# From Parallel Plants to Smart Plants: Intelligent Control and Management for Plant Growth

Mengzhen Kang and Fei-Yue Wang, *Fellow, IEEE*

***Abstract*—Precision management of agricultural systems, aiming at optimizing profitability, productivity and sustainability, comprises a set of technologies including sensors, information systems, and informed management, etc. Expert systems are expected to aid farmers in plant management or environment control, but they are mostly based on the offline and static information, deviated from the actual situation. Parallel management, achieved by virtual/artificial agricultural system, computational experiment and parallel execution, provides a generic framework of solution for online decision support. In this paper, we present the three steps toward the parallel management of plant: growth description (the crop model), prediction, and prescription. This approach can update the expert system by adding learning ability and the adaption of knowledge database according to the descriptive and predictive model. The possibilities of passing the knowledge of experienced farmers to younger generation, as well as the application to the parallel breeding of plant through such system, are discussed.**

***Index Terms*—Artificial intelligence, cropping plan, management system, precision agriculture, plant model.**

## I. INTRODUCTION

GREEN plants, our source of food, need fertilizer, water, light, $CO_2$ to grow. For controlled environment, artificial light, $CO_2$ as well as heating/cooling facilities are needed. Inappropriate operations lead to low production efficiency and damage to environment. Precision management [1] has been proposed for agriculture in order to achieve benefits in profitability, productivity, sustainability, crop quality, food safety, environmental protection, on-farm quality of life, and rural economic development. According to [2], precision agriculture comprises a set of technologies that combines sensors, information systems, enhanced machinery, and informed management to optimize production by accounting for variability and uncertainties within agricultural systems. Nevertheless, precision management of crop (plants) production is a challenging and long-term task, because of social and technical reasons. Multiple domain knowledge is needed for the management of complex agricultural system, including ecophysiology, soil science, climatology, computer science, automation, etc. One of the reasons for a multi- and inter-disciplinary approach is that plant growth is under control of numerous environmental factors, some being closely linked with each other, especially in controlled environment [3].

To describe and to have better understanding about the behavior of these green living organisms, plant models have been developed since 1960's [4]. Process-based (or explanatory) models have the advantage of simulating the growth of plant as the result of many processes, including light interception, gross photosynthesis, respiration, leaf area formation, dry matter partitioning, etc. [5]. However, such process-based models are often too complex [6] to serve for crop management, although they did bring much knowledge about the interaction between plant and environment, and also on greenhouse design [7]. One reason is that model calibrations are usually done under experimental conditions [8], while real situation is much more complex and variable. As the growth environment is essential for crop growth, for the greenhouse, mechanistic environmental models have been developed describing the heat exchange, humidity and $CO_2$ concentration [9]; they are the basis not only for greenhouse design [10], but also for the simulation, control and optimization of crop production. More recently, online parameter estimation of greenhouse model has been developed [11], so that they can serve more for environment control, yield prediction, crop management and not just for education.

Expert systems aim at aiding farmers in plant management or environment control, such as how to apply fertilizer or how to deal with diseases. Classically they are based on offline and static information, and even if being model-based, the model does not necessarily describe the actual situation. Recent advances in technologies and science bring new chances for the development of smarter expert system. Applications of IoT (internet of things) facilities are bringing much more data than ever about agricultural environment, such as the air temperature, light intensity, etc. [12]. Widely-used mobile phones are not only the tools of viewing the data but also giving the user behavior through agricultural information

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management system. Besides, there are enormous open data source that can be achieved through Web crawler, such as the price of agricultural products [13]. However, such data need to be deeply exploited to realize their value.

With the win of AlphaGo in 2016 [14], the idea of artificial intelligence is again warmly recognized by population. Algorithms in machine learning are available to solve practical problem [15], which can serve for intelligent decision support. With the above background, we present a new framework of smart plant management and control, which can upgrade the classical model-based expert system into a system that interacts with real situation. The system is achieved by virtual/artificial agricultural system, computational experiment and parallel execution [16]. This paper presents the key components for building the virtual agricultural system — the plant growth model, the approach of utilizing the real data and generating experimental scenarios, and the steps of finally achieving the parallel management of plant growth.

## II. Plant Model: A Key Component of the Artificial Agricultural System

Early generation of crop models include CERES [17], Hortisim [18], etc. Afterwards, the models became more and more sophisticated, describing most processes linked to plant growth, including plant photosynthesis, respiration, biomass production, allocation, remobilization, fruit setting, etc. Such advances have greatly driven forward the plant science and vice versa. In Netherlands, knowledge transfers are made successfully from modelers to farmers, pushing the advances in greenhouse and planting technology.

