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Primer

Crop models for future food systems

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SUMMARY

Global food systems face intensifying pressure from climate change, resource scarcity, and rising demand, making their transformation toward resilience and sustainability urgent. Process-based crop growth models (CMs) are critical for understanding cropping system dynamics and supporting decisions from crop breeding to adaptive management across diverse environments. Yet, current CMs struggle to capture extreme events, novel production systems, and rapidly evolving data streams, limiting their ability to inform robust and timely decisions. Here, we outline CM structure, identify key knowledge gaps, and propose six priorities for next-generation CMs: (1) expand applications to extremes and to diverse systems; (2) support climate-resilient breeding; (3) integrate with machine learning for better inputs and forecasts; (4) link with standardized sensor and database networks; (5) promote modular, open-source architectures; and (6) build capacity in under-resourced regions. These priorities will substantially enhance CM robustness, comparability, and usability, reinforcing their role in guiding sustainable food system transformation.

INTRODUCTION

Process-based crop growth models (CMs) are scientific tools that simulate crop growth and development based on biophysical principles. They integrate knowledge from crop physiology, soil science, agrometeorology, and agronomy to quantify crop responses to environmental and management conditions. CMs enable the exploration of "what if" scenarios, such as changes in climate, resource use, or cultivar traits, without the costs and constraints of field experimentation. Their process-based structure allows for simulations under both historical and future conditions, supporting analyses of productivity, resource-use efficiency, and environmental impacts. Retrospective simulations help identify system vulnerabilities, while prospective applications support adaptation planning and technology evaluation. CMs are also used to assess water, nitrogen, and carbon dynamics, contributing to the design of more sustainable and profitable cropping systems. When coupled with economic and food system models, they support broader assessments of food security and climate change mitigation policies.

Developing and applying CMs to real-world challenges requires interdisciplinary collaboration, including among crop physiology, soil science, agrometeorology, climate science, agronomy, agricultural economics, mathematics, and computer science. The Agricultural Model Intercomparison and Improvement Project (AgMIP; https://agmip.org/) was established to foster such a multi-disciplinary international collaboration capable of taking on grand challenges in current and future food systems. AgMIP brings together scientists worldwide to compare and improve CMs and their applications while also ensuring their accuracy and utility across diverse environments. This coordinated effort enhances CM transparency, helps identify uncertainties, and accelerates progress in applying CMs to address climate change, resource use, and food system challenges.

As agriculture faces increasing pressure to produce food more sustainably, boost cropping system resilience, and meet rising food demands, CMs have become popular tools to explore how to achieve these goals under uncertain and changing conditions. Their critical role has underscored the need for documentation of CM strengths and weaknesses as well as a sustained research and improvement agenda so that they can assist

Box 1. Examples of widely used process-based crop growth model platforms

(1) DSSAT (Decision Support System for Agrotechnology Transfer; https://dssat.net/): a widely used, comprehensive modeling suite for over 45 crops, DSSAT supports applications from field-scale management to global climate assessments, integrating weather, soil, genetics, and management data, continuously improved via user groups.
(2) APSIM (Agricultural Production Systems Simulator; https://www.apsim.info/): modular and extensible, APSIM simulates complex interactions between crops, soils, management, and climate. It is also widely used for cropping systems analysis and is under continuous development through the APSIM Initiative.
(3) STICS (https://stics.inrae.fr/eng/): a mechanistic CM simulating daily crop growth and soil-plant-atmosphere exchanges, STICS is suitable for annual and perennial crops, rotations, and intercropping, with strong capabilities for analyzing agri-environmental performance and long-term sustainability.
(4) WOFOST (World Food Studies; https://www.wur.nl/en/research-results/research-institutes/environmental-research/facilities-tools/software-models-and-databases/wofost.htm): a dynamic CM focusing on physiological crop responses to light and water, WOFOST supports regional yield forecasting and global food security analysis, including applications in the Global Yield Gap Atlas and EU-MARS.
(5) LPJ-GUESS (https://web.nateko.lu.se/lpj-guess/): LPJ-GUESS is a process-based dynamic global vegetation model that simulates ecosystem structure, composition, and function across climate zones using plant functional types. Widely applied from regional to global climate impact studies, it links crop, ecosystem, and earth system modeling.
(6) JULES-Crop (Joint UK Land Environment Simulator; https://jules.jchmr.org/): JULES-Crop is a community land surface CM that is used both as a standalone CM and as the land surface component in the UK Met Office Unified Model.

