiting factors, such as climate variability (e.g., Newton et al., 2011) through their outputs (Webber et al., 2014). It characterizes how the crops respond to those factors, allowing farmer response improvement and adaptation, which is crucial for future food production and availability (Webber et al., 2014). However, some crop models do not account for yield response to temperature stress because they consider daily mean temperature. Algorithms can become better responsive to heat stress when considering the daylight air temperature instead of the mean values (Jin et al., 2016), or the canopy temperature (Peng et al., 2018). Studies using crop models focusing on food security are current and a great method to decrease and avoid global food insecurity in the short and long-terms (see, e.g., Alvar-Beltrán et al., 2023; Jägermeyr et al., 2020; Karthikeyan et al., 2020; Kheir et al., 2022; Molotoks et al., 2021).

Researching and investing in predicting crop productivity, i.e., modeling and predicting types and magnitudes of crop yield losses, avoids food shortages and price spikes, directly affecting FS (Barrett, 2013). In this perspective, we outline the food security assessment of the three main staple crops: maize, wheat, and rice, through mathematical models. This review will focus on one FS dimension, food availability. In doing so, it will explore the applicability and performance of eight crop models designed to predict productivity and loss for maize, rice, and wheat, identifying model constraints, regions of application, and major findings.

2 | CROP MODELS

We identified ten crop models and summarized their applicability in a conceptual diagram (Figure 1) and tables along the text. It shows the most common variables and climate change factors modelers have been analyzing and the impacts that key weather and climate stressors cause on food production.

2.1 | APSIM

Agricultural Production Systems Simulator (APSIM) includes biophysical processes simulating interactions of animals, climate, management, plants, and soil characteristics at multiple levels from the field to the global scale (Holzworth et al., 2014, 2018). The input data required for crop phenology are planting date and density, crop variety, fertilization and irrigation date and amount; for weather are maximum and minimum air temperature, rainfall, and solar radiation, all in daily time steps; and, for soil characteristics are water content and upper and lower limits, water conductivity, bulk density, pH, texture, organic matter, and initial nitrogen content (Levitan & Gross, 2018). Researchers have used this model worldwide to predict crop growth, yield, and productivity.

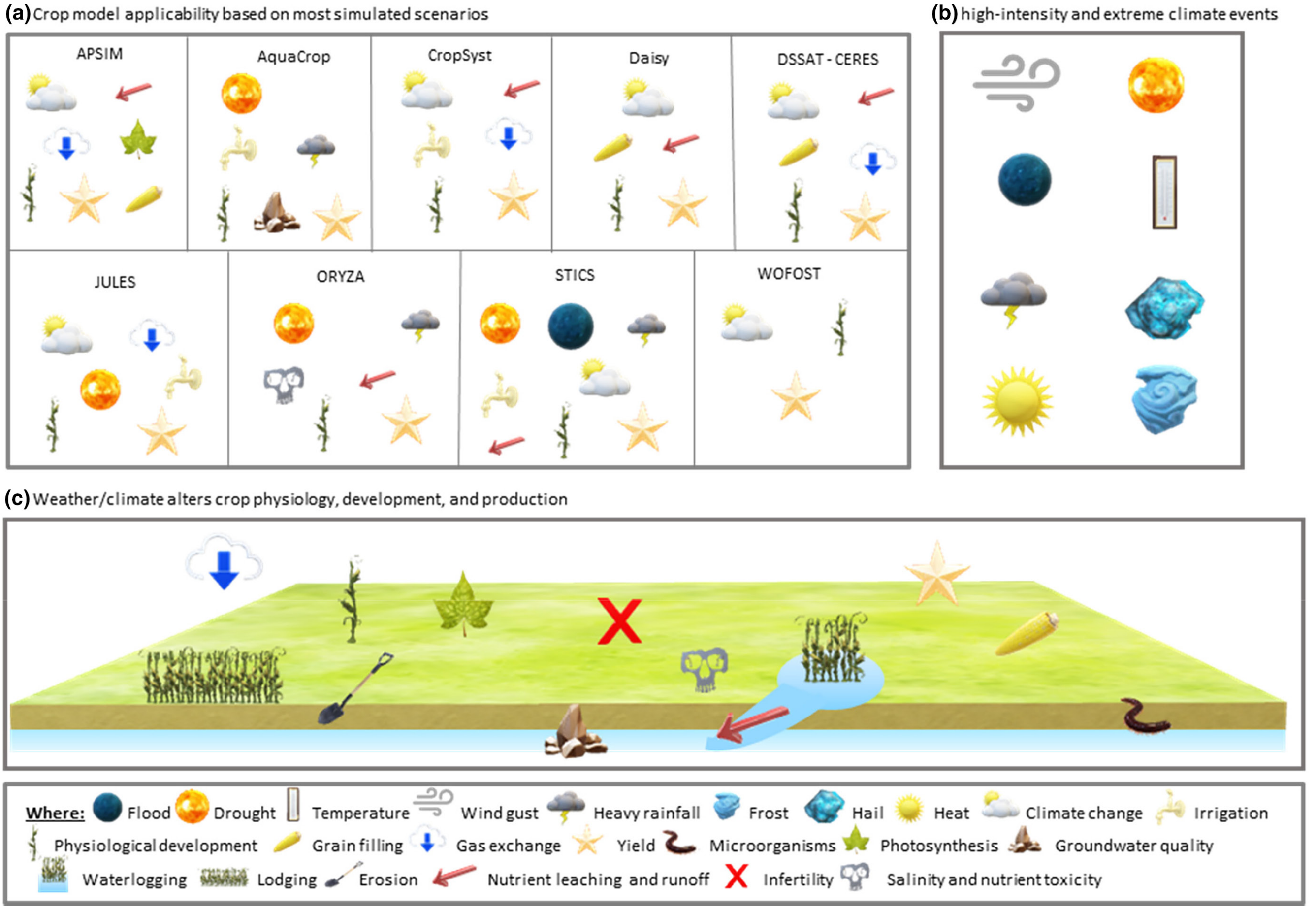

FIGURE 1 (a) Conceptual diagram of the most common crop model applicability based on most simulated scenarios, (b) high-intensity and extreme climate and weather events, and (c) aspects of crop physiology, development, and production altered by the events described in part b.

APSIM has been changed and adapted to current conditions more than once (Table 1), which improved the results of the simulations. In 2012, researchers identified an underestimation in the results by APSIM, which they related to the fact that this model used a triangular approach to the thermal period, considering 26°C as the peak value, and a considerable period of the season presented values above 34°C. Yet, they claimed that APSIM stood out for having a specific estimation method for senescence speed under extreme heat conditions (Lobell et al., 2012). The model showed a better fit when predicting the effects of extreme heat on maize production in the United States. The authors found APSIM appropriate for examining water stress on crops and serving as a decision-making tool (Lobell et al., 2013). Two years later, a study evaluating the effects of water and nitrogen limitation in different wheat cultivars showed that APSIM provided good phenological development simulations but overestimated the grain's nitrogen content. The authors concluded that this crop model could reasonably simulate grain yield to the wheat cultivars and sites studied (Deihimfard et al., 2015).

APSIM is also used to evaluate crop response to atmospheric CO_2 (Vanuytrecht & Thorburn, 2017); genomic and environmental effects (Millet et al., 2019); drought risk (Wang et al., 2020); to compute the photosynthesis impacts on crop yield with a cross-scale approach (Wu et al., 2019); to identify and mitigate management influences in yield gaps (Balboa et al., 2019); to assess impacts on the economy, food security, air quality, and public health (Balwinder-Singh et al., 2020); and radiation effect of aerosols on crop production (Zhao et al., 2020). Despite showing crop disparities, APSIM shows satisfactory and reliable results (Balboa et al., 2019; Millet et al., 2019; Wu et al., 2019; Zhao et al., 2020). It is a good model to determine soil water balance and crop yield at a country level for diverse crops (Wang et al., 2020). In addition, it can be coupled with other models to broaden is applicability (Peng et al., 2018; Rodriguez et al., 2018).

It is worth mentioning that, in APSIM version 2023.5.7206.0, the maize module accounts for yield response to water and nitrogen stresses, not temperature. In this module, the thermal time is calculated as a function of daily minimum and maximum temperatures. Generic temperature factors do not exist, but the temperature influences radiation use efficiency, grain nitrogen content, and senescence (Brown et al., 2014). In the wheat module, the temperature factor is a function of the daily mean temperature applied from planting to harvest dates. In this module, the temperature affects crop phenology, root development, radiation and CO_2 effects on biomass accumulation, leaf expansion, grain nitrogen content and filling, and vapour pressure deficit calculation (Zheng et al., 2015). More specifically, the frost factor causes leaf senescence, but has zero impact as default value, demanding alteration from users (Barlow et al., 2015; Zheng et al., 2015). Some researchers have implemented methods to account for heat and frost stress in APSIM simulations. They categorize temperature events to base yield reduction calculations (Bell et al., 2015), shortening time steps to simulate daylight temperature (Jin et al., 2016), calculating the heat stress factor over 36 and 40° C at the flag stage (Peng et al., 2018), and using vulnerability curves and extreme heat hazard level (Zhang et al., 2021).