To be integrated in a computer system, classical process-based models are too complex and have too many parameters to be estimated. For example, more than 500 state variables are concerned in TomGro [6]. It is also the case for most functional-structural plant model (FSPM, a more recent generation of crop model) which simulates the plant growth at individual organ level. In [19], for example, there are 111 parameters for wheat simulation. Tailoring the model complexity is thus a relevant issue. There should be a balance between the model simplicity and the physiological meaning of the parameters.

GreenLab model [20] shares the concepts close to process-based model with the philosophy of simplicity. Fig. 1 shows the main work flow of GreenLab. The model behavior can be controlled by limited number of parameters. The number of hidden parameters to identify is dependent on plant architecture, but in general they are about ten, which is a relatively small number. The plant growth can be expressed as a typical discrete dynamic system as follows [21]:

$$X_{n+1} = F_n(X_n, U_n, P) \tag{1}$$

where $X_n \in \mathbb{R}^x$ is the set of characteristic system variables at time $t_n$ ($n \in [0; \mathbb{N}]$), here referring to the biomass of all types of organs (leaves, internodes, flowers); $U_n \in \mathbb{R}^u$ is the set of exogenous variables at $t_n$, such as the light intensity, soil humidity, or air temperature, and $P \in \mathbb{R}^p$ the vector of model (hidden) parameters, such as the sink strength of organs. The initial biomass $X_0$ is observable.

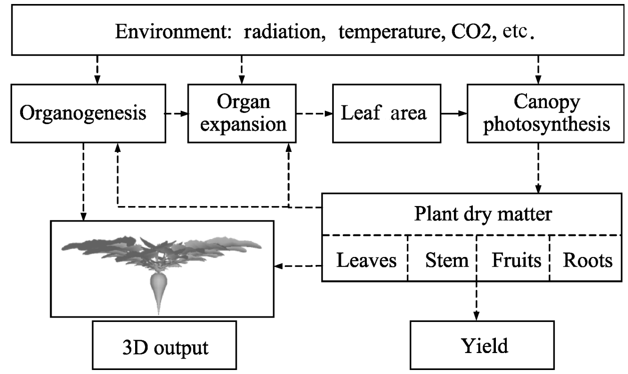


Fig. 1. A typical process flow in GreenLab model.

The harvestable part of plant is usually part of plant biomass, e.g., root for radish, leaves for lettuce, and fruits for tomato. Let $Y \in \mathbb{R}^y$ be a vector of experimental observations made on the real plant once or several times. The corresponding model outputs, deduced from $(X_n)$, are thus a function of parameter vector $P$:

$$\tilde{Y} = G((X_n)_n, P). \tag{2}$$

The parameters $P$ can be identified by minimizing the quadratic criteria as follows:

$$J(P) = (Y - \tilde{Y}(P))^T \sum^{-1} (Y - \tilde{Y}(P)). \tag{3}$$

Being a generic model, GreenLab has been calibrated for different kinds of plants grown under different conditions, such as tomato [22], chrysanthemum [23], wheat [24] and maize [25]. A by-product is that the model can give 3D visualization of plants, so that we can see virtual plants [23].

## III. Facing Reality: Data and Knowledge Driven Modeling Approach

In field circumstance, the environmental conditions may vary significantly due to unexpected weather or management, such that the originally calibrated process-based model is unable to handle. Data-driven model, being a key approach for the new generation of smart agriculture [26], has the advantage of the ability to approximate nonlinear functions, strong predictive abilities, and the flexibility to adapt to the inputs of a multivariate system, while the physical explanations or structural knowledge of a physical system are missing and the internal processes are usually considered as black-box [27]. Taking the advantages of both process-based plant models and data-driven models leads to the knowledge and data driven modeling (KDDM) approach, which can break the bottleneck of model applications from laboratory environment to real-world application.

An example can be found in [27], which couples GreenLab model with a neural network. The coupling of both models can be additive or multiplicative. The result shows that this approach adds flexibility of dealing with environmental variables to process-based model, and gives better prediction compared to existing data-driven model, as it enables the model to utilize domain knowledge. Fig. 2 shows the structure of an additive

KDDM between a process-based crop model and a radial basis function network (RBFN).

