Cover Article

Functional-Structural Plant Models and Artificial Intelligence: A Strategic Lever for Adapting African Agriculture to Climate Change

Beda Innocent Adji, Xiujuan Wang, Mengzhen Kang, Doffou Sélastique Akaffou, Véronique Letort, and Philippe de Reffye

***Abstract*—African agriculture, the pillar of food security and the economy for millions of people, is on the front line when it comes to climate change. Rising temperatures, more frequent droughts and variable rainfall are threatening the yields of traditional food crops. Conventional agronomic approaches are proving inadequate in the face of this challenge. This article proposes a paradigm shift by positioning functional-structural plant models (FSPMs), coupled with artificial intelligence (AI) methods, as a strategic tool for accelerating the adaptation of African agricultural systems. We present an integrated methodological framework (FSPM-AI) that starts with the collection of high-precision agro-physiological data in the field and culminates in the creation of "digital twins" of plants (i.e., dynamic virtual replicas of real plants). These models make it possible to simulate the complex interaction between a plant's genetics, its 3D architecture, its physiology (particularly photosynthesis), and its environment. Using AI techniques for model calibration, sensitivity analysis, and simulation of future climate scenarios (e.g., representative concentration pathways 4.5/8.5), this approach makes it possible to (1) identify the key morpho-physiological traits that confer resilience (e.g., leaf angle, biomass allocation, and photosynthetic efficiency), (2) optimise cultivation practices (density and fertilisation), and (3) guide varietal selections. Using C4 cereals such as millet and sorghum, which are essential for arid areas but scientifically under-modelled, as an example, we illustrate how this coupling of modelling and AI can fill a critical knowledge gap and provide robust decision support tools for farmers, researchers, and policy makers in Africa.**

***Index Terms*—Functional-structural plant models (FSPMs), artificial intelligence, climate change, food security, millet, sorghum**

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I. Introduction

THE African continent faces an unprecedented dual challenge: ensuring food security for a rapidly growing population while adapting its agricultural systems to an increasingly erratic and extreme climate [1, 2]. Climate projections for West Africa indicate rising temperatures and more frequent droughts, compromising the productivity of crops that form the basis of the local diet [3–8]. Paradoxically, the continent has exceptional agrobiological wealth, with traditional crops such as millet (*Pennisetum glaucum*) and sorghum (*Sorghum bicolor*) that have evolved over centuries to withstand harsh conditions [4, 9, 10]. These C4 plants, which are more efficient at photosynthesis in hot, dry environments, are ideal candidates for resilient agriculture [11, 12]. However, they have often been marginalised in favour of cash crops and suffer from a lack of agronomic modernisation and targeted research. Traditional experimental approaches (multi-year field trials) and conventional crop models are costly, time-consuming, and struggle to explore the vast range of possible interactions between genotype, environment, and cultivation practices ($G \times E \times M$), often because they oversimplify plant structure and function [13–15]. This is where artificial intelligence (AI) and advanced biophysical modelling can catalyse a transformation. This article argues that functional-structural plant models (FSPMs), which calculate the functioning and simulate the growth of a plant in 3D based on its physiology and environment, represent a disruptive technology [16, 17]. By combining them with AI tools for analysis and prediction, it becomes possible to dissect the mechanisms of plant adaptation and design tailor-made solutions for the African agriculture of tomorrow. Here, we propose a conceptual and methodological FSPM-AI framework for the application of this integrated approach, illustrating its potential through the case of resilient cereals in Africa.

II. The Integrated Approach: From Plant to Digital Twin

The success of predictive modelling relies on synergy between three pillars: the acquisition of high-quality field data, a robust biophysical model, and advanced computational methods for analysis (Fig. 1).