According to the studies reviewed, APSIM can accurately predict crop phenological development under extreme heat conditions and water stress but can overestimate yield under different nitrogen concentration effects. This model can be coupled with interdisciplinary models, especially for nitrogen analysis. In summary, APSIM modelers analyzed water availability, temperature changes and greenhouse gas concentration as the main key stressors to crop production. They mostly aimed to predict crop phenology, alteration in the photosynthesis process, biomass, yield gap and/or losses, grain filling and nutrients.

2.2 | AquaCrop

AquaCrop is a software system for a water–crop model developed by FAO (Table 2). It modifies an engineering approach as a tool for on-farm management decision-making. AquaCrop simulates crop growth and yield through canopy biomass, focusing mainly on water availability's crucial impact on agriculture and crop production by affecting crop development. It depicts the soil–crop–atmosphere system and analyzes their interrelations in a varied agricultural system at a canopy level. Its layered interface benefits new and more experienced users to formulate an accurate, simple, and robust model. This model allows the users to compare actual to reachable yield values and identify crop production limitations (Raes et al., 2009; Steduto et al., 2009). The air temperature stress in version 7.0 of this model can affect crop transpiration, pollination, and harvest index. It considers an air temperature stress coefficient and indicators, such as growing degrees and minimum and maximum air temperatures. This stress can dynamically affect the pollination at the time of the stress, further, the reduction in pollination can affect flowering and harvest index if the conditions do not improve after flowering (Raes et al., 2022). The input requires minimum soil, crop, weather, and field management data, such as minimum and maximum temperatures, evapotranspiration,

TABLE 1 Summary of the reviewed studies assessing food security in crops using APSIM.

Study	Crop	Location (# sites)	Evaluation criteria	Model performance & major findings
Lobell et al. (2012)	Wheat	India (4; 1km spatial resolution)	Extreme heat impact on wheat senescence	The models underestimated the effects of heat on senescence, the process advances with heat, limiting grain filling and yield
Lobell et al. (2013)	Maize	USA (3, Corn Belt, regional, experimental sites)	Extreme heat impact on maize production	APSIM extreme temperature and water stress simulations are good, high temperatures affect crop development and production
Deihimfard et al. (2015)	Wheat	Khorasan, Iran (14, major winter wheat growing area, regional)	Water and nitrogen limitation effects on wheat yield, yield gap	APSIM simulates crop physiology and grain yield reasonably well
Peng et al. (2018)	Maize	USA (7, Corn Belt, AmeriFlux sites, regional)	Model improvement, simulation accuracy, maize yield	CLM-APSIM model is more accurate when simulating maize yield under climate changes
Millet et al. (2019)	Maize	Experimental sites in France (4), Hungary (3), Chile (1), Romania (1), Italy (1), Germany (2), field level	Maize yield through a genomic approach, grain yield	Comparing the yield prediction with a genomic prediction improved the simulation accuracy.
Wu et al. (2019)	Wheat, +1	Global	Photosynthesis impacts crop yield, biomass and yield	APSIM models for maize and sorghum had a reliable connection for cross-scale simulations
Balboa et al. (2019)	Maize-soybean rotation	USA (6, Corn Belt, regional, experimental sites)	Management effects on yield gaps	APSIM showed more accurate results for maize than soybean. The model is adequate
Balwinder-Singh et al. (2020)	Rice-wheat system	India (2, farm-size data, regional)	Impacts on the economy, food security, air quality, and public health	Delays in the sowing, transplanting and harvest periods
Wang et al. (2020)	Spring maize	China (14, Liaoning province, regional)	Drought risk, water use efficiency, yield	APSIM has good applicability at a country level for diverse crops
Zhao et al. (2020)	Maize	China (10, maize planting area, Beijing, Xianghe, Taihu, Nanjing, Shanghai, Hefei, Baotou, Lanzhou, Qinghaihu, and Xuzhou)	Radiation effect of aerosols on crop production, crop growth, biomass and yield	APSIM shows accurate and consistent results, with good applicability

TABLE 2 Summary of the reviewed studies assessing food security in crops using the crop growth model AquaCrop.

Study	Crop	Location (# sites)	Evaluation criteria	Model performance & major findings
Katerji et al. (2013)	Maize, +1	Southern Italy (2, Rutigliano and Foggia, regional)	Evapotranspiration, productivity, water use efficiency	AquaCrop simulates the canopy cover and biomass accumulation appropriately in real and stress-applied scenarios. However, this model overestimated yield. Evapotranspiration simulations for maize were inadequate
Maniruzzaman et al. (2015)	Rice	Bangladesh (1, farm level)	Rice growth under different irrigation schemes, water use efficiency	AquaCrop had a good performance when predicting rice growth and yield under different irrigation schedules
Qin et al. (2015)	Wheat-soybean rotation	North China Plain (1, experimental site, field level)	Water and nutrient impacts on yield	AquaCrop simulated soil water balance, crop yield considering water content, fertilization, soil fertility over time, and soil organic amendments
Amiri (2016)	Rice	Northern Iran (1, experimental site, field level)	Rice response to different irrigation and nitrogen management	AquaCrop simulated total panicle biomass accurately, and canopy cover and grain yield satisfactorily
Stevens and Madani (2016)	Maize	Malawi (1, Lilongwe District, regional)	Maize yield response to rainfall and temperature	AquaCrop's performance was adequate when predicting maize yield under different climate scenarios
Babel et al. (2019)	Maize	Himalayan Region of India (1, experimental site, field level)	Maize growth and yield response to different irrigation and manure management	AquaCrop underestimated yield by 1%, total aboveground biomass by 0.15%, and leaf area index by 0.1%. AquaCrop is adequate for high-altitude simulations
Jalil et al. (2020)	Winter wheat	Afghanistan (2, experimental site)	Winter wheat response to water deficit, yield, water productivity and biomass production	AquaCrop predictions of different fields and water conditions are accurate
Xu, Chen, et al. (2020)	Summer maize, winter wheat	North China Plain (1, county level)	Environmental impacts on crop production, yield, water, energy, and carbon footprint under irrigation	AquaCrop simulated crop yield under rain-fed and irrigation systems at different water availability levels
Karandish et al. (2021)	Maize, rice, wheat + 24	Iran (30, provincial level)	Evapotranspiration and water footprint, food security in water-limited sites, water consumption	AquaCrop simulated crop yield and water consumption for crops in arid and semi-arid regions
Zhu et al. (2021)	Maize	China (241, prefecture-level administrative regions)	Maize response to drought	AquaCrop showed accurate results for maize vulnerability to water stress

rainfall, CO_2 concentration, cultivar parameters, soil texture, soil water content and conductivity, groundwater table depth below the surface, salinity, soil initial fertility amount, and irrigation and fertilization date, amount, and methods (FAO, 2016). The crop parameters are conservative and do not depend on geographic location (Raes et al., 2009; Steduto et al., 2009). In 2017 AquaCrop-OS was launched. This open-source version allows researchers to run this model in diverse programming languages and operating systems, which also facilitates its coupling with other models (Foster et al., 2017).

AquaCrop has been widely applied in maize, rice, and wheat water balance studies, especially in Asia. It is used to evaluate crop productivity, evapotranspiration, and water use efficiency under water stress (Katerji et al., 2013); crop response to different irrigation schemes and water level (Maniruzzaman et al., 2015); crop yield response to soil water content, fertilization, soil organic amendments and their interactions (Qin et al., 2015); canopy cover, panicle biomass, and grain yield under different irrigation and nitrogen management levels (Amiri, 2016); yield response to climate change scenarios, considering different rainfall and temperature (Stevens & Madani, 2016); crop response to different irrigation and manure management in high altitudes (Babel et al., 2019); crop response to water stress (Jalil et al., 2020; Zhu et al., 2021); crop yield, carbon, energy, and water footprints to understand their impacts on food production and solutions to water shortages (Xu, Chen, et al., 2020); and, assessments for food security, crop productivity, sustainability and efficiency focusing on water availability and consumption for crop production (Karandish et al., 2021).

Some studies found inadequate simulations in the past, with underestimated values of daily actual evapotranspiration for maize in all stages and water stress levels (Katerji et al., 2013). Also, acceptable under and overestimations in total aboveground biomass, leaf area index, and yield (Babel et al., 2019; Katerji et al., 2013). Yet, most of the studies found adequate accuracy and performance in AquaCrop results (Amiri, 2016; Jalil et al., 2020; Maniruzzaman et al., 2015; Qin et al., 2015; Stevens & Madani, 2016; Xu, Chen, et al., 2020; Zhu et al., 2021).

AquaCrop focuses on plant and soil water balance, water stress, and irrigation planning simulations. Although this model overestimates yield under water deficit, most studies considered it reliable. Even though some of the evapotranspiration simulations were unsatisfactory, recent studies show that the results are more accurate as the model has improved after updates. In summary, AquaCrop modelers analyzed water availability as the main key stressor to crop production. They mostly aimed to predict crop phenology in rainfed and irrigated systems, groundwater quality, and yield gap and/or losses.

