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Review

Temporal and spatial field management using crop growth modeling: A review

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Abstract: Precision agriculture (PA), defined as spatial/temporal management of agricultural practices, requires adequate knowledge about crop growth and development phenology, requirements, and the parameters affecting them. Despite the importance of temporal management of agricultural practices, it has not been dealt with in most of the reviewed literature. In this paper, temporal management of agricultural practices in precision agriculture is discussed and crop growth simulation models are suggested as robust tools to schedule the agricultural practices. Crop Growth Models (CGMs), by scheduling the crop production activities can help producers to temporarily manage the inputs, while the efficiency of production would be enhanced. Some of the well-known crop growth models are introduced as tools for simulating the required production inputs during the growth period. Finally, time-specific management (TSM) of agricultural practices base on these models is suggested as the next generation of PA.

Keywords: CGMs; precision agriculture; simulation; SSM; TSM

1. Introduction

Scarcity of the Earth's resources, global climate changes, increasing human population and elevated demand for food and fiber, along with environmental awareness, and economical concerns, propelled agricultural production in the 21st century towards precision agriculture (PA) as spatial/temporal management of agricultural practices.

Dealing with the climatic conditions of crop production may be the most significant factor in agricultural systems [1]. Limitations of the land resource and the importance of their protection, growing human population, and rapidly growing demand for agricultural productions created problems for global food security that persuaded agriculturalists to find innovative remedies [2]. The increasing demands for food, on the one hand, and the need for environmentally friendly strategies of sustainable agriculture, on the other hand, require special attention when addressing the issue of crop productivity enhancement and agricultural sustainability [3]. Agricultural water availability reduction, as well as growing population demand for higher agricultural productivity in irrigated areas, demonstrate the necessity of improving irrigation efficiency, especially in arid and semiarid regions by precision irrigation [4].

Conventional agriculture ignores the inherent spatial variability and manages the whole field uniformly. The procedure has led to the overuse of fertilizers in areas with high residual nutrients and the application of insecticides and herbicides in areas not infected by insects and weeds [5]. Crop growth and yield are frequently limited by nitrogen. On the other hand, if fertilization is not temporally and spatially adjusted to the current plant requirements, the applied nitrogen compounds may pollute the environment. Extra nitrate remained from fertilizers, or the nitrate obtained from nitrification may leach into the groundwater or may be released by denitrification as di-nitrogen (N_2) and nitrous oxide (N_2O). The N_2O is one of the major causes of global warming and considered a stratospheric ozone destructor [6]. Environmental concerns have led to the introduction of agricultural systems that aim to accomplish their objective of productivity in harmony with the environment. In this regard, traditional agriculture, which applies inputs non-uniformly based on need, can be considered as a system that has survived over centuries and achieves its objective of productivity in harmony with the environment [7].

The variability of agricultural systems and their uncertainties on one side, and the necessity of maintaining the environmental quality and improving food supply sustainability on the other, led to the development of PA as a set of technologies to optimize production by adapting inputs site-specifically to allow better use of resources [8]. Dobermann et al. [9] defined site-specific management (SSM) of nutrients as the dynamic management of these inputs by considering: (1) regional and seasonal variability in the crop potential yield under climatic conditions and nutrient demand; (2) field spatial variability; (3) field-specific during the seasonal changes in crop demand for nutrient; and (4) location-based cropping systems and management practices. Moral et al. [10] and Plant [11] described PA as SSM of crops at a spatial scale smaller than the whole field. Variability of the agricultural field can be managed generally in two ways: the map-based approach and the sensor-based approach [12].

2. Precision Field Management

Site-specific management of soil fertilizers [9,13–18], irrigation water [19–22], and protective chemicals [23–32] have been studied for many years. In addition to SSM, precision farming also entails "temporal management" of inputs [12,33,34] which has not received as much attention as spatial management.

Precision chemical management

Chemical application for crop production is the area receiving the most attention and investment. Some examples of precision chemical management will be discussed below.

For site-specific weed control, a weed treatment map was created to locate and determine the dosage of herbicide application [32]. The map-based sprayer was equipped with a differential global positioning system (DGPS) and its solenoid valves were opened automatically as the tractor entered a weed patch designated in the weed treatment map. [35] used the difference between the reddish color of weed stems and the greenish color of wheat and soybean stems as a machine-vision-based weed detection system. [36] processed the blue value of color images to detect weeds in paddy fields. Color-based machine vision was also employed by [37] to detect volunteer potatoes as sugar beet weeds. In another case study, image segmentation involving the acquisition of RGB (red-green-blue) original images, image binarization, crop line detection, grid cell partition, and attribute extraction was used to detect the *Avena sterilis* as a cereal weed [38]. As a weed monitoring tool for patch spraying, Weedcer has been developed to estimate the proportions of young weed leaves and cereal leaves in high-resolution RGB images [28]. The method computes a set of significant features for each component that is segmented by relative weed cover (= weed cover/(weed+crop cover)) and relative mayweed cover (= mayweed cover/(weed+crop cover)) measurements on RGB images, based on color and a set of shape parameters. A machine-vision-based intelligent weeding system was developed by [39] to identify the types of weeds in oil palm plantations. In their research, three techniques of image processing: statistical approach (gray level co-occurrence matrix (GLCM)) and structural approach (namely, fast Fourier transform (FFT) and scale invariant feature transform (SIFT)) were used and compared. Among the three techniques, the SIFT was reported to be better compared to FFT and GLCM for the task.

