ISBN: 978-93-48091-98-7

5. Advances in Crop Modelling for Sustainable Agriculture

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Abstract:

Amidst rapid population growth, diminishing natural resources, and the increasing impacts of climate change, the urgency for sustainable agricultural practices has never been greater. This section delves into the evolution and implementation of sophisticated crop modelling techniques to promote sustainable crop production. It begins with a historical overview, tracing the progression of agricultural system modelling from its initial economic focus to the contemporary interdisciplinary approach that encompasses ecological, economic, and technological elements. The section discusses the fundamental characteristics and categories of crop models, emphasizing their dual role: advancing scientific comprehension and facilitating decision-making. It delves into the incorporation of remote sensing data into crop models, highlighting the transformative potential of this method in enhancing yield predictions across diverse environmental conditions. Various data assimilation methods, such as the Kalman Filter, Ensemble Kalman Filter, and Particle Filter, which enhance the accuracy of crop yield predictions by merging remote sensing data with crop models, are explored. Additionally, the section examines the role of Big Data and artificial intelligence (AI) in crop modelling, demonstrating how these technologies can address spatial and temporal data gaps and provide new insights into crop-environment interactions. By utilizing machine learning and deep neural networks, researchers can capture complex nonlinear relationships between inputs and outputs, *offering a more comprehensive understanding of crop growth dynamics. This section emphasizes the significance of adopting advanced crop modelling approaches to address the challenges of sustainable agriculture in the 21st century and provides a glimpse into the future of agricultural research and policy-making.*

Keywords:

Crop Modelling, Agricultural Systems, Remote Sensing, Artificial Intelligence, Data Assimilation, Model Calibration, Model Validation.

5.1 Introduction:

Rapid population growth, dwindling resources like water, food, energy, and the intensifying impacts of climate change have created unprecedented global challenges. Due to the impact of these factors, there is a continuous and large-scale publications of information which is problematic in terms of managing all this knowledge (Wheeler and von Braun, 2013).

Historically, we preferred discipline-based outcomes where the inter-dependencies between the components was not considered. Understanding how different components within a system interact is crucial, as studying individual parts in isolation may not accurately reflect the overall system's behaviour. Thus, there is an increase in emphasis on ‘systems science’ (Hieronymi, 2013).

Systems science examines how the components are interconnected as defined by experts, and work together within a larger system like environment to determine the overall behaviour of the system. These systems can be influenced by environmental factors but might not affect them in return. While simplified representations of reality, these systems are valuable tools across various fields, including agriculture (Wallach et al., 2014).

Agricultural systems science investigates the operations of complex farming systems. While real-world observations are valuable, models are crucial for understanding and predicting system behaviour due to the complexities involved. These models require data to be developed and tested, allowing for simulated experiments to draw conclusions about real-world systems. The progress of agricultural systems science depends on the quality of models, data availability, and tools to interpret and communicate findings for informed decision-making.

Agricultural models are vital for sustainable land management as they allow for the efficient exploration of various management strategies across different conditions and timeframes. These models help in identifying potential risks and optimizing sustainability goals for farmers and policymakers (Teng and Penning de Vries, 1992).

Decision support systems make use of these models to offer tailored recommendations for pest control, financial planning, livestock management, and overall crop and land management. While mainly used by agricultural experts, some systems are accessible to farmers directly.

Apart from farm-level applications, agricultural models contribute to broader landscape, national, and global assessments, influencing public awareness, research investment, and policy development (Nelson et al., 2002; Fraisse et al., 2015).

Large-scale crop yield forecasts are affected by the diversity of soil conditions, plant traits, and weather patterns, making it difficult to accurately predict crop yields. These uncertainties have a considerable impact on the reliability of crop growth models, resulting in unreliable yield predictions (Hansen and Jones, 2000). The use of remote sensing technology has greatly improved our capacity to measure important crop and soil characteristics such as LAI, biomass, and soil moisture over extensive regions.