2.3 | Biome-BGCMuSo

Biome-BGCMuSo is a process-based biogeochemical model derived from the terrestrial ecosystem model Biome-BGC. These models were developed by the Numerical Terradynamic Simulation Group (NTSG) from the University of Montana (Hidy et al., 2016, 2022). Compared to Biome-BGC, Biome-BGCMuSo better simulates evapotranspiration, ecosystem respiration and exchange, and carbon and water fluxes with a multi-layer soil module (Yan et al., 2019). The minimum required data are distributed in four files. The first file is called Initialization File and includes site-specific physical and climatic information, the simulation period, and the names of all the files to be used as input and generated as output in the simulations. The second file is called Meteorological Data File and covers site-specific daily values of daylength, rainfall, air temperature, humidity, and radiation. The third file is called Ecophysiological Constants File. It contains a site-specific description of the vegetation, considering allocation ratio, fire and non-fire mortality frequency, maximum stomatal conductance, and leaf C/N ratio. The last required file is called Soil Properties File. It includes particularized information about the soil at the site, such as composition, bulk density, water content, nitrogen cycle, and decomposition parameters. In addition, there are seven optional files; the Management File is the most important optional file and includes human intervention, e.g., irrigation, fertilization, sowing, and harvesting (Hidy et al., 2021).

At first, researchers did not consider this model the best option for assessing food production (Dobor et al., 2022; Fodor et al., 2021). However, this model has been significantly improved and updated throughout the years. The newer version (v6.2) simulates crop development and yield similar to mechanistic crop models. Biome-BGCMuSo now runs simulations of varied management conditions for fifteen crops, including drought, heat and nitrogen stresses (Hidy et al., 2021; Hollós et al., 2022). However, most of the published studies assessed grasslands and carbon dynamics (Dobor et al., 2022; Hidy et al., 2022; Hollós et al., 2022; Huang et al., 2022), which does not qualify for a table of studies assessing food security.

2.4 | CropSyst

CropSyst is a user-friendly crop model that simulates soil water and plant nitrogen balances, crop phenology, growth, production and yield, root growth, production and decomposition of residues, soil salinity, and soil erosion caused by water. It works in a multi-year and multi-crop model over a single portion of uniform soil, including crop rotation. Initially, CropSyst incorporated extreme temperature impacts on growing through degree day accumulation, but after improvements, it now considers final yield response to heat stress by expressing harvest index as a function of harvest index daily increase and grain filling duration (Moriondo et al., 2011). The model requires location and daily weather data, including site latitude, rainfall, solar radiation, freezing parameters, and vapour pressure; crop-specific parameters to simulate phenology and morphology, growth, nitrogen use, and harvest index; soil characteristics including cation exchange capacity, pH, texture, bulk density, layer thickness, and water content; and, management data, such as application date, amount, and content for irrigation, fertilization, tillage, and residue operations. The CropSyst procedure focuses on a process-oriented approach, simulating the crop's relations and interactions with management and environmental aspects. The software has a simple interface and links to geographic information system mapping tools (Stöckle et al., 2003).

CropSyst has been primarily applied in regions of Eurasia and North Africa (Table 3). This model could accurately assess emergence, flowering, and maturity dates, yield and biomass in a semi-arid site (Singh et al., 2008); crop yield response to climate change (Bocchiola et al., 2013; Jalota et al., 2013), with different irrigation and temperature scenarios, enabling the authors to identify the water footprint (Bocchiola et al., 2013); crop response to water deficit and irrigation treatments, calculating daily water stress throughout the crop cycle (Mazhoud & Chemak, 2021; Noreldin et al., 2015); crop growth, grain yield and water balance in a rotation system to determine the soil's actual evapotranspiration and significant evaporation losses (Umair et al., 2017); and, atmospheric CO_2 impacts on grain yield, biomass, harvest index, evapotranspiration, and water use efficiency (Castaño-Sánchez et al., 2020).

Throughout the years, developers updated CropSyst and included features, such as a grid-based framework that allowed the model to analyze at regional levels. This model has been coupled with spatially distributed hydrological models, which allowed it to simulate agricultural water demand and supply at basin scales. They also specially designed tools for decision-support analysis. The model is faster and easier to use as a software system (Stöckle et al., 2014). This new version incorporated the Variable Infiltration Capacity (VIC) hydrological model and simultaneously simulates agricultural and hydrological processes. VIC-CropSyst is potent and capable of predicting spatial variations in climate, crop, irrigation, soil, and topography system (Malek et al., 2020).

CropSyst focuses on water and nitrogen dynamics affecting crop growth and productivity. This model is an excellent tool for decision-support analysis regarding water and nitrogen management on crop production because it incorporates hydrological models and shows more accurate water footprint results. In summary, CropSyst modelers analyzed water availability, temperature changes and greenhouse gas concentration as the main key stressors to crop production. They mostly aimed to predict crop phenology, water use efficiency in rainfed and irrigated systems, biomass, nutrient use efficiency, and yield gap and/or losses.

2.5 | DAISY

Daisy is an open-source software system of a one-dimensional soil–crop–atmosphere model. This system supports the exchange of process model descriptions and the linkage with other models, enabling distributed work and including various soil columns and inter-cropping management. Besides, this system grants a straightforward implementation of new processes and allows the selection of alternative process descriptions. It simulates crop production and yield, soil water, heat and organic matter balances, and carbon and nitrogen dynamics in the soil through various models. Doing so requires daily weather, soil, and management data as input, that include radiation, air temperature, rainfall, potential evapotranspiration, soil tillage, planting date and density, fertilization, pesticide and irrigation application date and amount, harvest date, and initial conditions. Interestingly, DAISY considers soil temperature as a primary factor to influence crop phenology and development, including freezing or melting impacts on yield. Still, it does not account for extreme air temperature stress. Each model inside the system demands a different set of data according to its objective. However, the system is flexible and allows data storage in different library directories for input and output definition according to the user's objectives (Abrahamsen & Hansen, 2000; Hansen, 2002). A summary of Daisy's applicability and accuracy is found in Table 4.

Daisy is mainly applied in Europe and Asia (Table 4). Mostly, to estimate crop response to nitrogen fertilization (Olesen et al., 2002); crop growth, grain yield, aboveground biomass, and harvest index response to climate (Palosuo et al. (2011); crop growth and nitrogen dynamics in the soil for monoculture and intercropping systems (Manevski et al., 2015); impacts of rainfall patterns on crop growth, yield, and harvesting dates in semi-arid sites, identifying drought stress and yield losses (Beyer et al., 2016); crop yield response to diverse temperature and radiation scenarios (Aydın et al., 2018); effects of soil organic carbon on nitrogen supply and water availability to crop production (Ghaley et al., 2018); crop yield, soil

TABLE 3 Summary of the reviewed studies assessing food security in crops using the cropping system CropSyst.

Study	Crop	Location (# sites)	Evaluation criteria	Model performance & major findings
Singh et al. (2008)	Wheat	India (1, experimental site, field level)	Crop model result comparison for different irrigation and nitrogen management	CropSyst showed good accuracy for emergence, flowering, and maturity dates. This model's yield and biomass predictions were more accurate than CERES's.
Confalonieri et al. (2009)	Rice	Italy (6, experimental sites, field level)	CropSyst, WARM and WOFOST models performance analysis	Individually, the models had similar and good validation performance. WARM requires fewer input data
Bocchiola et al. (2013)	Maize	Italy (1, Persico Dosimo, site-specific)	Maize yield under climate change scenarios	CropSyst reproduced maize growth under different water and temperature scenarios well, allowing a water footprint determination
Jalota et al. (2013)	Rice–wheat rotation	India (1, Ludhiana, county-specific)	Yield under climate change scenarios, water and nitrogen use efficiency	Calibration and validation of models is essential to find accurate results
Stöckle et al. (2014)	—	—	CropSyst evolution	Integrated decision-support tools, and grid-based frameworks and incorporated them with hydrological models
Noreldin et al. (2015)	Wheat	Egypt (1, Nubaria region, experimental site, field level)	Wheat response to different irrigation management	CropSyst accurately simulated grain and biological yield and daily water stress throughout the crop cycle
Umair et al. (2017)	Wheat-maize rotation	North China Plain (1, experimental site, field level)	Actual evapotranspiration, biomass, grain yield, and evaporation loss	CropSyst is accurate and reliable in predicting winter wheat and summer maize growth, grain yield and water balance
Castaño-Sánchez et al. (2020)	Maize +1	USA (6, Lancaster, Franklin and Centre in Pennsylvania and Jefferson, Wyoming and Cayuga in New York, county level)	Grain yield, biomass, harvest index, evapotranspiration, and water use efficiency	CropSyst showed limitations to simulating evapotranspiration but satisfactorily simulated crop production under different atmospheric CO_2 concentrations
Malek et al. (2020)	Maize, wheat + 7	Yakima river basin, USA (gridded, 0.0625 degrees)	Climate change impacts irrigated agriculture in a snow-dependent basin	VIC-CropSyst provided results that allowed a water stress assessment on irrigated fields
Mazhoud and Chemak (2021)	Wheat	Tunisia (2, Bouarada and Gaafour, county level)	Crop productivity under irrigation management	CropSyst could accurately simulate the wheat response to different irrigation scenarios

TABLE 4 Summary of the reviewed studies assessing food security in crops using the soil-crop-atmosphere model Daisy.