decision-makers in making more efficient and timely decisions in agriculture. This Primer reviews the current state and future directions of crop modeling as a means to advance profitable, resilient, and sustainable food production. We outline CM fundamentals; highlight the role of global collaborations, such as AgMIP, in CM evaluation and improvement; and explore opportunities from integrating data science, genomics, and emerging sensing technologies. We also address the need for stakeholder engagement, open data, and modular designs to co-develop adaptive, knowledge-based systems capable of guiding agriculture toward resilience and sustainability in an uncertain future.

THE STRUCTURE OF CROP MODELS

CMs simulate crop phenology and growth processes, determining how carbon is allocated to the harvestable organ, i.e., crop yield, by integrating daily weather, soil characteristics, crop management practices, and crop variety characteristics into dynamic, interacting biophysical processes. Crop models simulate virtual crops (not single plants) and their progress from germination to flowering to harvesting. Despite differences in complexity (Box 1), most CMs share a common structure that combines inputs from a static environment, such as initial soil characteristics and crop management, with dynamic aspects of an environment, such as weather, to simulate growth and yield responses over time (Figure 1).

Inputs typically include weather data (daily or sometimes hourly temperature, rainfall, and solar radiation, with some CMs using additional information, such as relative humidity or air vapor pressure and wind speed), soil properties (e.g., texture, organic matter content, pH, and water-holding capacity at various depths), crop management (e.g., planting date, planting density, and fertilizer and irrigation application rates and dates), and crop genotypic traits (e.g., degree-day requirements, vernalization requirements, photoperiod sensitivity, tolerance to stressors, and partitioning coefficients). Most CMs simulate crop responses to water deficit when soil moisture declines or is insufficient to meet atmospheric demand and to temperature using cumulative degree days and temperature threshold functions. Fewer CMs represent responses to excess water stress, such as flooding or waterlogging. The dynamics of nitrogen is usually the only nutrient explicitly modeled, with its deficiency reducing crop growth.

While some aspects of soils are typically considered static (e.g., texture), CMs dynamically simulate the water and nitrogen balance to capture soil-plant-atmosphere interactions and feedback. This enables the determination of water and nutrient availability within a CM at each crop stage and how their shortage influences crop growth and yield.

CMs also require crop species and variety genotypic information via crop and variety parameters, which consider how a specific crop type and variety grows and responds to the environment. Crop species parameters represent core physiological processes that are generally shared by all varieties of a given crop, such as, for example, the biochemical response to

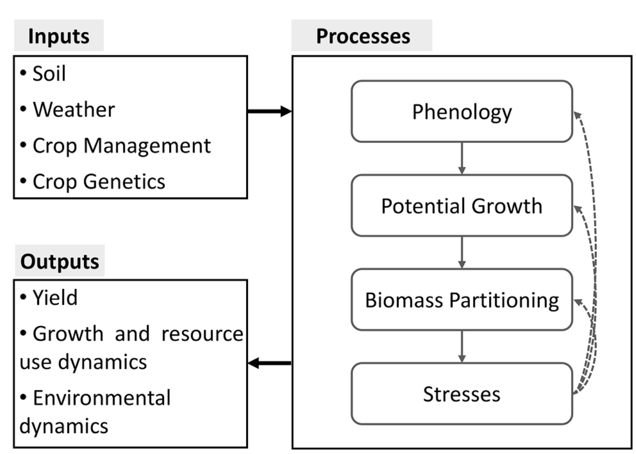

Figure 1. Simplified architecture of a process-based crop growth simulation model

