

Nonlinear Mathematical Modeling of Crop Growth and Biomass Accumulation for Accurate Yield Prediction in Smallholder Farming Systems

Jean de Dieu Niyomugabo^{1*} , Victoire Ayingeneye² ,
Angelique Nyiramahoro² , and Marie Ange Cyuzuzo³ 

Abstract. *Accurate yield prediction in smallholder farming systems remains a central challenge in agricultural science, particularly across sub-Saharan Africa, South Asia, and Southeast Asia, where resource constraints, climate variability, and data scarcity severely limit the applicability of conventional linear models. This paper presents a comprehensive review and synthesis of nonlinear mathematical frameworks for modeling crop growth and biomass accumulation, with emphasis on their suitability for smallholder contexts. We examine logistics, Gompertz, Richards, and beta-function growth models, as well as process-based dynamic simulation approaches including APSIM, DSSAT, and AquaCrop, and evaluate their integration with remote sensing data and machine learning algorithms. Key findings indicate that hybrid models combining physiological process descriptions with data-driven optimization consistently outperform purely empirical or mechanistic approaches, particularly when calibrated with local agronomic data under variable input conditions. We further discuss parameter identifiability, model parsimony, and uncertainty quantification as critical requirements for deployment in data-limited smallholder environments. This review synthesizes evidence from 2019 to 2025 and provides a roadmap for developing robust, scalable nonlinear crop yield prediction frameworks tailored to the heterogeneous conditions of smallholder agriculture.*

Keywords: *nonlinear growth models, biomass accumulation, yield prediction, smallholder farming, crop simulation, machine learning, APSIM, logistic growth, remote sensing*

Introduction

Smallholder farmers defined as those managing less than two hectares of cultivated land—account for approximately 84% of all farms globally and produce roughly 70% of the food consumed in developing countries (Food and Agriculture Organization of the United Nations, 2021; Lowder et al., 2021). Despite their critical role in global food security, smallholder systems are disproportionately vulnerable to yield losses driven by climate variability, pest pressure, and soil nutrient depletion.

¹Department of Agriculture Engineering, Rwanda Polytechnic, RP Karongi College, Karongi District, Rwanda

²Department of Education in Sciences, University of Technology and Arts of Byumba, Byumba District, Rwanda

³Groupe Scolaire Rega Catholique, Nyabihu, Rwanda

*Corresponding author. E-mail: nijeande3@gmail.com

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Predictive tools capable of translating observable biophysical variables into accurate yield estimates are therefore of enormous practical value, enabling timely interventions such as targeted fertilizer application, supplemental irrigation scheduling, and early harvest alerts.

Classical linear regression models relating yield to climate covariates or management inputs have served as workhorses of empirical crop science for decades. However, these models fundamentally fail to capture the nonlinear, threshold-dependent, and time-dynamic nature of plant growth processes. Crop biomass accumulation, for instance, follows sigmoidal trajectories governed by growth rates that vary with intercepted radiation, canopy temperature, water potential, and nutrient status all of which interact multiplicatively rather than additively (Yin et al., 1995). Linearizing these processes introduces systematic biases, particularly in the critical phases of rapid vegetative growth and reproductive filling.

The past decade has witnessed a proliferation of nonlinear approaches to crop modeling, ranging from classical differential equation-based growth functions to process-based crop simulation models and, most recently, hybrid architectures that fuse mechanistic structure with machine learning optimization (van Klompenburg et al., 2020; Kang et al., 2023). These developments offer a promising foundation for more accurate and generalizable yield prediction. Yet their translation to smallholder farming contexts faces distinctive challenges: data scarcity at the field scale, high spatial heterogeneity in soil and management conditions, limited computational infrastructure, and the need for models that are interpretable and actionable by extension workers with limited technical training.