Study	Crop	Location (# sites)	Evaluation criteria	Model performance & major findings
Olesen et al. (2002)	Winter wheat	Denmark (1, experimental site, field level)	Grain yield response to nitrogen fertilization, water and nitrogen uptake, green area index, radiation use efficiency	Daisy overestimated nitrogen uptake. Overall, the model showed a reasonable simulation
Palosuo et al. (2011)	Winter wheat	Denmark, Germany, the Czech Republic, Slovakia, and Turkey (8, experimental sites in Foulum, Flakkebjerg, Jyndevad, Müncheberg, Verovany, Lednice, Kirklareli, and Bratislava, field level)	Performance of eight crop models to winter wheat response to climate variety	Daisy showed good accuracy to crop growth, above-ground biomass, and harvest index predictions but sub-estimated the dynamics of above-ground biomass and leaf area development and presented the lowest error for grain yield
Manevski et al. (2015)	Maize	Denmark (2, field site, Foulum and Jyndevad)	Crop growth, soil N dynamics	Daisy performed accurate results for monoculture but not for intercropping system
Beyer et al. (2016)	Maize	Upper Zambezi River Basin, Africa (0.1° × 0.1°)	Effects of rainfall variability on rain-fed agriculture, crop yield	accurate performance in identifying drought stress and simulating yield
Aydın et al. (2018)	Winter wheat	Turkey (1, field data, Kirklareli)	Winter wheat response to varied temperatures, radiation	Daisy underestimated yield results for real temperature and radiation scenarios
Fan et al. (2018)	Winter wheat, +5	Denmark (5, farm level, Lejre)	Crop long-term conversion response to organic farming	Daisy showed limitations that could be solved with calibration and validation
Ghaley et al. (2018)	Winter wheat	Denmark (1, experimental site, field level, Askov)	Nitrogen supply and water availability to crops under varied fertilization	Daisy simulates soil organic carbon effects on nitrogen supply and crop water availability
Jabloun et al. (2018)	Winter wheat-summer maize	North China Plain (1, experimental site, field level)	Impacts of weather and nitrogen inputs on Daisy sensitivity on grain yield, grain nitrogen content at harvest, cumulated evapotranspiration, and nitrogen leaching	Daisy model sensitivity to input parameters depends on its calibration, and this model could be simplified
Manevski et al. (2019)	Maize, winter wheat	North China Plain (1, experimental site, field level, piedmont plain of the Taihang Mountains in Hebei Province)	Crop yield, soil water drainage, and nitrogen leaching	Daisy model underestimated the effects of nitrogen on crop yield, but the authors still consider this model suitable to simulate management impacts on crop production and nitrogen leaching
Yin, Kersebaum, et al. (2020)	Winter wheat, +3	France (1, experimental site, field level, Thibie)	Six-model comparison on nitrogen management in crop systems	Daisy shows better performance when simulating nitrogen dynamics

water drainage, and nitrogen leaching modeling responses to multi-weather and single-weather data and varied irrigation schemes (Manevski et al., 2019); and nitrogen export and uptake and transformations in cropping systems (Yin, Kersebaum, et al., 2020).

Historically, Daisy overestimated nitrogen uptake (Olesen et al., 2002), but is now able to appropriately simulate crop growth and nitrogen dynamics of mono and intercropping systems (Manevski et al., 2015). In 2018, researchers tested Daisy's sensitivity to weather and fertilization input parameters on crop yield, nitrogen content in the grain at harvest, cumulated evapotranspiration, and nitrogen leaching. The authors believe that Daisy could be simplified because 34 out of 128 parameters are influential, and many parameters showed minor sensitivity. They stated that the cropping season and weather conditions highly influenced the model results (Jabloun et al., 2018).

Studies with other crops showed a reduced performance when simulating grain nitrogen content (Yin et al., 2017). However, researchers found satisfying results when simulating soil water dynamics for white cabbage, working as a planning tool for irrigation (Seidel et al., 2016; Yin et al., 2017) and nitrogen content in pea and winter oilseed grains. The model predicts better results when simulating straight years than a single year for nitrogen content in winter barley, spring oat, and pea grains (Yin et al., 2017).

DAISY numerically represents the soil-crop-atmosphere interactions to simulate the effects of climate change, irrigation, and fertilizer management on crop production. Although this model underestimated yield and nitrogen responses in some studies, researchers considered DAISY an excellent method to simulate intercropping systems. In summary, DAISY modelers analyzed mainly water and nitrogen availability and some assessed temperature changes as the main key stressors to crop production. They mostly aimed to predict crop phenology, biomass, nitrogen and water use efficiency, grain filling, and yield gap and/or losses.

2.6 | DSSAT–CERES

DSSAT stands for Decision Support System for Agrotechnology Transfer. It is a software system that facilitates crop data modeling simulations and model improvement. Its current version includes models for more than 42 crops in monoculture and crop rotation in single or multiple seasons. Each crop has a file with parameters used in the simulations. The parameters are coefficients, rates, and functions regarding canopy height and width (plant crown diameter along and across the row), carbon and nitrogen mining and fixation, plant composition, growth and partitioning, phenology, photosynthesis, respiration, and senescence. In addition to the crop parameters, the model requires site-specific data about the management, soil, and weather conditions, in addition to plant genetics characteristics. This system considers biotic and abiotic factors and simulates crop growth, development, and yield under experimental or simulated management conditions (Hoogenboom et al., 2019; Jones et al., 2003).

DSSAT is coupled with multiple crop models. CERES (Crop Estimation through Resource and Environment Synthesis) is the crop model used to simulate maize, rice, and wheat production. When building this model, the developers aimed to assist with decision-making at the farm level, strategic-planning risk analysis, large-area yield forecasting, and policy analysis (Ritchie & Otter, 1985). It requires site-specific data, such as site latitude, sowing date and depth, plant density, and irrigation date and quantity. Crop genetics data requirements include photoperiod sensitivity, stem width, cold hardiness, grain-filling duration and rates, mass-grain conversion number, and vernalization requirements. Soil characteristic data requirements include water-holding capacity, initial and saturated soil water content, drainage and runoff, evaporation, and rooting preference coefficients. Weather data requirements are maximum and minimum temperature, solar radiation, and rainfall. It uses the input data to create biophysical, hydroclimatic, and phenological relationships. However, it does not include pest, disease, and weed effects on crop yield (Basso et al., 2016; Ritchie & Otter, 1985; Rodríguez et al., 1990). CERES does not consider extreme temperature impacts directly on grain yield and tends to show higher errors in simulations under extreme temperature conditions (Basso et al., 2016). However, CERES-Wheat has accounted for low temperature damages in crops for more than forty years under, what they called, cold hardening and winter kill conditions, but not for extreme heat and frost conditions (Ritchie & Otter, 1985). CERES-Maize simulates crop phenology by thermal accumulation, but it considers a constant thermal time as the optimum temperature if higher temperatures occur (Lizaso et al., 2017). The original CERES-Rice does consider heat stress when temperatures are above 35° C, altering the spikelet fertility, but researchers have used a modified heat function to reduce model uncertainty (Jagadish et al., 2007; Sun et al., 2022; van Oort et al., 2014).

DSSAT is one of the most applied crop models worldwide (Table 5). Its application involves long-term cultivation yield and nitrogen dynamics in the soil (Liu et al., 2011); rainfed crop productivity under soil textures impacted by long-term cultivation (He et al., 2014); crop yield under high nitrogen input in the soil and no pests and disease effects to analyze the costs of land-use change

TABLE 5 Summary of the reviewed studies assessing food security in crops using the Decision Support System for Agrotechnology Transfer—DSSAT.

Study	Crop	Location (# sites)	Evaluation criteria	Model performance & major findings
Liu et al. (2011)	Maize	Canada (1, experimental site, field level, Woodslee, Ontario)	Grain yield, nitrogen cycling	The model overestimated grain yield and soil nitrogen content, and leaching
He et al. (2014)	Spring wheat	Canada (2, experimental site, field level, Swift Current and Stewart Valley, Saskatchewan)	Soil texture impacts on rain-fed wheat productivity	The model is a good tool to assess crop water use of different soil textures and productivity
Searchinger et al. (2015)	Maize +1	Africa (Guinea Savannah, regional, resolution of 10 arc minutes)	Land-use change impacts on carbon content and biodiversity	DSSAT predicted similar results to observed data during calibration. The model was adequate to simulate yield under high nitrogen content in the soil without considering pests and disease effects.
Winter et al. (2017)	Maize, rice, wheat	USA (1, county level, Yolo County, California's Central Valley)	Crop water demand and growth integrated into regional water supply and management with WEAP-DSSAT	WEAP-DSSAT was more realistic, although the combination worked similarly to a single DSSAT simulation.
Nelson et al. (2018)	Maize, rice, wheat +58	Global (158 countries, country or country aggregates level)	Climate change impacts food production related to income growth and food security	Combining crop and socio-economic results should serve as a decision tool for fertilization management, crop choice and land use.
Tang et al. (2018)	Winter wheat	China (88, Huang-Huai-Hai Plain, regional, resolution of $2.8125 \times 2.8125°$)	Climate change effects on wheat potential yield and water demand, modified DSSAT	The evapotranspiration module of DSSAT was modified, which allowed similar simulated and observed data results
Ma et al. (2020)	Maize, rice, wheat +2	Philippines (1, experimental site, field level, Los Banos) Spain (2, experimental site, field level, Zaragosa) USA (4, experimental site, field level, Ohio, Kansas, Arizona)	DSSAT-PEST crop genetic parameters	DSSAT-PEST's performance was equal to or better than the other methods
Jiang et al. (2021)	Maize	China (9, experimental site, field level, Chaoyang and Changtu in Liaoning; Liufangzi, Taojia and Chaoyang in Jilin; and Qiangan, Shuangcheng, Binxian and Harbin in Heilongjiang)	Climate change impacts on maize production and nitrogen use efficiency and mitigation strategies	DSSAT accurately simulated climate change impacts on crop yield and nitrogen use efficiency
Tofa et al. (2021)	Maize	Nigeria (3, representative sites, Kano, Zaria and Abuja)	Drought-tolerant maize variety productivity under climate change scenarios	DSSAT is capable of predicting crop productivity accurately
Gunawat et al. (2022)	Wheat	India (1, experimental site, field level, Rajasthan)	Climate change impacts on wheat yield cultivated in a semi-arid environment and mitigation plan	DSSAT is reliable when well-calibrated and a significant tool for planning mitigation strategies