elevated CO_2 (e.g., differences between C3 and C4 species) or fundamental limits on canopy or root growth. Crop-variety-specific parameters capture genotypic differences among varieties of the same species—such as how quickly a crop develops, how it responds to drought or heat, and how efficiently it uses light for photosynthesis and growth. All these parameters are usually based on experimental evidence. Variety-specific parameters may be adjusted during calibration when supported by field data. However, calibration does not inherently ensure CM robustness. Calibration aims to improve CM agreement with observed data but may reduce predictive performance in new environments when overfitting parameters to a limited set of observations.

Once inputs are provided, a CM simulates crop phenology, growth, and stress dynamics (Figure 1). The crop phenology describes the growth stages of a crop from planting to harvest. The simulation of crop growth starts by estimating potential growth under ideal conditions, mainly driven by photosynthesis, partitioning biomass into different crop parts (leaves, stems, roots, and grains/fruits/tubers) based on crop-species-specific and sometimes crop-variety-specific rules that might change throughout growth stages. In response to any growing conditions that are not ideal for crop growth, CMs dynamically adjust growth to account for stresses. Water and nitrogen stress responses are determined based on dynamic simulations of soil processes. Drought can reduce leaf expansion and photosynthesis, accelerate senescence, and disrupt various physiological processes, ultimately limiting biomass accumulation and reducing yield. High temperatures may shorten the crop cycle by enhancing senescence, limiting the time available for photosynthesis and yield development. In some CMs, heat above critical thresholds during key stages can cause flower or grain/fruit loss, reducing yield. CMs generate outputs that assist researchers, farmers, agribusinesses, and policymakers in understanding current and proposed cropping systems' performance. These include daily or seasonal estimates of phenology, biomass accumulation, leaf area, soil moisture, water use, runoff, nutrient uptake, and projected yields. Some CMs simulate entire farm systems, with crop rotations, including carryover effects and potentially cover crops, or intercropping systems with crop types competing for sunlight, water, and nutrients. More advanced frameworks link CMs to broader system models that estimate land use, environmental footprints, or economic outcomes, supporting decisions on climate change adaptation, profitability, and sustainability.

DEVELOPING AND IMPROVING CROP MODELS

Developing and improving CMs requires balancing two objectives: capturing the main dynamics of crop production systems and representing enough system complexity to allow CM transferability to novel environments, such as new locations or future climate scenarios. At the same time, CMs must remain practical and transparent, meaning they should have manageable data and parameter requirements, reasonable computational demands, and interfaces that are accessible to diverse users. Overly simple CMs risk omitting key processes, while overly complex ones demand extensive data. Studies have shown that adding more detail can improve CMs, but too much complexity often increases errors from many functions and parameters, introducing additional CM uncertainties.

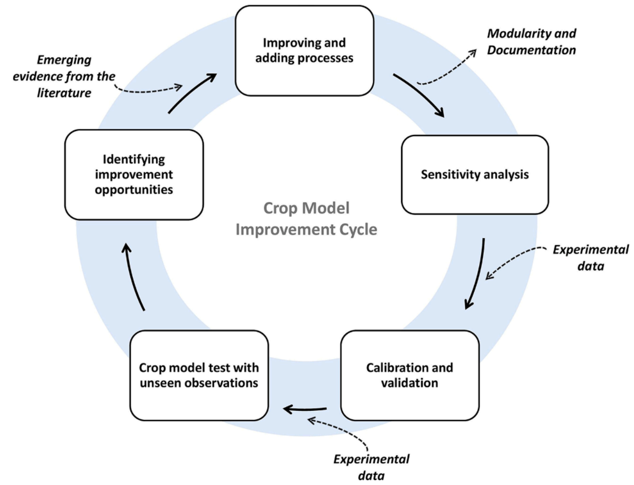

Figure 2. Best practices cycle for developing process-based crop simulation models