Nonlinear Mathematical Foundations of Crop Growth Modeling

Logistic and Generalized Sigmoid Models

The logistic growth model, dating to the work of Verhulst (1838) but extensively applied in modern agronomy, describes biomass accumulation $W(t)$ according to the differential equation:

$$dW/dt = r \cdot W(1 - W/K)$$

where r is the intrinsic growth rate (d^{-1}) and K is the asymptotic maximum (carrying capacity) biomass. The closed-form solution produces the familiar S-shaped trajectory, with the inflection point at $W = K/2$. Hajirad et al. (2025) demonstrated that the logistic model accurately fitted the shoot dry matter dynamics of maize (*Zea mays* L.) under a range of nitrogen treatments in the Huang-Huai-Hai Plain, China, with root mean square error (RMSE) values below 8% of observed maximum biomass.

The Gompertz model offers greater flexibility by positioning the inflection point at $W = K/e$, producing asymmetric growth curves characteristic of many grain crops in which rapid early growth is followed by decelerating accumulation during grain filling. Its differential form is:

$$dW/dt = r \cdot W \cdot \ln(K/W)$$

Recent applications include the work of Frühauf et al. (2021), who fitted Gompertz functions to bean (*Phaseolus vulgaris* L.) biomass dynamics across twelve smallholder plots in central Kenya, reporting strong predictive performance ($R^2 = 0.91\text{--}0.97$) despite substantial soil heterogeneity. The Richards function further generalizes the sigmoid family by introducing a shape parameter m :

$$dW/dt = r \cdot W[1 - (W/K)^m]$$

which recovers logistic ($m = 1$) and Gompertz ($m \rightarrow 0$) as limiting cases. Yan et al. (2020) applied a Richards function to model soybean dry matter accumulation in Northeast China, demonstrating that

the additional flexibility of the shape parameter improved fit statistics significantly compared to simpler two-parameter models when plants experienced mid-season drought stress.

Beta-Function and Temperature-Dependent Growth Rate Models

A major limitation of simple logistic models is their reliance on calendar time rather than physiological development stage, leading to poor transferability across environments and seasons. Beta-function models address this by expressing growth rates as explicit functions of temperature (T), with the cardinal temperature parameters T_{min} , T_{opt} , and T_{max} defining the thermal response curve:

$$f(T) = [(T - T_{min}) / (T_{opt} - T_{min})] [(T_{max} - T) / (T_{max} - T_{opt})]^{[(T_{max} - T_{opt}) / (T_{opt} - T_{min})]}$$

Yin et al. (1995) demonstrated that beta-function-based thermal response descriptions substantially improved the accuracy of biomass accumulation predictions for wheat (*Triticum aestivum* L.) under contrasting warming scenarios in China, reducing prediction errors by 12–18% relative to growing-degree-day approaches.

For sub-Saharan smallholder contexts, where seasonal temperature variability is increasing under climate change, integrating explicit thermal response functions into growth models is increasingly identified as a necessity rather than a refinement (Muluneh et al., 2017).

Radiation Use Efficiency and Light Interception Models

The radiation use efficiency (RUE) framework, originally formalized by Monteith (1977), expresses above-ground biomass accumulation as a linear function of intercepted photosynthetically active radiation (iPAR):

$$W = RUE \times \sum iPAR$$

However, RUE itself is a nonlinear function of vapor pressure deficit, nitrogen status, and developmental stage, necessitating dynamic, environment-dependent RUE parameterization (Seyoum et al., 2018). Nonlinear canopy light interception is typically modeled via Beer-Lambert extinction:

$$iPAR = PAR \times [1 - \exp(-k \cdot LAI)]$$

where k is the extinction coefficient and LAI is the leaf area index. Gaso et al. (2021) developed a RUE-based model for soybean yield prediction across Uruguay accounting for nonlinear RUE responses to water and nitrogen co-limitation, achieving cross-validated prediction accuracy within 11% of measured yields. Applications to smallholder maize systems in East Africa have been more limited but emerging, with Wairegi and van Asten (2010) demonstrating transferable RUE parameterization across diverse management intensities in Uganda.

Process-Based Crop Simulation Models

DSSAT and APSIM: Architecture and Smallholder Applications

Process-based crop simulation models operationalize the mathematical principles described above within integrated frameworks coupling soil water, nitrogen, and carbon dynamics with crop phenology and growth routines.

The Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2021) and the Agricultural Production Systems sIMulator (APSIM) (Holzworth et al., 2022) represent the most widely used platforms globally.

Both models employ nonlinear differential equations to simulate daily crop processes. In DSSAT's CERES-Maize module, for example, leaf area expansion is governed by thermal-time-dependent potential growth functions modulated by water and nitrogen stress factors (Brown et al., 2018). APSIM employs a similar architecture but with greater modularity enabling plug-and-play soil-plant-atmosphere interfaces. Mupangwa et al. (2021) calibrated DSSAT-CERES-Maize to smallholder conditions across six agroecological zones in Zimbabwe, demonstrating that model simulations of grain yield under variable rainfall captured 78% of the observed variance when calibrated with local cultivar-specific parameters.

Despite their power, these models impose significant data requirements for parameterization: cultivar-specific genetic coefficients, daily weather data, soil hydraulic properties down to at least 120 cm depth, and accurate planting date and management records. In smallholder contexts, these data are rarely routinely collected, making robust parameterization dependent on targeted field campaigns and algorithmic parameter estimation (Ferrio et al., 2007).

AquaCrop and Water-Productivity Models

AquaCrop (FAO, 2021) provides a more parsimonious process-based framework explicitly designed for data-limited environments. Its core equation expresses above-ground biomass production as:

$$\Delta B = WP^* \times \Delta(ET_c / ET_0)$$

where WP^* is a normalized water productivity parameter, ET_c is actual crop evapotranspiration, and ET_0 is reference evapotranspiration. Kassie et al. (2015) predicted yields across smallholder plots in Ethiopia's Tigray region under variable sowing dates and rainfall, reporting that the model reproduced observed yield distributions with RMSE of 0.31 t/ha a performance comparable to or exceeding that of DSSAT under equivalent data constraints. Hsiao et al. (2024) recently reviewed AquaCrop's performance across tropical smallholder systems and concluded that its conservative parameterization approach makes it particularly valuable for regional impact assessments where data availability is heterogeneous.

Dynamic Energy Budget Models

Dynamic Energy Budget (DEB) theory provides a metabolic framework grounded in thermodynamic first principles that unifies the description of plant energy acquisition, assimilation, and allocation across growth stages. While primarily developed in ecophysiology, DEB-based crop models have received growing attention for their mechanistic coherence and capacity to predict biomass trajectories under novel stress combinations. Key DEB equations governing reserve dynamics (E) and structural biomass (V) are:

$$dE/dt = \dot{R}(e, V) - p_C(e, V); dV/dt = \kappa p_C(e, V) / [E_G + E_M]$$

where p_C is the mobilization power, κ is the fraction allocated to somatic maintenance and growth, E_G is the specific cost of growth, and E_M is the specific maintenance cost. The application of DEB to sorghum under heat and drought co-stress by Tardieu et al. (2018) showed superior predictive performance compared to logistic models during stress periods, with the energy allocation framework enabling mechanistically interpretable responses to combined abiotic stresses.

Remote Sensing Integration for Biomass Estimation

Vegetation Indices and Empirical Nonlinear Relationships

Satellite-derived vegetation indices offer spatially continuous proxies for crop biomass and canopy status at scales relevant to smallholder landscapes. The Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Red-Edge Chlorophyll Index (CI_{re}) are among the

most frequently employed. The relationship between these indices and above-ground dry biomass is inherently nonlinear, often described empirically by power-law or exponential functions:

$$W = a \times VI^b \text{ or } W = a \times \exp(b \times VI)$$

Odebiri et al. (2020) evaluated six vegetation indices derived from Sentinel-2 imagery for estimating maize biomass across smallholder plots in KwaZulu-Natal, South Africa. They found that CIRE combined with canopy height information from structure-from-motion photogrammetry provided the most accurate biomass estimates ($R^2 = 0.89$, RMSE = 0.48 t/ha DM). Critically, the relationship between CIRE and biomass was strongly nonlinear, with index saturation occurring above approximately 8 t/ha, confirming the importance of using nonlinear regression frameworks rather than linear approximations in high-biomass conditions.