This information can be seamlessly integrated into crop models to enhance their precision. Monitoring crop growth stages (phenology) through remote sensing further enhances the accuracy of crop model simulations (Guyot, 1996; Sakamoto et al., 2005).

Since crop models are formulated using linear relationship between components it poses difficulty in estimation of yield or other inputs over large scale using remote sensing platform. The major problem lies in dimensionality difference between various remote sensing-based outputs (Jones et al., 2003).

Artificial Intelligence has proven to be an effective method for crop yield estimation using remote sensing data because it nonlinearity between the input variables and crop yield (Khaki et al., 2020).

Thus, in this chapter we are going to see the advanced approaches in crop modelling for sustainable crop production in various scales and their mechanism behind applications.

5.2 History:

The evolution of agricultural system modelling has been a dynamic journey influenced by a variety of factors and milestones. Here is an overview of significant events and trends:

5.2.1 Early Influences (1950’s-1970’s):

Economic Emphasis: Groundbreaking research by Earl Heady and others concentrated on farm-level decision-making and the analysis of policy impacts.

Ecological Awareness: The International Biological Program (IBP) encouraged ecological modelling approaches to comprehend agricultural systems.

5.2.2 Scientific Progress (1970’s-1980’s):

Pioneers in Crop Modelling: C.T. de Wit and W.G. Duncan established the foundation for process-based crop growth simulation models.

Interdisciplinary Collaboration: The necessity to control pests and diseases resulted in the integration of crop models with insect and disease dynamics models.

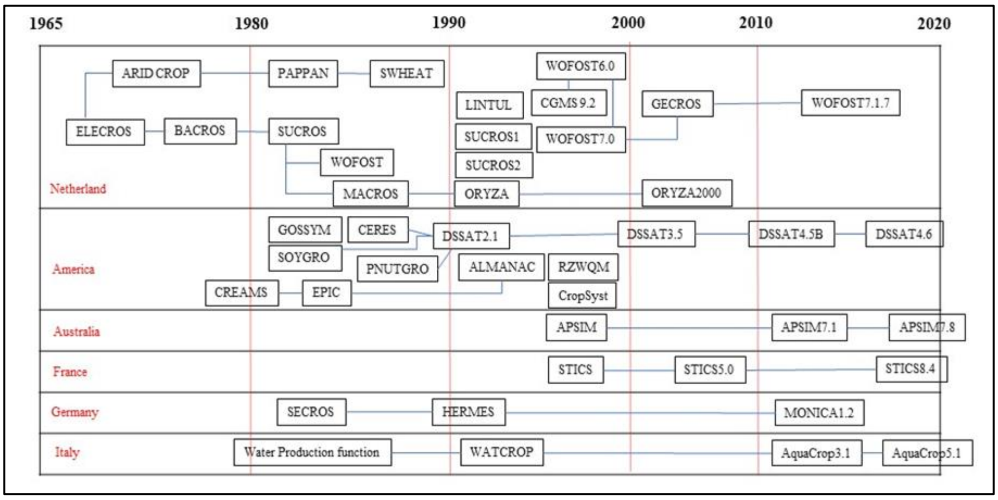

Figure 5.1: Models developed in different countries

Knowledge Exchange Platform: The creation of the journal "Agricultural Systems" facilitated scientific communication and model enhancement.

5.2.3 Institutional Backing and Cooperation (1980's-present):

Government Support: Funding from US, Netherlands, and Australian programs contributed to the development of major crop, livestock, and economic models (e.g., EPIC, DSSAT, ORYZA, APSIM) **Figure 1**.

Global Partnership: Initiatives like SEAMLESS promoted international collaboration for model development and data sharing.

Advancements in Economic Modelling: Continuous progress in economic modeling addressed various requirements at national and international levels.

5.2.4 Technological Progress (1980's-present):

Personal Computers: The PC revolution made models more accessible, empowering individual researchers and developers.

Internet and Web: Enhanced communication and collaboration among scientists accelerated model development and data accessibility.