from wet savannahs to cropland in high carbon production and biodiversity (Searchinger et al., 2015); climate change effects on crop potential yield and water demand (Tang et al., 2018); climate change impacts on crop production, yield and nitrogen use (Jiang et al., 2021); drought-tolerant crop variety productivity under climate change scenarios in the savannas (Tofa et al., 2021); and, crop yield response to climate change impacts in a semi-arid environment (Gunawat et al., 2022). In the past, the model overestimated grain yield, nitrogen content, and nitrogen leaching in the soil. However, the authors claimed that its yield predictions were more adequate than nitrogen ones (Liu et al., 2011). It showed higher accuracy in soil moisture predictions during the growing season than before seeding or after harvest (He et al., 2014). However, the model is constantly updated and most of the past issues have been improved (Hoogenboom et al., 2019).

This model can be coupled with hydrological models to assess regional water supply and management to crop growth and regional water requirements (Winter et al., 2017); to socio-economic models, to assess climate, crop, and socio-economic impacts on food security by climate change (Nelson et al., 2018); and, to model-independent parameter estimation software to estimate crop genetic parameters, which allows more agricultural and environmental research applications to DSSAT (Ma et al., 2020).

DSSAT can be coupled with diverse interdisciplinary models. Some studies found yield and nitrogen overestimated results. However, most studies show the importance of calibration to determine the accuracy of results. DSSAT modelers analyzed water availability, temperature changes and greenhouse gas concentration as the main key stressors to crop production. They mostly aimed to predict crop phenology, biomass, soil characteristics and land use changes, grain filling, nitrogen and water use efficiency, and yield gap and/or losses. Overall, DSSAT is a reliable model for planning mitigation strategies.

2.7 | JULES

JULES is the Joint United Kingdom (UK) Land Environment Simulator. It is a land surface model developed by UK researchers under the United Kingdom Meteorological Office (UKMO) and the UK Centre for Ecology and Hydrology (CEH) coordination. JULES builds a framework with land surface processes and interactions, enabling impact assessment. It requires meteorological forcings as input, such as the downward component of shortwave and longwave radiation at the surface, rainfall and snowfall, wind components, air temperature, air humidity, and surface pressure. The required soil data are bare soil albedo, dry soil thermal conductivity and capacity, volumetric saturation, soil moisture and wilting point, and saturated hydraulic conductivity. It is important to set the crop-specific cardinal temperatures for physiological processes as they base the growing degree days calculations on JULES (Best et al., 2011; Clark et al., 2011; Vianna et al., 2022).

In 2015, researchers used JULES to find the best crop parametrization for maize, rice, soybeans, and wheat on a global grid. They found significant differences between the simulations and the observed data. However, the model did not account for the nitrogen cycle or irrigation at that time. The authors suggested an update to consider the yield gap and anthropogenic behaviour (Osborne et al., 2015). The latest version of JULES (JULESvn7.2) was released in April 2023 and includes all those nitrogen and irrigation analyses (see the release notes here). Researchers have applied JULES globally and regionally (Table 6) to analyze the impacts of altering land use to expand crop production for food under varied future climatic scenarios, to project the terrestrial carbon cycle of natural landscapes, crops, and grassland, and to simulate yield under seasonal and regional climatic scenarios (Harper et al., 2018). JULES can provide daily net primary productivity for agriculture at global or regional scales, which allows planning for future food security through vulnerability assessment, plant analysis, and yield prediction (Singh et al., 2021). As such, it helps identify and quantify detrimental events to the environment. When coupled with atmospheric models, it is also a good method to predict how land use and climate change influence carbon and hydrological cycles (Buechel, 2021), determine climate change effects on ecosystems, allowing mitigation and restoration (Littleton et al., 2021), identify drought occurrence and its impact on soil moisture (Zeri et al., 2022) find the effects from climate and greenhouse gases on crop production (Leung et al., 2022) compare the evaluation of anthropogenic and climatic impacts on crop production (Leung et al., 2022) and create an index to food security stability from JULES outputs of productivity (Singh et al., 2022).

Although JULES was developed to simulate lands in the UK, it has been improved and expanded. It is now used globally to mainly determine land–atmosphere interactions, food-security-related influences, greenhouse gas effects on agriculture, and land use implications.

2.8 | ORYZA

ORYZA2000 is a single-crop model for lowland rice developed by the International Rice Research Institute (IRRI). It simulates lowland rice development and growth and water balance in potential production or limited by water or nitrogen availability. In doing so, it considers impacts on

TABLE 6 Summary of the reviewed studies assessing food security in crops using the Joint United Kingdom Land Environment Simulator—JULES.

Study	Crop	Location (# Sites)	Evaluation criteria	Model performance & major findings
Osborne et al. (2015)	Maize, rice, soybeans, wheat	USA (3, site level, Mead in Nebraska, Bondville and Fermi in Illinois)	Crop parameterization; global grid	JULES can overestimate the magnitude of yield variability from climate change; the model might be too sensitive to different management conditions
Betts et al. (2018)		Globally (20; grid cells at 0.5° ×0.5°)	Vulnerability to food insecurity resulting from climate change. Changes in run-off from rainfall, evaporation, and transpiration	The authors used JULES outputs to produce run-off tendencies and projections and impacts on freshwater
Harper et al. (2018)		Globally (2.5° latitude × 3.75° longitude grid)	Land-climate-carbon cycle interactions; large-scale crop production environmental impacts	JULES based on IMOGEN grid scale patterns favours the evaluation of land-use change losses and gains under climate change impacts and mitigation
Littleton et al. (2020)	Bioenergy crops	United Kingdom (1); globally (68 grid cells at 0.5° ×0.5°)	Second-generation bioenergy crops; Harvesting regimes; JULES-BE	This model focused on bioenergy crops allows evaluating carbon cycle and climate systems. Although the model could estimate yield for the USA and Europe with the assisted expansion, it could not account for large variability across and within locations
Leung et al. (2020)	Soybean-corn	USA (4, experimental site, field level, Bondville, Feri, Mead, Nebraska)	Crop parameter and ozone damage calibration	The model underestimated water stress and overestimated carbon at ambient ozone levels, but JULES estimated seasonal leaf area index satisfactorily, although minimizing its amplitude
Singh et al. (2021)	C3, C4, trees, shrubs	The South Asian Association for Regional Cooperation (8 nations; gridded 0.5° ×0.5°)	Climate change influences agriculture productivity to ensure food security	JULES specified the daily net primary productivity for agriculture and forestry at the regional scale
Zeri et al. (2022)	C3, C4, trees, shrubs	Northeast Brazil (360, gridded 0.5° ×0.5°)	Drought monitoring; soil moisture	JULES could accurately identify drought events, allowing the determination of anomalies in soil moisture
Leung et al. (2022)	Maize, rice, wheat +1	Global (regional, USA, China, Brazil, Argentina, Europe, India, Bangladesh, Indonesia)	CO_2 and Ozone impacts on crop production; yield loss; global food security implications	JULES showed CO_2, O_3, and climate change impacts on global and regional crop production
Singh et al. (2022)	Agriculture and forest land	The South Asian Association for Regional Cooperation (8 nations; gridded 0.5° ×0.5°)	Food security estimation for the year 2050; agriculture and forest land, crop yield, and food supply requirement	The authors created a food security stability index from indicators and used JULES crop productivity results to identify food security dimensions
Prudente Junior et al. (2023)	Maize	Brazil (16, climate zones, county level, Ponta Pora, Itapeva, Brasnorte, Querencia, Sorriso, Campos Lindos, Alto Parnaiba, Balsas, Tasso Fragosso, Ribeiro Goncalves, Barreiras, Rio Verde, Campina da Lagoa, Corbelia, and Pimenteiras do Oeste)	Off-season maize growth and yield; water stress; water-limited potential yield	JULES yield results under a limited water environment showed influences during the vegetative phase

crop phenology under extreme low temperatures, which may simulate the crop death if the event happens for more than three consecutive days. However, it does not consider the effect of disease, pests, and weeds on the yield. After some years, IRRI released a new and improved version called ORYZA (v3). This new model considers more variables, environments, and soil-crop-atmosphere dynamics on rice development, growth, and yield. It includes root growth and carbon and nitrogen balances. It links nitrogen uptake to water uptake, connecting the crop limitations regarding their availability. Information about the location, air temperature, radiation, evapotranspiration, planting or transplanting date and density, and water and nitrogen management and initial conditions are necessary to run the model (Bouman et al., 2001; Li et al., 2017). ORYZA2000's and ORYZA's (v3) studies and application summary are available in Table 7 and discussed below.