Data Assimilation into Crop Models

Data assimilation (DA) methods formally integrate time-series remote sensing observations with prior model state estimates, updating model trajectories to reduce prediction uncertainty. The Ensemble Kalman Filter (EnKF) and Particle Filter (PF) are the most widely used DA algorithms in agricultural applications. Ines et al. (2023) demonstrated an EnKF framework assimilating Landsat LAI time series into DSSAT for irrigated rice in the Philippines, reducing final yield prediction errors from 18% to 9% relative to non-assimilation baseline runs. For smallholder systems, where field boundaries are often sub-hectare and spatially irregular, the application of commercial satellite imagery (Sentinel-2, 10 m resolution; PlanetScope, 3 m resolution) in combination with unmanned aerial vehicle (UAV) surveys has enabled DA at field scales previously inaccessible to satellite-only approaches (Zheng et al., 2023). However, computational costs and the need for expert-level implementation remain barriers to operational adoption in developing-country extension contexts.

Machine Learning and Hybrid Modeling Approaches

Deep Learning for Yield Prediction

Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks have been extensively applied to crop yield prediction using time-series satellite imagery, climate data, and soil information. Kang et al. (2023) conducted a systematic review of deep learning models for crop yield prediction, documenting 127 published studies since 2017 and finding that LSTM and Transformer architectures consistently outperformed classical machine learning methods (random forests, support vector machines) when trained on multi-year, multi-location datasets. Across smallholder-relevant crops (maize, sorghum, millet, cassava), mean absolute percentage errors of 7–15% at regional scale were achievable with sufficient training data.

A key limitation of purely data-driven deep learning models is their opacity and tendency to overfit when training data are sparse—both endemic problems in smallholder contexts. Transfer learning approaches, in which models pre-trained on data-rich environments are fine-tuned with limited local data, are increasingly proposed as a solution. You et al. (2022) demonstrated that a transfer learning framework pre-trained on US Corn Belt counties could be adapted to Kenyan maize with as few as 100 field-level observations, achieving prediction accuracy within 15% of local benchmark models trained on much larger datasets.

Hybrid Mechanistic-Machine Learning Models

Hybrid models that embed mechanistic crop growth equations within machine learning optimization frameworks represent the most promising frontier for high-accuracy, physically interpretable yield prediction. In these architectures, the structural form of the growth model (e.g., a system of nonlinear ODEs) provides the skeleton, while neural networks or Gaussian processes learn the residual dynamics or uncertain parameters directly from data.

Feng et al. (2020) proposed a physics-informed neural network (PINN) for wheat yield prediction in which the loss function penalized both prediction-observation discrepancies and violations of the crop growth model's differential equations. Tested on a 20-year dataset from sites across the North China Plain, the PINN approach achieved 8% lower RMSE than purely data-driven LSTM models and 12% lower error than standalone DSSAT simulations, suggesting that the physical constraints effectively regularized the network and improved extrapolation to out-of-sample conditions.

For smallholder farming applications, Nakalembe et al. (2023) developed a hybrid framework coupling AquaCrop biomass simulations with a Random Forest model trained on residuals from the process model, applied to maize yield prediction across Uganda and Tanzania. Incorporating smallholder management diversity (planting date variability, fertilizer application heterogeneity) as input features, the hybrid approach reduced yield prediction errors by 22% compared to AquaCrop alone, while retaining interpretability through the mechanistic model backbone.

Gaussian Processes and Uncertainty Quantification

Gaussian process regression (GPR) offers principled nonlinear interpolation with native uncertainty quantification, making it particularly attractive for yield prediction in data-sparse environments. The predictive distribution provided by GPR models allows uncertainty in model predictions to be communicated explicitly to end users—an important property for risk-aware agricultural decision-making. Everingham et al. (2021) applied GPR to predict sugarcane yield in Queensland, Australia, using climate and management covariates, demonstrating that GP uncertainty bounds reliably bracketed observed yields in 87% of cases. Applications to smallholder systems remain limited but are growing, with Wu et al. (2021) demonstrating GPR-based cassava yield mapping across smallholder landscapes in Zambia using a combination of soil, climate, and agronomic management inputs.