Open-Source Movement: Initiatives such as open-source versions of APSIM and DSSAT encouraged community-driven model enhancement.

Agricultural system modelling has evolved significantly, transitioning from a primarily economic focus to a comprehensive, interdisciplinary approach. Early efforts concentrated on optimizing farm-level operations and assessing policy implications has been carried out by Earl Heady (Heady 1957). However, the discipline expanded to encompass ecological (Van Dyne and Anway, 1976) and crop-specific factors (Duncan et al., 1967), driven by advancements in these areas. The integration of these components has resulted in sophisticated models capable of simulating complex agricultural systems. This evolution equips researchers and policymakers with powerful tools to address contemporary challenges such as food security and climate change.

5.3 Characteristics of Crop model:

5.3.1 Purposes for Model Development:

Agricultural models have dual functions: to enhance scientific understanding and to aid in decision-making processes. Scientific models are designed to delve into the fundamental processes, whereas decision support models are geared towards forecasting outcomes in various scenarios. Together, these models play a crucial role in tackling agricultural issues (Ritchie and Alagarswamy, 2002).

5.3.2 Approaches for Modelling Agricultural Systems:

Agricultural decision-making models can be categorized into two main types- statistical models, which involve analysing historical data, and dynamic simulation models, which consider how systems respond to external factors. While statistical models are simpler, they have limitations such as extrapolation and predicting future scenarios. On the other hand, dynamic models are more complex but provide greater flexibility through features like multiple response simulation and decision comparison. The complexity of a model typically varies based on the type of decision being made, whether it is tactical or strategic planning. Moving forward, there is a growing emphasis on assessing model uncertainty to ensure reliable strategic planning (Wallach et al., 2014).

5.3.3 Spatial and Temporal scales of Agricultural System Models:

Agricultural models and their users vary widely making their applications in both spatial and temporal scales. Researchers utilize intricate models to examine possibilities, then convert results into easily understandable formats (such as fact sheets and decision support systems) for extension agents, farmers, and policymakers.

5.4 Types of Crop Model:

The complexity of a crop model is largely determined by its intended purpose. Simple models are commonly used for estimating yields over large areas and require less detailed input regarding the soil-plant system. On the other hand, complex models offer detailed explanations of the soil-plant-atmosphere system but necessitate extensive input data that may be challenging to acquire. Crop models can be categorized as deterministic or stochastic. Deterministic models yield specific outcomes based on set conditions but are subject to uncertainties due to spatial variability in soil and weather. Stochastic models address this variability and uncertainty in input data, although true stochastic crop models are not yet widely utilized.

Currently, deterministic models are frequently employed with aggregated data from small, homogeneous soil units to estimate field yields, especially when considering year-to-year weather variations. There are three main types of deterministic crop models: statistical, mechanistic, and functional. Each type varies in complexity and input requirements.

1. **Statistical Models** rely on historical data and trends in agricultural technology for large-scale yield predictions. However, they have limited applicability outside their developed regions due to changing weather patterns and agricultural technologies.
2. **Mechanistic Models** simulate plant and soil processes by modelling fundamental biological mechanisms like photosynthesis and soil water evaporation. These models require detailed input data and are commonly used for academic research rather than practical problem-solving. While they can predict potential crop production under uniform conditions, they are complex and not widely used outside research settings.
3. **Functional Models** use simplified approaches to simulate complex processes, often utilizing empirical relationships and daily input data like solar radiation and temperature. These models are easier to use than mechanistic models and provide sufficient detail for assessing potential crop production. Functional models, such as those in the Decision Support System for Agrotechnology Transfer (DSSAT), are widely used for climate change assessments and other applications.

5.4.1 Input Data for Crop Model:

Precise estimation of crop yields requires high quality input data. The Minimum Data Set (MDS) was introduced to simplify data gathering and model implementation by International Bench Mark Sites Network for Agrotechnology Transfer (IBSNAT) **(IBSNAT, 1984)**. This set consists of two key data categories:

- **Core Model Inputs:** Basic data components necessary for the functioning of crop models, such as weather patterns, soil attributes, and crop management techniques.
- **Model Calibration and Validation Data:** Additional data used to fine-tune model parameters and evaluate predictive precision, including recorded crop yields, phenological stages, and biomass measurements.