CMs simulate core crop processes such as phenology and leaf area and biomass dynamics, capturing their responses to environmental and crop management conditions (Figure 1). As scientific understanding advances, new processes, such as phosphorus dynamics, salinity tolerance, or disease responses, are added to increase CM relevance and applicability. However, each addition introduces new functions and parameters requiring calibration. When calibration data are insufficient or poorly distributed, CMs may match observations but fail to generalize under new conditions. Thus, process inclusion should be guided by clear research questions and supported by sufficient data for testing.

Calibration involves adjusting parameters to improve the reproduction of field measurements, usually from well-managed experiments. A validation with independent datasets from diverse environments is essential to assess CM robustness. This is particularly important when applying CMs in extrapolations to other environments and future climates.

CM development follows a continuous improvement cycle (Figure 2). The cycle begins by identifying crop responses not well captured by current CMs, often through field observations, literature reviews, new research questions, or multi-model intercomparison exercises. Crop modelers then determine which physiological or agronomic processes need to be improved or added. These steps require collaboration with experimental teams, as CM refinement depends on high-quality field data, such as from studies of crop responses to various conditions. Coordinated collection and sharing of experimental datasets remain essential for CM improvement.

Modular CM architecture supports continuous improvement by enabling targeted updates of specific components, such as phenology, without full CM reconstruction. It also facilitates integration with other modeling tools and system components. Clear documentation and evaluation of each update, ideally through peer-reviewed publications, is essential. Testing and reporting changes help assess how new routines affect overall CM performance. Each update should include a full testing cycle to ensure robustness and reliability.

AgMIP AS A GLOBAL COLLABORATIVE PROJECT FOR CROP MODEL IMPROVEMENT

Much of the recent progress in crop modeling stems from increased global collaboration, with AgMIP playing a central role in coordinating international CM intercomparisons and improvement. Launched in 2010, AgMIP connects diverse communities across disciplines, observations, and modeling frameworks to better understand agricultural systems under past and future conditions. AgMIP promotes transparent, standardized protocols that allow multiple modeling teams to simulate identical scenarios using shared inputs and standardized simulation protocols. Importantly, AgMIP connects modelers across world regions, promoting both capacity building and improved modeling of global agricultural systems.

AgMIP's CM-intercomparison process follows a clear, collaborative pathway. A team of researchers first identifies an important scientific or policy-relevant problem. They demonstrate that existing data and CMs can be combined to address this problem effectively. Next, the team designs a rigorous protocol that enables multiple modeling groups to execute the same simulations under uniform conditions. AgMIP activities are openly advertised, inviting scientists to join, with each team documenting their CM's characteristics to ensure transparency and fit-for-purpose participation. The team then establishes mechanisms to share input data—covering weather, soils, crop management, and cultivar information—and to collect and analyze simulation results. Access to observational data is often initially restricted to modelers to reflect real-world situations where limited observations may be available. After all modeling groups complete a simulation experiment, a joint analysis identifies where CMs agree or diverge and where further improvements are needed. This iterative process drives continuous CM evaluation, improvement, and application.

Since its inception, AgMIP has conducted over 60 multi-model intercomparison activities covering more than 40 crop species, led by staple crops such as wheat, maize, rice, and soybean, as well as several less commonly modeled crops, such as potatoes, sugarcane, canola, barley, and tomatoes. This approach also extends to global gridded CMs that assess climate change impacts, virtual breeding trials, fertilizer intensity, or applications such as assessing the impact of solar dimming from nuclear winter scenarios on global food supply. The scope of AgMIP includes modeling of cropping systems of specific regions (e.g., low-input systems), methodological aspects (e.g., calibration methods, analyses of spatial resolution effects, and machine learning [ML]), improvements of individual components (e.g., soil processes, ozone damage, and disease impact), and contributions to regional and global integrated assessment efforts (e.g., adaptation evaluation and food system transformation pathways).