A. Phase 1: Detailed Agro-Ecophysiological Characterisation

The creation of an accurate "digital twin" of a plant begins

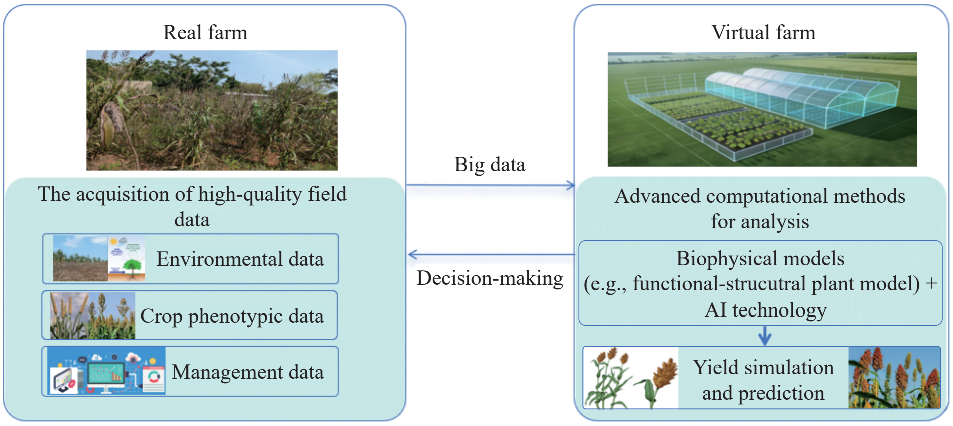

Fig. 1 The framework of FSPM-AI.

with detailed observations of its real-world counterpart in the field. Unlike traditional crop models that consider plant canopy as a whole, the FSPM approach requires disaggregated data at the organ level. This collection phase, conducted at experimental sites representative of African climate gradients (e.g., dry Sahelian zone vs. wetter Sudanian zone), must capture the following aspects.

a. Local Environmental Data

A critical component of the FSPM-AI framework implementation is the collection and integration of high-frequency local environmental data, which primarily includes temperature, solar radiation, relative humidity, and rainfall. These key environmental variables are recorded at short, regular intervals (e.g., hourly or daily) using automated weather stations (AWS) to capture the dynamic temporal variations in the growing environment that directly regulate critical physiological processes such as photosynthesis, transpiration, nutrient uptake, and phenological development.

This comprehensive, high-frequency environmental database serves for training and validating the FSPM-AI model. Without accurate, temporally dense environmental data, the model would be unable to reliably simulate the real-world interactions between crop structure, function, and the surrounding environment undermining its ability to quantify resilience, identify adaptive traits, and guide sustainable crop management.

b. Architectural and Phenological Dynamics

Monitoring of development stages (emergence, tillering, flowering, etc.), measurements of the dimensions of each organ (leaf length and width, internode length and diameter), and assessment of their topology (phyllotaxy) and geometry (leaf angles) are performed. These data are collected using a combination of manual measurements (rulers and protractors) and modern high-throughput techniques such as 3D digitizers, laser scanning (light detection and ranging, LiDAR), or photogrammetry. These comprehensive phenotypic data are of crucial significance for plant growth and productivity research, because the spatial architecture of plants directly determines the efficiency of light interception and canopy light distribution. Light interception, as the primary energy source driving photosynthetic carbon assimilation, further regulates the accumulation of photosynthates and ultimately affects crop yield formation [17].

c. Plant Physiology

Physiological trait measurements focus on the photosynthetic capacity and nutrient status of plants at the leaf level, which are core indicators of plant growth potential. Photosynthetic parameters are determined using portable photosynthesis systems (e.g., LI-COR LI-6800), which can generate A-Ci curves (the relationship between net photosynthetic rate A and intercellular CO_2 concentration Ci) and A-Q curves (the relationship between net photosynthetic rate A and photosynthetically active radiation Q).

These curves allow for the quantitative calculation of key photosynthetic indicators such as the maximum rate of carboxylation (V_{cmax}) and the maximum rate of electron transport (J_{max}), thereby comprehensively evaluating the photosynthetic efficiency and CO_2 fixation capacity of leaves under different environmental conditions.

Meanwhile, the leaf nitrogen status is rapidly estimated using a soil and plant analysis development (SPAD) chlorophyll meter, which measures the relative chlorophyll content of leaves. Since chlorophyll is the main carrier of photosynthetic pigments and nitrogen is an essential component of chlorophyll and photosynthetic enzymes, the SPAD value is directly correlated with leaf nitrogen content and further reflects the photosynthetic capacity of plants [18].