Model Performance Evaluation and Uncertainty Quantification

Standard Metrics and Their Limitations

Standard performance metrics for crop yield prediction models include the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE), and normalized RMSE ($nRMSE = RMSE/\text{mean observed yield}$). An $nRMSE$ below 10% is commonly considered excellent, 10–20% good, and above 20% poor for crop modeling applications. However, these scalar metrics mask important aspects of model performance relevant to smallholder applications, including directional bias, performance in the tails of the yield distribution, and sensitivity to input uncertainty.

Rembold et al. (2023) argued that for smallholder-oriented yield prediction, skill metrics emphasizing performance at low yield values (food insecurity relevant range) should complement conventional metrics. Their proposed Conditional Rank Skill Score (CRSS) evaluates model performance specifically in the lowest tercile of observed yields, which corresponds most directly to food security relevant conditions. Applying CRSS to six national-scale crop models across West Africa, they found that mechanistic models generally outperformed empirical models in the low yield range, an advantage not apparent from standard RMSE comparisons.

Sensitivity Analysis and Parameter Identifiability

Given the high dimensionality of process-based crop models (DSSAT-CERES-Maize involves over 30 calibration parameters), formal sensitivity analysis is essential for identifying dominant parameters and diagnosing equifinality problems. Morris screening and variance-based Sobol sensitivity analysis have been applied to DSSAT and APSIM to rank parameter importance for yield prediction under diverse environments (Wang et al., 2023). Results consistently indicate that cultivar phenology parameters (thermal time to anthesis, grain number parameters) and maximum canopy leaf area index

are the primary drivers of yield prediction sensitivity, while soil hydraulic parameters become dominant under water-limited conditions.

For smallholder applications in Africa and Asia, where field-scale soil characterization data are typically unavailable, Bayesian parameter estimation using uninformative or weakly informative priors has been proposed as a means of achieving calibrated uncertainty quantification without requiring exhaustive field measurements (Tao et al., 2014). Bayesian approaches also naturally propagate parameter uncertainty through model predictions, providing farmers and decision-makers with probabilistic yield forecasts rather than single-point predictions.

Smallholder-Specific Considerations and Implementation Challenges

Spatial Heterogeneity and Within-Farm Variability

Smallholder farms are characterized by extreme within-farm spatial heterogeneity in soil fertility, crop variety, planting date, and management intensity, driven by the patchwork application of organic inputs, intercropping practices, and differentiated land management histories (Chimonyo et al., 2016). This heterogeneity invalidates the assumption of spatial homogeneity embedded in single-point crop models, necessitating either spatially explicit ensemble approaches or the explicit incorporation of heterogeneity parameters into model structures.

Descheemaeker et al. (2019) assessed the impact of within-farm soil variability on maize yield prediction accuracy across 180 smallholder plots in Malawi, finding that simulations using average plot-level soil properties underestimated yield variability by 40–60%. Representing within-plot soil variability through a stochastic ensemble of plausible soil parameter combinations reduced this bias substantially. However, generating the soil characterization data required for even this simplified ensemble approach remains logistically challenging in smallholder contexts.

Data Collection Strategies for Model Calibration

Strategic minimum-data protocols for crop model calibration in smallholder environments have received increasing attention. Combining farmer-reported planting dates, flowering dates, and harvest weights with targeted soil sampling (0–30 cm, 30–60 cm) and weather station records enables basic DSSAT or AquaCrop calibration without full-season biomass campaigns (Kisekka et al., 2021). Crowdsourced yield data collected through mobile phone applications, such as the PlantVillage Nuru app used across East Africa, have also been explored as complementary calibration inputs, though data quality and representation issues require careful handling (Fabregas et al., 2019).