Accordingly, Asia, the world's first rice producer, is where this model is most applied (Table 7). It is widely used to estimate the impacts of the El Niño and Southern Oscillation (ENSO) on rice yield (Zhang et al., 2008); water balance, productivity, and nitrogen dynamics in rice production (Amiri & Rezaei, 2010); rice production under limited nitrogen and water conditions for varied rice genotypes (Sailaja et al., 2013); best sowing date to achieve rainfed rice potential yield under drought events' impacts (Li et al., 2015); high-yielding cultivars in different nitrogen concentrations, plant densities and seedlings per hill (Yuan et al., 2017); rice growth and yield under salinity effects for various genotypes (Radanielson et al., 2018); transferability and predictability in simulating rice grain yield for direct-seeded or transplanted rice (Ling et al., 2021); global sensitivity and uncertainty analysis for drought stress parameters (Tan et al., 2021); and, yield gap, water use efficiency (UE), pesticide UE, nitrogen UE, labour UE and energy UE, and associated global warming potential in global rice production (Yuan et al., 2021).

ORYZA2000 and its improved version ORYZA (v3) focus on analyzing rice production instabilities caused by climate changes, soil salinity, drought, water and nitrogen management, and environment and genotype interactions. Although these models do not consider pests' and weeds' effects, they can predict rice growth and yield accurately. In summary, ORYZA modelers analyzed water and nitrogen availability as the main key stressor to crop production. They mostly aimed to predict crop phenology, biomass, nitrogen and water use efficiency, salinity, and yield gap and/or losses.

2.9 | STICS

STICS stands for Simulateur mulTIdisciplinaire pour les Cultures Standard [multidisciplinary simulator for standard crops]. It was developed in 1996 by the French National Institute for Agronomic Research (INRA), teaching institutes, and collaborators. The developers aimed to provide outputs of quantity and quality related to crop yield, drainage, and nitrate leaching, with a focus on environmental conservation. It is used to simulate soil–crop–atmosphere interactions for single or inter-cropping systems coupled with nitrogen and water dynamics, recognizing heat, water, and nitrogen stress effects (Brisson et al., 2003, 2008). The heat stress causes leaf senescence that alters or stops grain filling, impacting yield (Brisson et al., 2003; Webber et al., 2017). STICS requires careful calibration of crop parameters, as it can underestimate crop development and productivity with standard parameters (Beaudoin et al., 2008). However, some researchers use standard crop parameters to evaluate the model's performance and maintain its consistency (Coucheney et al., 2015; Levavasseur et al., 2021). The input data include daily time-step weather, soil, and crop characteristics. The soil data are divided into horizontal layers, describing water and nitrogen (mineral and organic) contents. The daily weather data require air temperature, rainfall, wind speed, air humidity, and solar radiation during the simulation period. The crop ecophysiology and agronomy are planting date and depth, fertilization application date, type of fertilizer and N rate, irrigation amount and application date. Besides, the initial conditions of water and nutrient contents in the soil are required to start a simulation (Brisson et al., 2008).

STICS has primarily been used in Europe (Table 8). This model is a good method to determine the impacts of different sites, soil characteristics, and irrigation strategies on rainfed and irrigated crop systems (Khila et al., 2014). Notably, this model can assess multiple categories at once by simulating biophysical processes and yield components and quality considering varied management strategies (Constantin et al., 2015). Researchers apply STICS to assess water deficit, irrigation and water use efficiency (Constantin et al., 2015; Katerji et al., 2010), irrigation strategies and soil properties (Khila et al., 2014), soil water and nitrogen dynamics (Coucheney et al., 2015), crop production under climate change (Yang et al., 2019), crop rotation and nitrogen dynamics (Yin, Beaudoin, et al., 2020), and fertilization (Levavasseur et al., 2021).

In summary, STICS can predict crop development, fertilization and irrigation practices, nitrogen leaching, and crop yield response to different management and water availability. It is primarily applied in Europe and Canada.

2.10 | WOFOST

WOFOST stands for World Food Studies. It is a model developed by the Centre for World Food Studies in

TABLE 7 Summary of the reviewed studies assessing food security in rice using the lowland rice model ORYZA2000 and ORYZA (v3).

Study	Location (# sites)	Evaluation criteria	Model performance & major findings
Zhang et al. (2008)	China (29, provincial level, Tianjin, Hebei, Shandong, Henan, Shanxi, Shaanxi, Ningxia, and Gansu; and, field level, Zunhua, Gushi, Xinyang, Yinchuan)	El Niño/Southern Oscillation (ENSO) impacts on rice yield	ORYZA2000 accurately simulated rice yield under ENSO for three rice varieties
Amiri and Rezaei (2010)	Iran (1, experimental site, field level, Rice Research Institute of Iran, Guilan province)	Water balance and productivity and nitrogen dynamics in rice	ORYZA2000 adequately predicted total aboveground biomass and yield
Sailaja et al. (2013)	India (1, experimental site, field level, Rajendranagar, Hyderabad)	ORYZA2000 validation under limited nitrogen and water scenarios	The model overestimated the leaf area index but showed satisfactory results when varying rice genotype, fertilization and water management
Li et al. (2015)	Asia (6, gridded 5 × 5 arc minutes)	Drought impacts on rainfed rice	ORYZA2000 could accurately simulate drought stress in rice production after detailed calibration and validation in South Asia
Yuan et al. (2017)	China (1, experimental site, field level, Dajin County, Wuxue City, Hubei Province)	ORYZA (v3) evaluation and application for high-yielding cultivars under different management	ORYZA (v3) overestimated nitrogen content on the leaf but accurately estimated rice biomass, leaf area index and yield
Radanielson et al. (2018)	Philippines (2, experimental site, field level, Los Baños and Infanta Quezon)	Rice growth and yield under salinity effects, comparison between ORYZA (v3) and APSIM-Oryza models, osmotic stress, and ion toxicity stress	ORYZA (v3) and APSIM-Oryza results showed similar and adequate accuracy for aboveground biomass, leaf area index, grain yield for various genotypes and soil salinity levels.
Lu et al. (2020)	China (9 experimental sites with 3 counties each, Jiangsu Province, regional)	ORYZA (v3) evaluation for rice varieties under different management	ORYZA (v3) performed simulations of rice biomass and leaf area index appropriately
Ling et al. (2021)	China (1, experimental site, field level, Zhougan Village, Dajin Town, Wuxue County, Hubei Province)	ORYZA (v3) transferability and predictability simulating yield under different management	Parameters for direct-seeded rice were suitable to simulate yield in transplanted rice system, but the opposite did not work well without modifications
Tan et al. (2021)	China (1, experimental site, field level, Nanchang, Jiangxi Province)	ORYZA (v3) sensitivity and uncertainty analysis for drought parameters	Simulations under severe drought levels overestimated yield
Yuan et al. (2021)	Global (country level), Asia (8), Africa (6), Australia (1) North America (1), South America (2)	Yield gap, water, pesticides, nitrogen, labour and energy use efficiency, and associated global warming potential	ORYZA2000 and ORYZA (v3) were reliable tools when well-calibrated

cooperation with the Wageningen University & Research in the Netherlands to simulate yield and its variations through risk analysis and climate change assessment. It also examines and quantifies land use. The input data are divided into general, timer, and reruns which are editable files, and crop, weather, and soil files that the user adds. Required data include maximum and minimum air temperatures, global radiation, windspeed, vapour pressure, evapotranspiration, and rainfall, soil type and texture, soil water content and conductivity, free drainage, and groundwater influence, and initial conditions. Model outputs are presented in map formats of yield simulations. Although it does not account for heat and frost stresses yet (de Wit & Boogaard, 2021), this model generates results for diverse annual field crops with a dynamic and exploratory approach at a farmer level (Boogaard et al., 2014; Bouman et al., 1996).

WOFOST has most commonly been applied in Asia and Europe for crop simulations (Table 9). Researchers mostly use this model to analyze climatic yield potential and yield gaps, nitrogen uptake, rice response to fertilizer management and nitrogen use efficiency in long-term crop cultivation (Dobermann et al., 2000); crop growth, yield (Bussay et al., 2015; Shekhar et al., 2008) and soil-crop water balance (Bussay et al., 2015); crop phenology response to different sowing dates and varieties (Wu et al., 2017); crop response to rising temperatures (Biswas et al., 2018); crop quality, development, and yield during low, medium, and high-yielding years under extreme events (van der Velde et al., 2018).