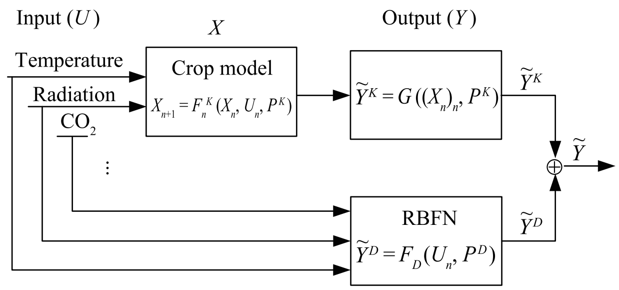


Fig. 2. A data and knowledge driven modeling approach [27].

Here, although one can distinguish the data-driven and knowledge-based model, in wider sense, the process-based model is also data/observation based. When one chooses the level of model complexity, the degree to which the process has to be described is decided. For example, in FSPM the biomass production and allocation process are modeled, while the leaf expansion law is described by an empirical law such as a Beta function, which is based on observation data [27].

## IV. Toward Parallel Management of Crop Growth

KDDM provides a key solution for answering well the questions like "what happened in history", "why did it happen". For application, often the question is "what to do next". This need leads to the parallel precision management system of plant growth. Typically a parallel system is achieved by ACP approach: artificial/virtual system for descriptive analytics, computational experiments for predictive analytics, and parallel execution for prescriptive analytics [26]. For parallel plant management system, the scheme is shown as in Fig. 3.

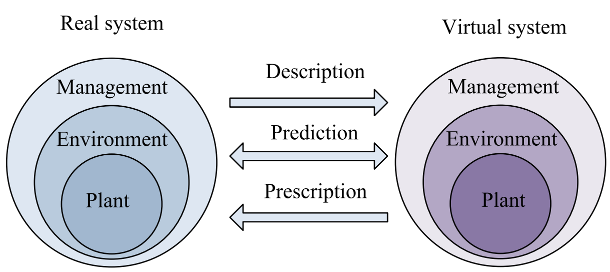


Fig. 3. Schematic presentation of parallel plant management system.

### A. Description

This process is to build a representation of the real system in cyberspace. To have a sound basis, it is necessary that the virtual correspondent fits well the data of the real one, so this process is regarded as "speaking with data" [28]. Given its genotype, the plant growth is under control of both the environment (E) and management by human being (M), e.g., fertilizing, harvesting, pruning, etc., the latter influencing the plant growth either directly or indirectly via environment. Each component has its way to achieve data. Fig. 4 shows the key components and their corresponding descriptive models.

For plants, the observable data includes their development stages (flowering, fruit set, etc.), yield and/or nutrition level, partly available in an automatic way. The above mentioned KDDM can serve as the descriptive model for plants. Fig. 5 shows two plants, simulated under two different temperatures: given the model rules, the plant under low temperature produces fewer flowers, with its corresponding curves of biomass.

For the environment data, most of them can be obtained with (cheap or expensive) sensors in real time, thanks to IoT technology, while the nutrition level in soil is more difficult to get. The management behavior, such as the fertilizing and irrigation, can be recorded by information system. In the agricultural system, human is part of the agricultural system: an experienced farmer makes decisions (e.g., timing of pruning, irrigation) in a different manner from a new practitioner. The descriptive model of human being can be assessed by prevailing User Profile technology, popular in commercial domain [29].

### B. Prediction

Predictive analytics is supposed to answer "what will happen", "when will it happens", and "why will it happen" in future. It must be based on the descriptive model and historical data to be realistic, but it can easily produce much more data than the reality, giving a source of virtual "big data". This step is about conducting computational experiment [30], providing a cheap way of obtaining desirable scenarios with certain control and management policy, for example, the reaction of plants under different temperature, humidity and light combinations.

According to [26], [28], [30], the virtual predicted future can be regarded as the virtually created future in cyberspace, because one of the computational results can be chosen for implementation in real world. In agriculture, for example, before planting, setting up the cropping plan is a tedious work and should be based on the knowledge of the plant's life cycle, market, the compatibility between successive crops, etc. [31]. The prediction of plant growth according to environment model can serve for scheduling, before a cropping plan is finally applied. Fig. 6 shows an example of prediction by setting different planting dates of tomato plants. Based on the trained model (solid lines) [27], yield evolution for other condition (dashed lines) is deduced.

### C. Prescription

Prescriptive analytics is developed to find beneficial/optimized policy from predictions through parallel execution, during which the real and virtual systems interact with each other. For example, the optimal cropping plan can be computed given the crop cultivar, constraints and the target [32], which is a key information for the arrangement of cash flow, human resource and farming machines for a modern farm manager.