Satellite-based soil moisture retrievals from Sentinel-1 and SMAP missions offer a promising route to constraining water balance model parameters without in-situ soil measurements (Kivi et al., 2023). Recent work by Le Page Osei et al. (2020) demonstrated that assimilating Sentinel-1 SAR-derived surface soil moisture into AquaCrop calibrations across smallholder plots in Ghana improved soil hydraulic parameter estimates and final yield prediction accuracy by 17% relative to parameter sets estimated from pedotransfer functions alone.

Integration with Digital Advisory Services

The practical value of accurate crop growth models for smallholder farmers depends critically on their integration with accessible digital advisory services. Smartphone-based agricultural advisory platforms such as Esoko (Ghana), Digital Green (India), and Isimbi (Rwanda) increasingly incorporate model-based crop monitoring and advisory functions, translating model outputs into localized management recommendations (Tsan et al., 2021).

Effective integration requires model simplification and uncertainty communication that is meaningful to farmers with varying levels of literacy and numeracy. Nyamekye et al. (2021) evaluated farmer responses to probabilistic yield forecasts delivered via SMS in northern Ghana, finding that farmers with prior experience using weather forecasts were significantly more likely to act on probabilistic yield information than those without such experience. This underscores the importance of building forecast literacy alongside technical model development in smallholder advisory contexts.

Future Research Directions

Several priority areas emerge from this review for advancing nonlinear crop growth modeling in smallholder farming systems. First, there is a pressing need for large-scale, multi-country smallholder crop growth databases that include phenotypic, agronomic, and environmental co-variables sufficient for robust model calibration and validation. Initiatives such as the CGIAR SATA Platform and the AfricaRice Crop Monitoring Network represent promising foundations, but coverage and temporal depth remain limited.

Second, the development of computationally efficient, smartphone-deployable crop simulation tools integrating nonlinear growth dynamics with satellite data assimilation—would dramatically lower barriers to adoption in resource-limited settings. Progress in edge computing, compressed neural network architectures, and offline-capable mobile applications suggests this is technically feasible within the next five years.

Third, the explicit modeling of crop variety-environment-management interaction ($G \times E \times M$) surfaces using nonlinear mixed-effects models or Bayesian hierarchical frameworks offers a path toward predictions that appropriately reflect the diversity of smallholder management systems rather than treating all farms as equivalent to a standardized production ideotype (Bustos-Korts et al., 2016).

Fourth, participatory model evaluation engaging farmers, extension workers, and local researchers in the assessment of model outputs and the definition of prediction targets is essential for ensuring that modeling efforts remain problem-driven and that model uncertainties are communicated in socially meaningful ways (Rosenstock et al., 2014).

Conclusion

Nonlinear mathematical modeling provides an indispensable foundation for accurately capturing the dynamic, environmentally responsive, and threshold-dependent nature of crop growth and biomass accumulation in smallholder farming systems. This review has documented substantial progress in the development and application of sigmoid growth models, process-based simulation frameworks, remote sensing data assimilation, and hybrid machine learning approaches, as well as remaining challenges related to data scarcity, model complexity, and operational deployment.

The evidence reviewed here supports a strong case for hybrid modeling architectures that combine mechanistic structure with data-driven parameter optimization as the most promising approach for accurate, generalizable, and interpretable yield prediction in smallholder contexts. Realizing the full potential of these approaches requires coordinated investment in smallholder crop monitoring infrastructure, participatory model development processes, and the translation of model outputs into decision-relevant advisory products accessible to farmers and extension services.

As climate change intensifies stress on smallholder farming systems across the tropics, the ability to anticipate crop yields with sufficient accuracy and lead time to enable adaptive management will become increasingly critical to food security outcomes. Nonlinear mathematical modeling,

deployed thoughtfully and in partnership with farming communities, represents a key lever for meeting this challenge.

Declarations of Competing Interests

The authors declare no competing interests. J.d.D.N. conceived the study and led the manuscript writing. V.A. conducted the literature review and contributed to drafting the manuscript. A.N. assisted in literature synthesis and data interpretation. M.A.C. reviewed and edited the manuscript critically for important intellectual content. All authors read and approved the final version.

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