A. Weather Data:

The variability of weather poses a significant risk to agricultural production, emphasizing the importance of considering weather fluctuations in agricultural system analysis. Necessary weather data for crop modelling includes rainfall, solar radiation, air temperature, and more. Rainfall distribution and amount are crucial in most agricultural regions, while solar radiation and temperature are essential for processes like photosynthesis and evapotranspiration. Temperature plays a key role in modelling crop development and growth rates, while rainfall intensity is vital for erosion and runoff simulations.

It is recommended to gather weather data from a nearby location to ensure accuracy. While temperature and radiation data can be generalized for larger areas with similar elevations, rainfall measurements should be specific to the model site. Ensuring the quality of weather data is crucial to prevent biases from instrument calibration errors.

Although many weather stations provide rainfall and temperature data, solar radiation data may be lacking. In such cases, sunshine hours or percentage sunshine can be used to estimate solar radiation through empirical equations. Furthermore, long-term weather sequences can be generated using weather generators like those found in the DSSAT package.

B. Soil Data:

When validating a model at a specific location, on-site soil property measurements are crucial. Field measurements are generally more dependable than laboratory analyses, especially when soil water availability significantly impacts crop production.

In such scenarios, determining the lower limit of available soil water and rooting depth in the field, where plants are grown until they are close to wilting or becoming dormant due to water scarcity, is vital.

For soils without internal drainage constraints, the drained upper limit of available moisture can be determined by assessing the soil water content of thoroughly saturated soils left to naturally drain.

Minimum Data:

- Lower limit water content at 10-20 cm depths
- Field capacity soil water content at 10-20 cm depths
- Crop rooting depth
- Hydraulic conductivity at soil depths restricting water flow

Desirable Data for Specific Applications:

- Hydraulic conductivity and water retention curves at 10-20 cm depths
- Run-off curve number
- Surface albedo
- pH at 10-20 cm depths

Initial Conditions:

- Water content at 10-20 cm depths
- Nitrate concentration at 10-20 cm depths
- Ammonium concentration at 10-20 cm depths
- Extractable phosphorous at 10-20 cm depths (if phosphorus sub-routine is run)
- Organic carbon in upper depths
- Fresh plant residues or manure amounts and depth of incorporation
- Textural characterization for 10-20 cm depths
- Surface water ponding capacity
- Bulk density at 10-20 cm depths
- Groundwater depth by-pass flow fraction

Acquiring all the necessary soil input data can pose challenges. Nonetheless, soil attributes like texture, bulk density, and organic matter content can help estimate soil hydraulic properties for water movement. Accessing comprehensive soil data is crucial for accurate modelling.

C. Crop Management Input Data:

Crop management input data are essential for running the model. Important factors to consider include planting date, planting depth, row spacing, plant population, irrigation details, and nutrient dynamics. When it comes to nutrient availability, most climate change yield assessments assume it to be sufficient.

Minimum Data:

- Crop cultivar characteristics
- Planting information
- Irrigation inputs
- Fertilizer inputs
- Crop residues or manure inputs

Optional Data:

- Row spacing
- Row direction
- Pesticide inputs
- Harvest date

In order to use models like CERES and DSSAT, it is crucial to have information about the crop variety, genotype, or cultivar. Variations in cultivars impact the duration of development phases and the distribution of assimilates to different plant parts. Understanding cultivar sensitivity to photoperiod and vernalization is important, especially for photoperiod-sensitive cultivars. Genetic coefficients play a key role in simulating crop duration across different latitudes and planting times in DSSAT models. Additionally, genetic coefficients account for variations in cultivar yield components such as potential kernel number, grain growth rate, and grain filling duration (Ritchie and Alagarswamy, 2002).