Optimization method is necessary at this stage to give an optimal (suboptimal) choice from the virtual outputs. For example, Wu *et al.* [33] computed an irrigation policy for a given amount of water so that the sunflower product is most (Fig. 7). The target is to obtain the optimal water supply strategy to maximize yield with the given amount of water. The visual output of plant can help to observe the result in a direct way, e.g., the size and color of organs, to see quickly the result of a strategy.

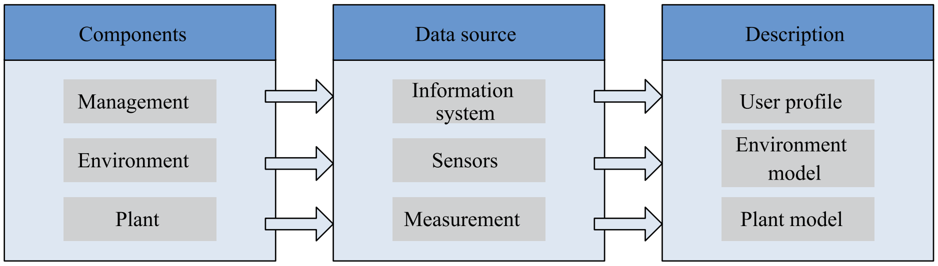


Fig. 4. Components in an agricultural system and the descriptive models.

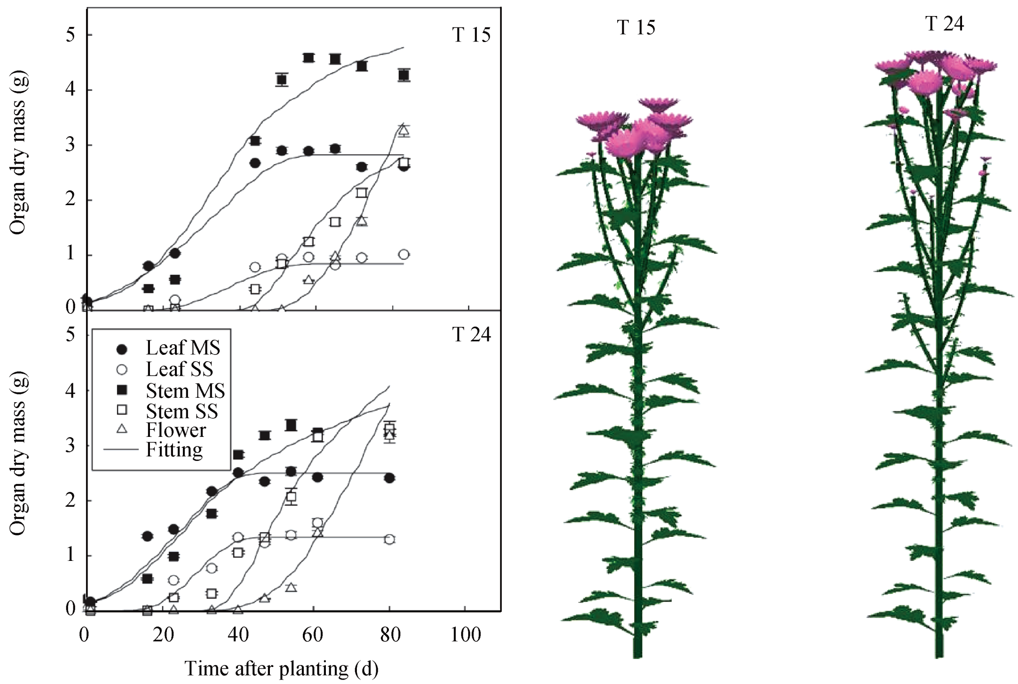


Fig. 5. Calibrated GreenLab model for chrysanthemum [23].

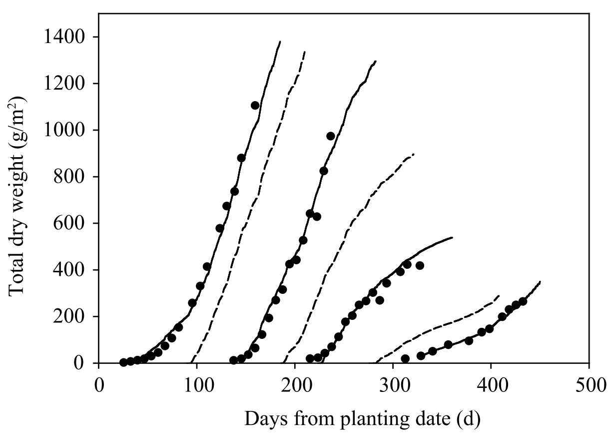


Fig. 6. Prediction of total dry weights of tomato plants for different planting date. Dots and solid lines represent the trained model, and the dashed line represents the predicted result.