AgMIP's foundation is built on the biophysical understanding that enables out-of-sample analysis, involves extensive field experimentation, and the integration of crop, economic, and climate models to assess agricultural systems under global change. AgMIP also serves as an interface across application areas, facilitating connections that allow for more efficient utilization of land, water, carbon, and nutrient resources.

To enhance CM robustness, AgMIP combines scenario analysis with rich experimental datasets collected worldwide. Notable examples include the Free-Air CO_2 Enrichment (FACE) studies that provide critical data on crop responses to elevated CO_2 levels and the Hot Serial Cereal (HSC) trials conducted to create realistic warming under field conditions. These experiments allow a rigorous validation of CMs, revealing structural differences and key physiological processes across diverse climatic conditions.

AgMIP's global collaboration has advanced crop modeling by coordinating multi-model intercomparisons that quantify uncertainties, guide improvements, and provide key insights into the future of cropping systems. For example, ensembles of 29 wheat CMs suggest that global wheat yields could decline by about 6% per 1°C of global warming (when excluding any other effect), yet individual CM results vary widely. Similar variation is seen in maize evapotranspiration estimates, which can range from a 24% loss to a 29% gain under 3°C warming. Such differences illustrate the complexity of simulating crop responses and the need for continuous CM improvements.

A key finding from AgMIP intercomparisons shows that no single CM consistently outperforms other CMs across all contexts. Instead, multi-model ensemble means or medians provide more reliable and robust simulations across diverse environments. Additionally, CM improvements, like the introduction of a new heat stress function in wheat CMs, have lowered simulation errors in comparison to observations by 42%, reducing both individual CM and ensemble uncertainty in yield projections under warming scenarios.

AgMIP has identified underlying causes of productivity losses, helping farmers and policymakers target interventions that boost production without expanding cropland. This complements global efforts such as the Global Yield Gap Atlas (GYGA), which employs CMs to provide region-specific benchmarks and pathways for sustainable intensification. Since nitrogen fertilizer availability and inefficiency are major drivers of yield gaps, improving nutrient management in cropping systems is essential and can be explored and guided using CMs.

A persistent challenge for CMs remains in the lack of representing common soil restrictions (such as aluminum toxicity, and potassium and micro-nutrient deficiencies), and crop losses from extreme weather events, as these impacts are often underestimated due to the complex, non-linear interactions among stressors. AgMIP is advancing multi-hazard modeling and is incorporating ML to reduce systematic biases and improve predictive performance. Continued progress relies on a modular CM architecture that facilitates the exchange and reuse of CM components, detailed field datasets, and transparent, standardized simulation protocols that foster collaboration and ensure that CMs continue to improve in robustness and actionability.

OUTLOOK

CMs are advancing with new data, tools, and scientific insights. To meet the challenges of climate change, food security, and sustainable farming, the next generation must be more accurate, flexible, and accessible. Here, we outline six priorities to guide this evolution.

Expand CMs for extreme events and diverse systems

Crop modeling faces new and urgent demands as food insecurity becomes a global humanitarian challenge in providing an adequate and healthy diet, with climate change causing additional challenges. Extreme weather events are becoming more frequent and often co-occur. Climatic stresses interact in complex ways, leading to compound effects. CMs struggle to capture these complex stress interactions adequately. Improving their ability to capture multi-stress dynamics is critical for more reliable predictions and for developing effective adaptation strategies to support farmers.

Expanding CM applications to diverse production systems is equally important. This includes intercropping, agroforestry, agrivoltaics, controlled-environment farming, and integrated crop-livestock systems, each with complex biological and management interactions. Enhancing CMs to represent these systems, alongside extreme climate events and soil constraints, will strengthen their role in supporting resilient, productive, and sustainable food systems under global change.