Researchers found more accurate phenology and yield predictions at regional levels when coupling this model with the Crop Yield Forecasting System. However, they found significant errors in wet locations in Europe, which implies that this model performs well in dry places (Ceglar et al., 2019). The model also fails to simulate heat stress impacts on photosynthesis and grain yield (Jin et al., 2016). Studies assimilating remote sensing data into WOFOST can also improve this model's accuracy, enhancing crop yield predictions at the regional level (e.g. Zhuo et al., 2022). The authors compared simulations with and without assimilated data to official statistical yield forecasts, and simulations with assimilated data showed lower relative errors and higher correlations, which the authors concluded to improve the yield forecasting accuracy.

WOFOST analyzes crop yield, land use and risk factors to food security. This model can better estimate crop growth and development than yield. This model's performance improves with remotely sensed data input. In summary, WOFOST modelers analyzed water availability and temperature changes as the main key stressors to crop production. They mostly aimed to predict crop phenology, biomass, and yield gap and/or losses.

2.11 | AgMIP

The Agricultural Model Intercomparison and Improvement Project (AgMIP) links climate, crop, and economic modeling. This project focuses on defining global FS and agricultural production over climate change, mitigating the potential adverse effects on the sector, and intensifying resilience and adaptability in developing and developed countries. Researchers have evaluated agriculture and FS from multi-disciplinary, multi-model, and multi-scale frameworks (Rosenzweig et al., 2013). Researchers have compared models within this project to reduce modeling uncertainties and work with an exploratory approach. When simulating crop production and food security, they use the median of the ensemble crop models of total growing season output, such as yield, biomass at maturity, and maturity date, to assess climate and management impacts on yield trends. Researchers found that this crop model's intercomparison results are more accurate and reproduce observed data response and relationships better than a single model. It has also decreased the effect of cultivar information on yield trends (Asseng et al., 2013, 2015; Bassu et al., 2014). Many studies use this path to assess maize, wheat and rice yield projections that can evaluate food security (Table 10). This collaborative approach has benefited shareholders and communities by allowing decision-making and problem-solving of climate change impacts on food security at all scales (Jat et al., 2016).

Authors state that the multi-model ensemble is reliable for predicting climate impacts on the world's food security. However, global-scale results are not suitable for regional or local scales (Liu et al., 2016). Furthermore, the number of models added to the ensemble determines the reliability of the median results (Zhao et al., 2016). Accordingly, the number of models necessary to increase the accuracy of the median value can be statistically assessed (see Asseng et al., 2013). Besides, Porfirio et al. (2018) claimed that the AgMIP database is limited regarding an optimistic CO_2 reduction. The authors also noted that settling an actual optimistic CO_2 mitigation could be challenging. And so, researchers do not assess it frequently. Finally, Rattalino Edreira et al. (2021) compared two data collection and modeling approaches. The top-down takes gridded input data and estimates potential yield. The bottom-up takes input from representative sites in the crop area and calculates the potential yield for each site or country level. Their results showed a disagreement between the methods. They remarked that AgMIP top-down approach uses a data set that relies on a coarse world's crop calendar and may simulate an area's non-representative or inexistent crop system, such as wrong sowing period. However, the other method performs with a generic coefficient without a proper validation for the systems analyzed. They concluded that the top-down approach presents a subjective result that includes the errors for areas with no interest. At the same time, finding the correct data set of climates, crop system, and soil for the bottom-up approach is challenging. Thus,

TABLE 8 Summary of the reviewed studies assessing food security in crops using the Simulateur mulTIdisciplinaire pour les Cultures Standard—STICS

Study	Crop	Location (# sites)	Evaluation criteria	Model performance & major findings
Beaudoin et al. (2008)	Winter wheat, maize +7	France (36, field level, Bruyeres catchment)	Model evaluation against a French database in reset and continuous mode (eight years)	The model simulated cumulative drainage, nitrogen leaching, major crop biomass, and yield satisfactorily. Re-estimation of some crop parameters was necessary to obtain adequate results
Katerji et al. (2010)	Maize	Italy (3, experimental site, farm level, Foggia, Rutigliano, Metaponto)	Long-term simulations of crop response to irrigation regime, water deficit, and water use efficiency	The model validation showed acceptable results. STICS allowed the determination of climatic variability, which may assist in strategy development when uncertainties are not overly high
Khila et al. (2014)	Winter wheat	Tunisia (3, experimental site, field level, Nabeul, Bizerte, Tunis)	Impacts of irrigation and soil properties on wheat yield over 20 years	STICS showed good validation after the calibration of four conservative parameters. It accurately simulated yield, biomass, soil water content
Coucheney et al. (2015)	Maize, wheat +11	France (76. regional, agro-pedoclimatic classes)	Evaluation of crop development, water, and nitrogen outputs under varied environmental circumstances	STICS had a simulation performance from very good to satisfactory when testing scenarios, accurately simulating varied conditions
Constantin et al. (2015)	Maize +2	France (4, exprimental site, field level, Bouillac, La Mirandette, Gaillac, and Auzeville)	Limited data to predict soil water content and yield for an irrigated system; model comparison	STICS showed a very good performance in simulating soil water dynamics and good for irrigation and location impacts on maize yield. More input data is necessary to predict water flow and related aspects
Guest et al. (2017)	Spring wheat	Canada (3, experimental sites, field level, Saint Bruno-de-Montarville, Saint Jean-sur-Richelieu, and Ottawa)	STICS, DNDC, and DayCent model comparison of soil processes	There was no statistical difference in simulating soil moisture. All the models underestimated nitrogen-related results, and STICS was the least accurate.
Yang et al. (2019)	Winter wheat	Portugal (1, regional, 250-m resolution, Alentejo Region)	Rainfed winter wheat under climate change effects and adaptation strategies	The model showed a robust performance when simulating the yield
Yin, Beaudoin, et al., 2020)	Winter wheat +5	France (1, experimental site, field level, Fagnieres, Champagne)	Long-term crop rotation, nitrogen mineralization and leaching impacts	The research model simulated well the major crops' aboveground biomass and yield, N uptake and grain N content, drainage, N leaching, and nitrate concentration. Although, it showed more accurate results for wheat, sugar beet, and spring barley.
Levavasseur et al. (2021)	Maize, winter wheat +1	France (1 6-ha field; 40 450-m^2 plots, Feucherolles)	Organic and mineral fertilization; Carbon and Nitrogen crop-soil dynamics	STICS can simulate carbon and nitrogen dynamics accurately. However, the calibration method and data are crucial to a good modeling process
Saadi et al. (2022)	Maize	Canada (1 27-ha field, experimental site, near Ottawa)	Maize evapotranspiration and soil moisture prediction in wet and dry growing seasons using two methods in STICS, the crop coefficient (CC) and the resistance method (SW)	Both methods had good performance predicting evapotranspiration in both growing seasons, but SW showed better results: the SW better-simulated leaf area index and biomass in the wet season. Overall, biomass was the variable with the best accuracy in the simulations. Both methods showed similar results in soil moisture

TABLE 9 Summary of the reviewed studies assessing food security in crops using the World Food Studies model—WOFOST.

Study	Crop	Location (# sites)	Evaluation criteria	Model performance & major findings
Dobermann et al. (2000)	Rice	Philippines (1, experimental site, field level, Los Banos)	ORYZA2000 and WOFOST, rice yield	Dry and wet season yields, and aboveground dry matter did not statistically differ from ORYZA2000 to WOFOST, but dry matter partitioning did
Shekhar et al. (2008)	Wheat	India (1, experimental site, farm level, Hisar)	Wheat growth and yield	WOFOST underestimated grain yield for two agricultural years but overestimated yield for another year, leaf area index and harvest index. Overall, the predictions were satisfactory
Bussay et al. (2015)	Maize	Hungary (31 administrative units, 7 regions, regional level, 25-km soil grid)	Maize growth, yield and water balance	WOFOST needed improvement on the partitioning biomass and harvest index modules
Wolf et al. (2015)	Winter wheat	Europe (continental)	Winter wheat growth and yield with modified model parameters	WOFOST results were better without the modified parameters
Wu et al. (2017)	Wheat	North China Plain (4, experimental sites, field level, Shangzhuang in Beijing, Quzhou in Hebei province, Zhoukou in Henan province, and Huimin in Shandong province)	Wheat model comparison, phenology response to different sowing dates and genotype	All the models accurately predicted jointing, flowering, and maturity dates. Yield predictions were more accurate for higher temperatures. WOFOST and SPASS showed the best performance in simulating growing phases with different varieties and sowing dates
Biswas et al. (2018)	Rice	India (1, regional level, Kalyani)	Rice production under rising temperature impacts	WOFOST was 96% accurate
Van der Velde et al. (2018)	Wheat	Europe (25, national level, 25-km resolution)	Wheat quality, development, and yield under extreme events in low, medium, and high-yielding years	Yield values were overestimated in low-yielding years and underestimated in high-yielding years
Ceglar et al. (2019)	Winter wheat	Europe (gridded, 25 × 25 km)	WOFOST improvements to predict winter wheat phenology and yield at regional levels with MCYFS	Coupling WOFOST with MCYFS resulted in more accurate phenology and yield predictions at regional levels, especially for dry locations
Wu et al. (2021)	Winter wheat	North China Plain (1; gridded, 25 km × 25 km)	Winter wheat yield predicted with WOFOST with assimilated remote sensing input data	WOFOST results from assimilated data showed good accuracy at the field and regional levels
Zhuo et al. (2022)	Winter wheat	China (10, regional level, 500-m spatial resolution, Hebei Province)	Winter wheat yield predicted with WOFOST with assimilated leaf area index data	Including the assimilated data in WOFOST improved its accuracy at regional levels

TABLE 10 Summary of the reviewed studies assessing food security in crops using the Agricultural Model Intercomparison and Improvement Project—AgMIP.