This non-destructive and rapid detection method provides a convenient way to dynamically monitor the nutritional and physiological status of plants throughout the growth cycle.

d. Biomass Allocation

Destructive sampling experiments are carried out at key stages to measure the distribution of dry mass between different organs (leaves, stems, roots, and reproductive organs). This involves separating the organs, drying them in an oven until a constant weight is achieved, and then weighing them precisely. This measurement method can clearly reveal the source-sink relationships and resource allocation strategies of plants: source organs (e.g., leaves) produce photosynthates through photosynthesis, while sink organs (e.g., roots and reproductive organs) consume or store these photosynthates. The dynamic changes in biomass allocation among different organs reflect the adaptive adjustments of plants to growth environments and growth stages, which is of great significance for understanding the mechanisms of plant growth regulation, yield formation, and stress resistance [16]. For example, under drought stress, plants often allocate more biomass to roots to enhance water absorption capacity, while during the reproductive growth stage, more photosynthates are transported to reproductive organs to ensure seed development.

In recent years, the rapid advances in plant phenotyping technologies, collectively referred to as high-throughput phenotyping (HTP), have greatly expanded researchers' ability to quantify plant responses across developmental stages and environmental conditions [19, 20]. Traditional phenotyping methods, which rely on manual measurements or destructive sampling, are time-consuming, labor-intensive, and limited in throughput, making it difficult to collect accurate, repeatable phenotypic data at scale. HTP approaches overcome these limitations by using automated imaging systems, proximal and remote sensors, and advanced data processing techniques to capture morphological and physiological traits non-invasively and with high precision at multiple time points throughout growth. These technologies include visible imaging, hyperspectral and multispectral imaging, thermal infrared imaging, fluorescence imaging, three-dimensional reconstruction, laser scanning, and sensor fusion platforms, which are applicable both under controlled environments and in field conditions. High-throughput phenotyping has become an essential tool in modern plant science, enabling dynamic monitoring of growth, stress responses, and complex adaptive traits, and significantly accelerating the phenotyping bottleneck in breeding and stress resilience studies [19–23]. These advanced technologies make it possible to efficiently, accurately, and continuously obtain massive phenotypic information related to plant structures, phenology, and physiology. These large-scale phenotypic data not only provide a solid data foundation for exploring the genetic basis of plant traits but also promote the integration of phenotypic data with genomic data, accelerating the process of crop genetic improvement and precision agriculture development.

B. Phase 2: Crop Growth Modelling

Crop growth is characterized by strong seasonality and long developmental cycles, which make exhaustive experimental monitoring difficult, particularly under highly variable climatic conditions. In this context, crop growth models have become indispensable tools for simulating plant development, forecasting yield, and assessing the impacts of climate variability and climate change on agricultural production [24, 25]. Conventional crop models, such as those in the DSSAT [24] or APSIM families, generally operate at the canopy or field scale. They often treat the plant canopy as a uniform layer (a "big leaf" approach) and focus on empirical or semi-mechanistic relationships between environmental drivers and biomass accumulation.

While powerful for large-scale assessments, this simplification presents a major limitation: it prevents the analysis of traits related to plant 3D architecture, such as leaf angle, branching patterns, or tiller arrangement. Consequently, these models cannot accurately predict how changes in plant shape affect light interception, resource use efficiency, and ultimately, yield under stress conditions. This is where FSPMs represent a major advance. By explicitly coupling plant architectural development with physiological processes, such as photosynthesis, biomass production, and allocation, the model provides a comprehensive framework for analyzing plant growth. By describing plant growth at the organ level and reconstructing three-dimensional plant architecture, FSPMs enable a mechanistic representation of genotype × environment × management ($G \times E \times M$) interactions and provide a powerful framework for analysing crop adaptation and resilience under changing climatic conditions (FSPMs provide a more mechanistic framework to dissect and predict complex $G \times E \times M$ interactions) [26–28]. This allows for a more accurate comparison of different genetic traits and management practices, offering a distinct advantage over traditional methods for identifying specific adaptation levers [29–33].