5.5 Model Development:

5.5.1 Model Structure:

The process of constructing a model begins with the accumulation of scientific knowledge about growth patterns, controlling factors, and interactions within a cropping system. The first step involves identifying the primary equation for the desired output, such as crop yield. Subsequently, factors influencing daily growth are determined, and biomass is categorized into economic yield and residue. These factors are represented as mathematical functions with conditional rules, iterated over a selected time step:

- [Yield yesterday] = [seed planted]

- /START/

- Read today’s solar radiation

- Calculate the proportion of intercepted radiation based on canopy status

- Determine plant growth using the formula:

  [{Plant growth} = {Solar radiation} X % {radiation intercepted} X {Radiation use efficiency}]

- Update yield:

  [{Yield today} = {yield yesterday} + {growth today}]

- Return to /START/ until an /END/ condition is met.

For example, in a maize simulation model (Muchow et al., 1990), major crop reactions and interactions are outlined. Phenological development, such as vegetative growth and canopy expansion, is controlled by thermal time. Photosynthesis is modelled as a function of light interception and radiation use efficiency, with biomass allocation occurring post-silking until crop maturity.

Models are typically programmed in languages like FORTRAN due to complex equations and looping. The initial model is complete once all programming and numerical errors are resolved. These models generally simulate crop growth under ideal conditions to determine potential yields. Since real-world conditions often involve limitations, additional relationships must be incorporated to account for factors like water or nutrient stress.

Modelling crops like sugarcane requires more complex equations due to factors such as carry-over effects between ratoons, economic focus on vegetative rather than reproductive parts, and simultaneous vegetative growth and ripening, which necessitate frequent biomass partitioning adjustments. The development of crop models requires collaboration among specialists from different disciplines, as the complexity of factors such as carry-over effects, economic focus, and simultaneous growth and ripening necessitates frequent adjustments in biomass partitioning.

5.5.2 Model Calibration:

Model calibration involves modifying model parameters to match simulated results with observed data. It deals with differences between model forecasts and actual data, which can be caused by sampling errors, incomplete system comprehension, or using the model in a different context from its original development.

5.5.3 Model Validation:

Model validation confirms that the adjusted model accurately reflects the real-world system. This process entails comparing simulated and observed data that were not utilized during the adjustment phase. Ideally, verification should cover both the overall system performance and individual components. However, due to data limitations and model complexity, it is often necessary to focus on key variables.

Best practices highlight the importance of meticulous data collection, clear model documentation, and continuous improvement of both model structure and parameters. Striking a balance between the need for model precision and practical limitations is crucial for the successful application of the model.

5.6 Advanced Approaches in Crop Modelling:

5.6.1 Integration of Remote Sensing in Crop Modelling:

Accurately predicting crop yields is essential for making informed decisions in agriculture, especially with the rising demand for agricultural products and the necessity for increased profits. Agriculture has undergone significant changes in recent years, incorporating innovations like pesticides, advanced machinery, irrigation technologies, and high-yielding crop varieties to meet global production requirements.

Researchers have created crop models to simulate the connection between crop growth and environmental elements. These models have progressed from basic qualitative simulations to comprehensive quantitative models of entire growth cycles over the last four decades.

Noteworthy models such as WOFOST, DSSAT, APSIM, STICS, MONICA, DAISY, and AquaCrop have been enhanced to better replicate crop growth and yield, improving our comprehension of crop responses to field management and environmental alterations.

Nevertheless, estimating crop yields across vast regions necessitates considering spatial variations in soil characteristics, canopy variables (e.g., LAI, biomass, nitrogen content), and meteorological data, which are frequently uncertain. This uncertainty impacts physiological growth simulations and results in inaccuracies in yield forecasts.

The rapid progress of remote sensing technology provides more precise data for estimating soil properties and canopy variables on a regional scale. Remote sensing has been utilized to estimate variables like LAI, FAPAR, canopy cover, biomass, nitrogen content, and evapotranspiration. These variables, crucial for crop growth stages, are combined with crop models to enhance predictions.