Study	Crop	Crop models	Location (# sites)	Interest	Performance & major findings
Asseng et al. (2013)	Wheat	27	Africa (5), Asia (8), Australia (5), Europe (2), North America (5), South America (3)	Model simulation of crop response to climate change (CO_2 and temperature rise), grain yield (t ha^{-1})	Single crop models can fail to predict some uncertainties regarding climate change, while model ensembles are more accurate
Asseng et al. (2015)	Wheat	30 (29 deterministic process-based and one statistical)	Africa (2), Asia (10), Australia (2), Europe (8), North America (6), South America (2)	Global temperature impact on grain yield (t ha^{-1}), grains per m^2, kernel weight (seed size), anthesis and maturity dates, aboveground biomass at maturity (t ha^{-1})	Global temperature increases cause grain yield loss
Deryng et al. (2016)	Maize, wheat, rice, +1	6 (global gridded)	Australia (1), China (1), Germany (3), Japan (1), USA (4)	Water limitation, climate change with or without CO_2 and temperature effects on crop production, global average yield, actual evapotranspiration, crop water productivity	Climate change with less CO_2 benefits crop production
Liu et al. (2016)	Wheat, +1	30 (29 deterministic process-based and one statistical)	Worldwide (30)	Greenhouse gas emission (without CO_2), fertilization, and temperature effects on global wheat yield compared in three methods using AgMIP	The method with the model's ensemble is reliable when assessing global food security; models diversity in assessment leads to different results, and calibration is difficult but necessary
Zhao et al. (2016)	Rice	5	China (25), India (6), Japan (9), Korea (6), Nepal (4), Philippines (7), Portugal (2), USA (24)	Global warming effects on rice production compared in three modeling approaches	The multi-model ensemble underestimated the impacts of global warming, but it has a significant negative effect on rice production
Wang et al. (2017)	Wheat	29	Bangladesh (1), Brazil (1), Egypt (1), India (1), Mexico (2), Sudan (1)	Wheat-crop-model response comparison to temperature and plant physiology	The author's new temperature function decreased the error in grain yield simulations

TABLE 10 (Continued)

Study	Crop	Crop models	Location (# sites)	Interest	Performance & major findings
Porfirio et al. (2018)	Wheat, Rice +2	7 (global gridded), 5 (Earth System)	Africa (37), Asia (22), Australia (3), Europe (43), Latin America (18), North America (4)	Climate change's effect on global agricultural trade, CO_2, water, temperature, and nutrient impact	Global prediction is irregular, regional-scale impact on agricultural trade
Hasegawa et al. (2018)	Maize, Rice, Wheat +9	3 (global gridded) 8 (agricultural economic or integrated assessment)	Africa (42), Asia (40), Australia (3), Europe (29), North America (4), South America (13)	Climate change effects on crop yield, food security, agricultural economic market	Food security implications, mitigation policies, and increase in the risk of hunger
Tui et al. (2021)	Maize	2 (crop), 1 (livestock), 1(economics)	Zimbabwe (160)	Climate change effects and adaptation for dryland crop cultivation, crop grain and stover yield at the field, farm, and population levels	The climate change impact is more extensive in systems with better soil conditions; mitigating the effects shows a promising future
Rattalino Edreira et al. (2021)	Maize, Rice, Wheat, +2	14 (AgMIP)	Asia (242), Australia (22), Eastern Europe (244), The Middle East and North Africa (135), South America (91), Sub-Saharan Africa (218), USA + Mexico (91), Western Europe (240)	Yield gaps and potential production at a global scale are compared in two methods, GAEZ and AgMIP vs GYGA	Results vary more according to the methods at regional and country scales, input data alters the accuracy of the models

using interpolated data from the top-down approach could be a good solution.

The Gridded Crop Models (GCMs) used by AgMIP, previously mentioned as the top-down approach, are spatially distributed versions of single and multi-crop models. They may differ in methodology, input, and minimum data structure and requirements. Thus, the simulations perform differently. Yet, the spatial distribution allows modelers to contribute with datasets and analysis worldwide (Müller et al., 2019). But, for the most part, the GCMs may simplify and assume sowing date, soil characteristics and genetic variety data homogeneously for large areas, especially for areas where historical crop production data is unavailable. This practice does not contemplate input data variability, mainly at the farm and regional levels, where the weather, labour and machinery highly impact crop management (Müller et al., 2017). Hence, considering that crop varieties and management technologies change throughout the years, including human interactions, remote sensing data and the farmer's behaviour, improve the results when analyzing future production and impacts on crop yield based on historical data (Han et al., 2019; Müller et al., 2017; Wallach et al., 2006).

Methodological improvements have vastly enhanced how GCMs reproduce data variability for maize, wheat, and rice. Therein, spatial variability predominates over time since the data varies more between regions than in years (Müller et al., 2017). Some researchers are combining statistical (based on historical data) and process-based (based on crop phenology) approaches in GCMs as a statistical emulation to find yield projections under different CO_2 concentrations, temperatures, and water and nitrogen availability, linking to their impacts on agriculture (Franke et al., 2020) (see more about statistical emulators from GCMs in Blanc, 2017). Studies show that the emulators are flexible on crop models, performing well with various climate sensitivities. Their errors are primarily insignificant and happen in non-agricultural land. Hence, emulators promote potent improvements to model comparisons and impact assessments, easing crop yield estimation, especially in the long term (Blanc, 2017; Franke et al., 2020).

But, although the GCMs have shown reliable results, improvements may be necessary at regional levels and for extreme events. Folberth et al. (2019) used machine learning to predict maize yield from simulated crop model outputs. They found that over and underestimating crop yields are rare at large scales. However, results show under and overestimations at regional scales. Even so, they stated that the difference in results did not impact the predictions' reliability. Further, Heinicke et al. (2022) observed that most GCMs detected extreme event signals, such as heat waves and droughts' impacts on yield simulation. But there was an apparent underestimation of yield decrease for wheat and rice production, which did not reproduce losses accurately.

According to the studies reviewed, the AgMIP is reliable for assessing global food security and agricultural production under climate change impacts. This project provides fewer modeling errors by comparing models and creating model ensembles. Most studies focused on climate change and its impacts on agriculture and crop production, mostly globally. They aimed to predict yield gaps and/or losses and impacts on food security caused by a rise in temperature, water deficit, and elevated greenhouse gas emissions.

3 | FINAL CONSIDERATIONS AND CONCLUSION

Having reviewed all ten crop models and associated literature, while all crop models described can assess yield and thus be used as a tool to examine food production, availability, and security, APSIM and DSSAT allow the assessment of more outputs than the other crop models described. Researchers have used both models globally and at the regional and field levels, predominantly in the northern hemisphere. AquaCrop specializes in water balance and is the most indicated to investigate water footprint, quality and use efficiency in rainfed and irrigated systems, especially in Asia. But, besides evaluating irrigation, CropSyst and STICS also weigh fertilization effects on crop production and are reliable models to apply to the northern hemisphere. Biome-BGCMuSo has expanded as a crop model and will bring new studies in the following years. With respect to fertilization, most of the models described analyze nitrogen dynamics and its use efficiency. Modelers have not used AquaCrop exclusively for this purpose. WOFOST is also used for such analysis. APSIM, DAISY, and DSSAT modelers have assessed grain filling and nutrient content, which are very important to research nutrient requirements and, therefore, food security. JULES focuses on food security assessment through vulnerability, land use, carbon and water cycles. ORYZA is specialized in paddy rice in Asia and, thus, was the only crop model that modelers used to verify salinity toxicity for the crop. Most of the studies focused on the northern hemisphere, hence more studies focusing on new areas and countries are necessary to broaden the shareholders' knowledge and improve the adaptation and impact mitigation in crop production.

We verified that all crop models reviewed are interdisciplinary, focused on soil–water–plant–atmosphere interactions. They require crop genetics, field management, soil characteristics, and weather data to run, which are sometimes challenging to gather. Comparing models and creating model ensembles provide fewer modeling errors than single models. Hence, AgMIP provides reliable outputs to assess global food production. Crop model simulations are fast and reliable methods for assessing food availability, which is crucial to preventing food insecurity. However, this dimension is not sufficient to mitigate and solve food insecurity. Studies that integrate the five dimensions of FI and their interactions, instabilities, and out-farm approaches are necessary to help alleviate the issue.

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CONFLICT OF INTEREST STATEMENT

The authors declare no competing interests.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this review since no new data were analyzed in this study.

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