FSPMs, such as the GreenLab model [16, 17], simulate plant growth as the result of the interaction between "source" processes (biomass production) and "sink" processes (organ growth demand).

a. Source

Biomass production is calculated from canopy photosynthesis (common pool). The model simulates the distribution of biomass in the plant's 3D architecture (reconstructed from phase 1 data), distinguishing between shaded and sunlit leaves. It then integrates biochemical models of photosynthesis (e.g., Farquhar's model for C3 plants [34] or its extensions for C4 plants [18]) to calculate the total amount of assimilates produced.

b. Sink

Each growing organ (leaf, internode, and fruit) exerts a "sink force", i.e., a demand for carbohydrates for its development. This demand depends on the plant's stage of development each day.

c. Allocation

The model distributes the biomass produced (the source) to the different organs according to their respective demands and their positions. This dynamic allocation determines the evolution of the plant's architecture, which in turn influences light interception for photosynthesis the following day, thus creating a fundamental feedback loop.

C. Phase 3: The Role of Artificial Intelligence and Computational Methods

It is at this stage that AI transforms FSPM from a simple simulation tool into a powerful analysis and prediction machine.

a. Advancements of AI Techniques

The synergy between FSPMs and AI is rapidly advancing agricultural science. Machine learning algorithms are increasingly used not only for parameter estimation but also for emulating complex FSPM outputs, accelerating sensitivity analyses, and integrating multi-source data (e.g., genomics and phenomics) into the modeling framework [35, 36].

b. Model Calibration (Parameter Estimation)

Model parameters (well forces and photosynthetic parameters such as V_{cmax} and J_{max}) are not directly measurable. They must be estimated by adjusting the model outputs to data observed in the field (biomass and architecture). This complex optimisation problem, known as the "inverse problem" (the process of deducing model parameters from observed data), is solved using advanced algorithms. These can include frequentist methods or Bayesian approaches, often implemented with techniques like genetic algorithms or Markov Chain Monte Carlo (MCMC) methods, which explore a vast parameter space to find the best match [35, 36].

c. Global Sensitivity Analysis

Once the model has been calibrated, we can ask: which traits most influence yield or drought resilience? Global sensitivity analysis answers this question by quantifying the impact of the variation of each model parameter (e.g., leaf angle, sink strength, and photosynthetic efficiency) on an output of interest (e.g., final biomass or overall trophic pressure). This makes it possible to identify the most effective "levers" for varietal or agronomic improvement.

d. Scenario Simulations and in silico Ideotyping

The calibrated digital twin becomes a virtual laboratory. It can be used to:

(1) Exploring climate scenarios: By subjecting the model to the temperature and rainfall conditions projected by Intergovernmental Panel on Climate Change (IPCC) scenarios (e.g., representative concentration pathways 4.5/8.5) [7], we can predict the future performance of current varieties.

(2) Testing agronomic practices: Simulate the effect of a change in planting density, supplemental irrigation, or nitrogen fertilisation.

(3) Designing virtual ideotypes: By virtually modifying certain traits (e.g., making leaves more upright, geometrically reorienting the direction of the axes, and increasing grain allocation), we can design an "ideal" plant architecture and physiology for a target environment, a process known as ideotyping. These ideotypes can then guide breeding programmes.

D. Application of FSPM-AI to Strategic African Crops: The Case of Millet and Sorghum

As two of the most strategically important cereal crops in Africa, millet and sorghum are not only staple foods for millions of people in arid and semi-arid regions but also play a pivotal role in sustaining local food security and agroecological stability. These crops possess remarkable adaptive capacities to harsh environmental conditions, particularly heat and water scarcity, which makes them well-suited to the climate characteristics of many African regions. However, their full productive potential remains underutilized, largely due to the lack of in-depth, quantitative understanding of their growth and developmental behaviors under changing climatic conditions—including shifts in temperature, precipitation patterns, and extreme weather events.

Against this backdrop, the application of the FSPM-AI framework to millet and sorghum presents a promising solution to bridge this knowledge gap and unlock their potential. Specifically, this integrated framework can facilitate the following key advancements.