Use CMs for crop breeding

Advances in crop modeling are increasingly converging with crop breeding, creating new opportunities to accelerate genetic improvement. CMs can help prioritize traits and assess their potential impacts across diverse environments and management practices. To achieve this, models must capture a high level of biological realism, accurately representing trait-trait and trait-environment interactions. Initiatives such as AgMIP play a key role in evaluating and improving how well CMs represent crop responses to trait variation. While genomic prediction based on genetic markers is powerful for estimating complex traits, it often struggles to capture genotype-by-environment interactions. Integrating genomic prediction with process-based CMs combines the strengths of both approaches. This integration enables breeders to assess new genotypes across environments and management options, identify key traits, and simulate ideotype performance *in silico*, including stress tolerance and nutritional quality. This synergy between crop modeling and genetics has great promise to address future food security by guiding and accelerating the genetic improvement of crops for changing environmental conditions.

Combine CMs with ML

Advances in data science are opening new opportunities for CM improvement. ML can uncover patterns in complex datasets that are often missed in traditional analysis. ML can help improve CM parameter estimation, correct biases, and reveal complex relationships between crop genotypic and environmental factors. However, ML lacks the biological meaning of CMs and performs poorly outside its training data, especially with inadequate cross-validation. Combining the strengths of ML and CMs in hybrid modeling can overcome some of these problems. Hybrid modeling uses the biological understanding underlying process-based CMs to guide ML, resulting in better model skill while maintaining the interpretability of results.

Integrate sensors and dynamic databases

Data from sensors, drones, satellites, and Internet of Things (IoT) devices form the foundation of field-based phenomics, which is essential for linking CMs with genetics. These technologies also enable the development of digital twins of cropping systems—dynamic virtual models of cropping systems that support decisions on management and cultivar selection. CMs are the core of digital twins of cropping and farming systems. These can integrate crop breeding, climate variability, and change to guide adaptation; support emerging systems, such as intercropping; and optimize farming efficiency (Figure 3).

Promote modular, open-source architectures

Continued CM advancement depends on access to high-quality, openly shared data. Experimental data from field trials, farms, and controlled environments are essential for testing, calibration, validation, and improvement. Initiatives like FairAgro (https://fairagro.net/) and the AgMIP Data Interoperability Group promote international data standards to enhance sharing and interoperability. In parallel, modular architectures supported by open-source modeling frameworks such as Crop2ML (https://crop2ml.org/) increase the transparency of CMs and support component exchange and reuse, supporting collaborative CM development across crops, environments, and a range of scientific and societal actors. This approach also calls for better communication between scientists, developers, and end users.

Build CM capacity in under-resourced regions

AgMIP continues to play an important role in ensuring capacity building in general and expanding CM accessibility in under-resourced regions. Strengthening local modeling capacity, improving data infrastructure, and fostering collaborations in these areas will help to close regional gaps in data, technology, and expertise. This not only broadens the applicability and robustness of CMs worldwide but also ensures that farmers and decision-makers in regions most vulnerable to climate change can benefit from advances in crop modeling.

In conclusion, CMs are essential tools for analyzing agricultural cropping systems under changing environmental and socio-economic conditions. Their potential is best realized when they are linked with observational data, grounded in the latest scientific understanding, and subjected to rigorous evaluation. Integrating advances in crop physiology, stress response, and soil processes, supported by real-time data and ML, can further enhance CM relevance and performance. Initiatives such as AgMIP can play a central role by coordinating CM development, benchmarking, and application. Moving forward, transparent methods, modular design, and open data sharing will be key to improving CMs' credibility and usability. Sustained collaboration across disciplines and continued investment in crop modeling will support the transition toward more resilient and sustainable food systems.

AUTHOR CONTRIBUTIONS

A.C.R. and S.A. supervised the study. R.d.S.N.-J. drafted the first version of the manuscript. All authors contributed to the design and revision of the manuscript.