Advancements in remote sensing encompass the deployment of high-resolution satellites (e.g., Sentinel-2, Landsat 8) and the utilization of synthetic aperture radar (SAR) to monitor crop growth under diverse weather conditions. SAR technology can penetrate canopies and supply valuable data on LAI, biomass, and other essential variables.

Remote Sensing Data Assimilation Methods:

The data assimilation algorithms commonly used are the Kalman Filter (KF), Ensemble Kalman Filter (EnKF), Three-Dimensional Variational Data Assimilation (3DVAR), Four-Dimensional Variational Data Assimilation (4DVAR), Particle Filter (PF), and Hierarchical Bayesian Method (HBM).

1. **Kalman Filter (KF):** Primarily suitable for linear systems, KF faces challenges with high-dimensional data, limiting its effectiveness in complex crop models.
2. **Ensemble Kalman Filter (EnKF):** Developed by Evensen (1994) to overcome KF's limitations, EnKF is beneficial for integrating crop models with remote sensing data, offering improved handling of uncertainties.
3. **3DVAR and 4DVAR:** Variational methods, especially 4DVAR, enhance 3DVAR by accounting for temporal changes, leading to better outcomes in dynamic settings. While well-established in weather forecasting, they can be computationally intensive.
4. **Particle Filter (PF):** Unlike KF-based approaches, PF does not assume Gaussian errors, enabling better management of nonlinearities and utilization of parallel computing.
5. **Hierarchical Bayesian Method (HBM):** Introduced by Berliner (1996), HBM utilizes conditional probabilities to break down complex issues into simpler layers, making it well-suited for data assimilation tasks. Although still in development, it shows promise for future advancements.

These data assimilation techniques combine remote sensing data with crop models to enhance the precision of crop yield predictions at regional levels. This integration involves optimizing crop model parameters using observed data from remote sensing, resulting in improved simulations of crop growth.

The main objective of data assimilation is to integrate remote sensing information into crop models to optimize parameters and improve the accuracy of yield estimates. This process entails defining observed variables (from remote sensing), state variables (from crop models), and model.

Three primary assimilation techniques are utilized:

1. **Calibration Approach:** Modifies crop model parameters to match remote sensing data with simulated state variables, utilizing algorithms like simplex search and particle swarm optimization. While this technique enhances prediction accuracy, it necessitates numerous optimization iterations.
2. **Forcing Approach:** Directly substitutes simulated crop model data with remote sensing observations at each time interval, such as daily or weekly. Although easy to implement, it introduces observational errors into the models by bypassing crop model dynamics.
3. **Updating Approach:** Constantly updates crop model simulations with remote sensing data, enhancing future predictions. This approach reduces computation time compared to calibration but necessitates careful management of measurement uncertainties.

Each approach presents advantages and obstacles. The calibration method yields the most promising theoretical outcomes but demands substantial computational resources. The forcing method is uncomplicated but may transmit errors from remote sensing data. The updating method strikes a balance between computation time and accuracy, although it requires precise timing of remote sensing data acquisition. In general, these approaches aim to enhance crop yield predictions by efficiently integrating remote sensing with crop models (Jin et al., 2018).

5.6.2 Big Data and Crop Modelling:

The digitization of the world is progressing rapidly, and agriculture is not exempt from this trend. The combination of geospatial data archives, real-time data from satellites and UAVs, weather data, digitized soil information, and data from smart sensors allows for a deeper understanding of how crops interact with their surroundings.

This data-centric approach offers insights that were previously out of reach, leading to more efficient and cost-effective agricultural practices. However, the value of this abundance of data, often referred to as “Big Data,” lies in our ability to translate it into practical insights that farmers can utilize to enhance their operations.

Big data storage facilities enhance input efficiency and boost crop production, supporting farmers in attaining superior agricultural results in combination with crop models. Examining past patterns for individual crops in specific areas can enhance forecasts of harvest potentials. Data-driven analysis of large datasets aids agricultural professionals in forecasting and capitalizing on crop yields, offering farmers essential insights into their crops and potential market prospects (Cheema and Khan, 2019).