Applying the FSPM-AI framework to these crops would make it possible to:

(1) Quantify their resilience to environmental stress: For the first time, the FSPM-AI framework enables the accurate and dynamic modeling of how the unique architectural traits (e.g., plant height, tiller number, and leaf arrangement) and C4 photosynthetic mechanism of millet and sorghum synergistically function to maintain their productivity under adverse stress conditions (such as drought, high temperature, and nutrient deficiency). This quantitative characterization of resilience not only enhances our understanding of their adaptive strategies but also provides a scientific basis for evaluating their performance under future climate scenarios.

(2) Identify key adaptive traits and their regulatory mechanisms: Through systematic sensitivity analysis embedded in the FSPM-AI framework, it is feasible to clarify the relative importance of different functional and structural traits in mitigating environmental stresses. For instance, the analysis can reveal how leaf angle affects light interception and minimizes light stress, how root system architecture (if incorporated into the model) influences water and nutrient uptake efficiency under drought conditions, and how grain filling speed determines final yield and quality. Such insights are crucial for guiding targeted crop improvement and breeding programs.

(3) Guide the sustainable reintroduction and rational management of these crops: By simulating different combinations of varieties and planting densities, and agronomic practices under diverse climatic and soil conditions, the FSPM-AI model can generate science-based agroecological recommendations tailored to specific regions. These recommendations aim to optimize crop yields while minimizing resource consumption (e.g., water and fertilizers) and reducing environmental impacts. For example, in water-scarce regions, the model can help define the optimal planting density that maximizes water use efficiency and ensures stable yields, thereby promoting the sustainable reintroduction and large-scale cultivation of millet and sorghum.

In summary, the application of the FSPM-AI framework transforms these traditional African cereal crops from understudied subjects into focal points of cutting-edge agricultural research. By providing a robust quantitative basis for their revaluation, this modeling approach not only contributes to the conservation and utilization of crop genetic resources but also supports the development of climate-resilient agriculture in Africa, ultimately enhancing regional food security.

In doing so, modelling transforms these "traditional" crops into subjects of cutting-edge science, providing quantitative bases for their revaluation.

III. Discussion

The integration of FSPMs and AI into agricultural research in Africa offers transformative prospects.

A. Expected Impacts

Scientific impact: This approach aims to produce open-source models for previously neglected African crops, thereby promoting a new wave of research and providing a deeper understanding of climate adaptation mechanisms.

Societal and political impact: This approach provides decision-making tools for ministries of agriculture, enabling them to anticipate food crises and promote science-based agricultural policies. It also supports the co-design of technical data sheets for farmers.

Training impact: This approach focuses on strengthening local capacities by training African researchers in these cutting-edge tools, while promoting balanced North-South collaboration and sustainable technology transfer.

B. Challenges

The deployment of this approach is not without challenges. It requires initial investments in physiological measurement equipment, interdisciplinary skills (agronomy, physiology, and computer science), and computing power for simulations. In addition, collecting high-quality data in the field remains a demanding and critical step.

C. Prospects

The future of this approach lies in its integration at other scales. Upstream, coupling FSPMs with genomic models could accelerate model-assisted selection. Downstream, integrating FSPM outputs into landscape- or agricultural system-scale models would make it possible to assess the impacts of changes in practices at a territorial scale.

IV. Conclusions

Faced with the climate emergency, African agriculture can no longer be content with incremental approaches. The combination of plant structure-function modelling and artificial intelligence represents a qualitative leap forward, offering a means of moving from reactive to predictive and proactive agriculture. By creating digital twins of African food crops, we can explore the realm of possibilities, test adaptation strategies *in silico*, and design agricultural systems that are both productive and resilient. Investing in this interdisciplinary field is not only a scientific opportunity, it is a strategic imperative to ensure food security and sustainable development on the African continent.

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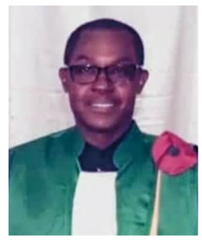

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