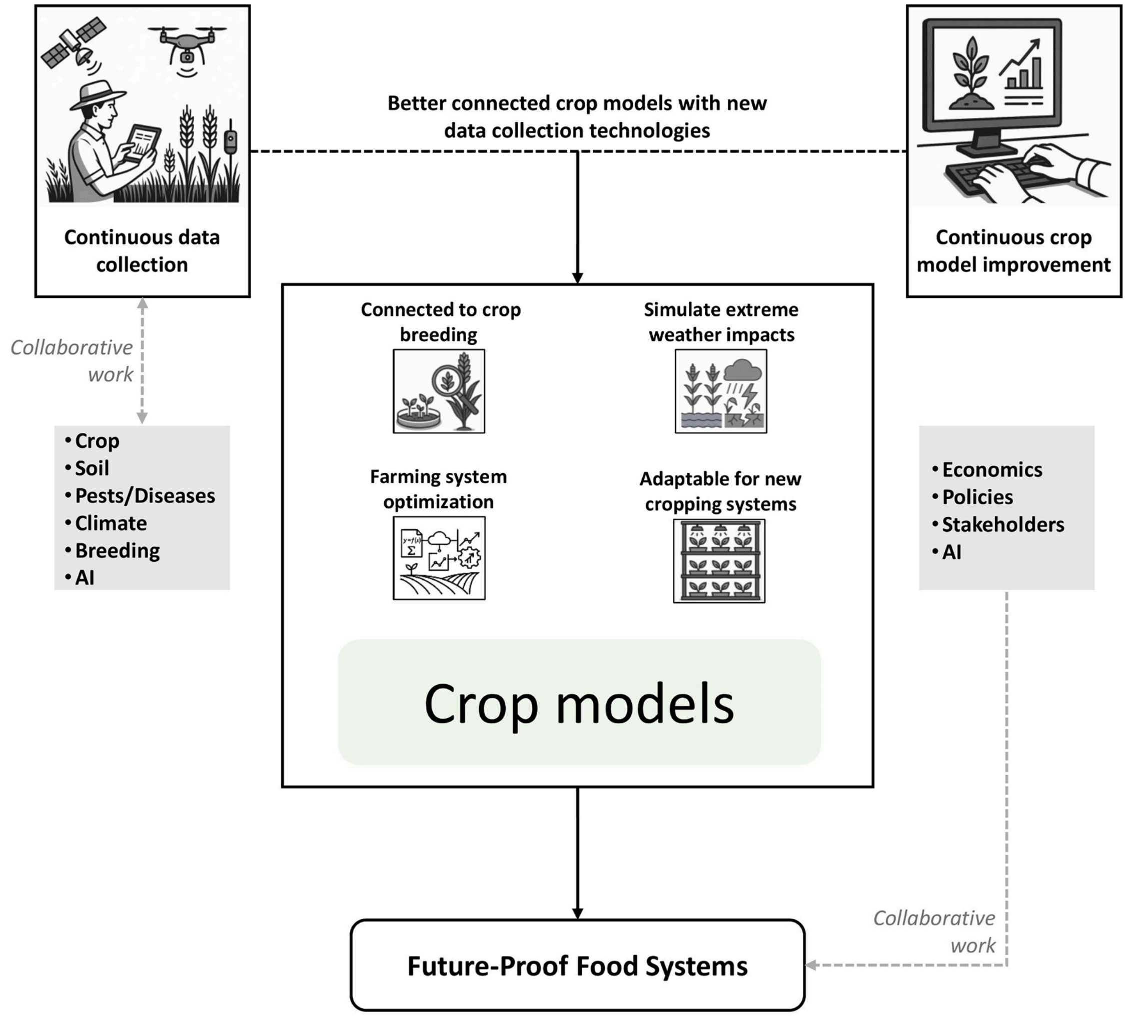

Figure 3. Process-based crop simulation models adapted for future food production systems

DECLARATION OF INTERESTS

The authors declare no competing interests.

RECOMMENDED READING

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