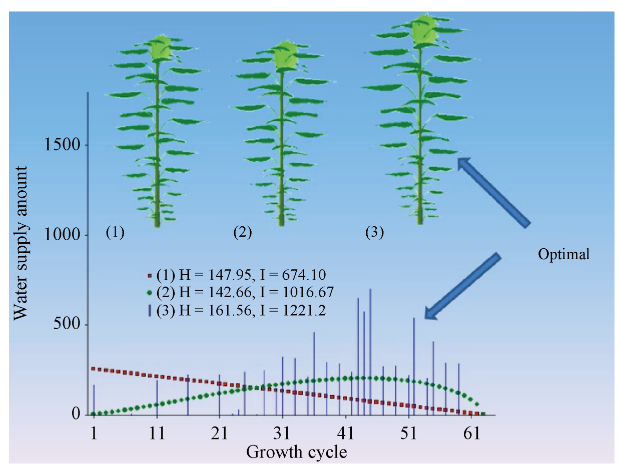


Fig. 7. Optimal control of irrigation policy [33].

Moreover, online learning and adaption are needed during the implementation as the behavior of the real system may deviate from the predicted one. Algorithm like particle filtering [34] can serve for this purpose. It has been applied to predict online the leaf area index with data from remote sensing using a crop model [35] (Fig. 8). Such work is useful for the prescription in case that the real situation deviates from the expected one.

## V. Conclusion and Discussion

In China, promoting information and intelligence technologies in agronomy is being strengthened by the government over the years. With

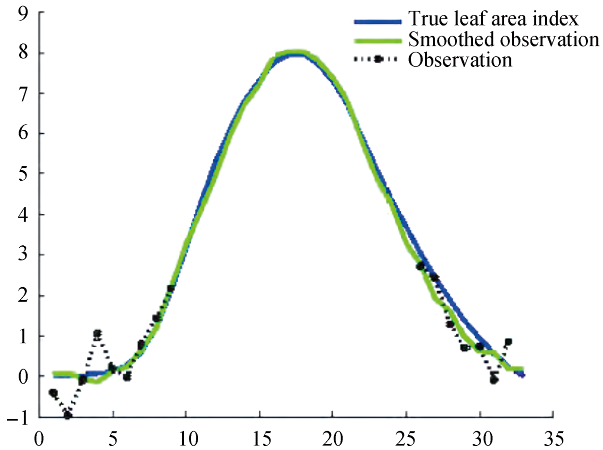


Fig. 8. Online prediction of leaf area index based on a crop model [35].

the transition from the small-scale and family-based farming mode to the big-scale and company-based mode, the need of new techniques is higher than ever. The information systems, usually available in industry, are coming into agriculture to develop the industrialized agriculture. The cyber-physical-social system (CPSS) [36] is necessary in agriculture to augment the production efficiency. The application of artificial intelligence is opening a new era of modern agriculture. The above parallel system for management and control defines a generic framework for future management systems. This also updates the expert system by learning and adaption of knowledge database according to the descriptive and predictive model. While previously many agricultural applications are focused more on data acquisition through IoT technology, parallel management provides a feasible solution of utilizing such data.

The full system as in Fig. 4 includes human being, which can take decisions proposed by an expert system, according to his/her experience. This kind of "human-in-loop" system adds a new dimension and the human behavior can influence the final system behavior. Actually, adding human in the greenhouse control system has been proposed already [3], in order to compensate the situation that the crop models are not reliable and leave room for the experienced grower. It is expected that, with an experienced user, by learning from its decision, the system may finally give smarter decision than the one given by an ordinary user, as proved by the AlphaGo [14]. This gives a way for saving, analyzing and spreading the knowledge of experienced farmers, which is becoming scarce with younger generation who mostly choose to abandon agricultural work. In this way, the parallel system is served for training. If the descriptive model is well setup, and data acquisition is easy, parallel dynamic programming [28] can be applied to train a highly intelligent virtual farmer that can give decision. However, for the moment, there are still many research works left to be done.

Similarly, the proposed idea can be extended to parallel breeding. Genetic models are being developed in past years that link the quantitative train locus (QTL) with the plant phenotypes [37]. In this circumstance, plant production has another dimension, and the model parameters as in (1) are functions of genetic information $G$, i.e., $P = g(G)$. To conduct a full field experiment and compare the genetic behavior is a lengthy and tedious work. Computational experiments can be conducted on the different combination of QTLs on the final yield. Such kind of theoretical study has started which can give promising prescription [37] that may guide real breeding.

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