5.6.3 Crop Modelling using Artificial Intelligence:

Crop growth simulations through process-based models are reliable but often limited by complex spatial inputs and parameters. Remote sensing can help observe spatial variations in crop growth, and combining it with crop models can improve both methods, addressing spatio-temporal data gaps.

The integration of remote sensing data with crop models, such as the RS-integrated crop model (RSCM), can simulate crops like barley and wheat by utilizing leaf area index (LAI) or vegetation indices (VIs).

However, challenges exist due to dimensional differences between LAI and VIs, varying relationships with remote sensing platforms, and crop-specific growth patterns. Advanced machine learning and deep neural network techniques can enhance crop modelling by capturing nonlinear relationships between inputs and yields, although direct integration into mathematical crop models is an area that requires further exploration. This study aims to develop a hybrid approach that combines ML and DNN techniques with process-based crop models to estimate the LAI of rice (Oryza sativa) and analyse its relationship with weather factors (Jeong et al., 2022).

5.7 Challenges:

While crop modelling offers significant potential for improving agricultural practices, several challenges hinder its widespread adoption and implementation:

5.7.1 Data Availability and Quality:

i. **Insufficient and Inconsistent data:** Many regions lack comprehensive and consistent data on soil properties, weather patterns, crop management practices, and yields, limiting the accuracy and reliability of crop models.
ii. **Data Sharing and Access:** Restrictions on data sharing and access hinder model development and validation.
iii. **Data Integration:** Combining data from various sources (e.g., remote sensing, ground observations, weather stations) often requires significant effort and expertise.

5.7.2 Model Complexity and Computational Requirements:

i. **Model Complexity:** Sophisticated crop models often require substantial computational resources, limiting their accessibility to researchers and farmers.
ii. **Parameterization Challenges:** Determining appropriate model parameters can be complex and time-consuming, requiring expert knowledge and data.
iii. **Model Uncertainty:** Crop models inherently contain uncertainties due to simplifications and limitations in representing complex biological processes.

5.7.3 Adoption and Transferability:

i. **Knowledge Gap:** Many farmers and extension workers lack the necessary knowledge and skills to effectively use crop models.
ii. **Trust and Acceptance:** Building trust in model outputs and convincing stakeholders of their value can be challenging.
iii. **Model Transferability:** Crop models developed for specific regions or conditions may not be directly applicable to other areas without significant adaptation.

5.7.4 Economic and Institutional Factors:

i. **Investment Costs:** Developing and implementing crop modelling systems requires substantial financial resources, often beyond the reach of small-scale farmers.
ii. **Lack of Support:** Inadequate government support and policies hinder the adoption of crop modelling technologies.
iii. **Institutional Barriers:** Complex institutional frameworks and fragmented responsibilities can impede the effective use of crop models.

Addressing these challenges requires concerted efforts from researchers, policymakers, and stakeholders to develop user-friendly tools, invest in data infrastructure, and promote capacity building. By overcoming these obstacles, crop modelling can become a valuable asset for sustainable agriculture and food security.

5.8 Conclusion:

The field of crop modelling has undergone remarkable transformation, transitioning from basic statistical approaches to intricate, process-oriented simulations. This progression, alongside advancements in computing technology, remote sensing, and artificial intelligence, presents significant opportunities for enhancing agricultural practices and safeguarding food security. By synthesizing various data sources and utilizing advanced modelling methodologies, both researchers and policymakers can acquire critical insights into the complexities of agricultural systems.

Nonetheless, challenges concerning data accessibility, model intricacy, and widespread adoption remain. To surmount these hurdles, it is essential to make concerted investments in data infrastructure, create user-friendly tools, and promote collaboration among researchers, policymakers, and farmers.

The future of agriculture is contingent upon our capacity to leverage the capabilities of crop modelling. By tackling these challenges and seizing emerging opportunities, we can develop agricultural systems that are more resilient, sustainable, and productive.

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