Precision fertilization

To efficiently manage nutrients, crop production and environmental protection, the principles of soil fertility need to be understood. Among the 17 essential elements for plant growth, 14 of them come from the soil. The essential nutrients are obtained in different amounts based on the plant characteristics, mobility of the nutrients within the plant, and analyses of harvested crop components [40]. Koch et al. [41] developed a map-based site-specific nitrogen management system utilizing the management zones determined by a geographic information system (GIS) that integrated the bare soil aerial image of conventionally tilled land, along with field topography, and previous crop and soil management data layers. Based on the layers, the areas of the field with high, medium, and low productivity were distinguished. Then, soil sampling was done to determine nitrogen application rates. Elsewhere, to detect calcium deficiency in lettuce, several methods were compared [42]. Among the methods, top projected canopy area (TPCA), energy, entropy, and homogeneity were the most promising for the timely detection of calcium deficiency in lettuce. They could identify the problem one day before visual stress detection by human vision.

Precision irrigation

Some of the studies on precision irrigation are referred to in this section. In one such study, to irrigate site-specifically, irrigation management zones were delineated based on soil electrical conductivity (EC) that was measured by sensors. Then, variable amounts of irrigation water were delivered using a remote real-time, distributed irrigation control and monitoring system [4]. A feedback site-specific irrigation system, with a network of infrared thermometer (IRT) wireless sensors, was utilized to develop dynamic recommendation maps to plan adaptive irrigation of cotton [43]. Rojo et al. [44] used a continuous leaf monitoring system based on temperature and microclimatic variables to detect water stress in grape and almond crops for precision irrigation. A wireless network was employed to interface the leaf monitors with soil sensors and pressure sensors that measured the pressure in the pressure chamber.

Importance of precision farming

Increasing agricultural crop yields demands soil fertilization with a constant impact on soil quality [45]. In other words, sufficient nutrient supply during the crop growth and development is needed to support soil fertility for crops. Nutrient use efficiency can be defined as the crop output per unit of nutrient input, while, the International Plant Nutrition Institute proposed a definition as the adoption of the best management practices in agriculture, namely, the 4R concept. Here, 4R refers to applying the Right source of nutrient at the Right rate, Right time and Right place [3]. Changing attitudes toward AP regard the environment as an important factor, therefore, wildlife and habitat protection have resulted in several changes in agricultural systems' management [1]. The application of organic and chemical nitrogen fertilizers and pesticides in agriculture resulted in significant economic benefits, at the cost of negatively impacting the environment and human health [46]. Agricultural soils contaminated with organochlorine [47] and arsenic-based pesticides [48] rose health hazards. The increased regulation and supervision regarding the use of fertilizers, pesticides and other chemicals in agriculture, has made PA a promising system, while this technology is recognized as an environment-friendly farming practice [49]. Permissible levels of phosphorous and nitrogen fertilizers and specific limitations on their dates and methods of application have gradually decreased in the environmentally friendly agricultural policies [50]. Effective matching of crop nitrogen requirements and the appropriate fertilizer application increase fertilizer use efficiency while reducing environmental risks [51]. Therefore, appropriate methods are required to help farmers schedule their agricultural practices more efficiently. In this field of view, CGMs are appropriate alternatives in governing the procedure of scheduling.

3. Crop Growth Simulation Models

To analyze any logically described agricultural system, mathematical models are often used [1]. A simple mathematical representation of a crop would lead to the development of a CGM which is used to predict crop reaction to the environment. Crop growth models which are increasingly utilized to assist agricultural research and development, are two general types; 1) descriptive or empirical models, that simulate the behavior of a system in a simple way, in which, experimental data are utilized to find one or more mathematical equations capable of describing the behavior of a system, and 2) explanatory models, that involve a quantitative description of the system. These process-based models are also called mechanistic models [52,53]. The interaction between the crop and weeds, the impact of weeds on crop growth and yield, and providing a basis for forecasting the crop yield loss and weed biomass can be simulated using CGMs [54]. In the meantime, it has to be kept in mind that field suitability for weed growth and development, their characteristics, and dispersal agents are variable, temporally and spatially [55].

Empirical models

Descriptive models, also known as empirical models [56], simulate the behavior of a system in a simple way, in which, experimental data are utilized to find one or more mathematical equations capable of describing the behavior of the system [52]. This approach examines the data, fits an equation or set of equations to them, but provides no information about the mechanisms that give rise to the response [56]. The behavior of a system in these models is defined in a simple manner [2].

Mechanistic models

From a differential equation relating growth rate to size, a mechanistic model is usually derived, which is a mathematical relationship representing the mechanism governing the crop growth process [57]. The system is analyzed and its processes and mechanisms are separately quantified to be used for yield predictions, agricultural planning, farm management, climatology and agrometeorology [52]. These models have to be calibrated for each region to give accurate and reliable results, while they are highly data-demanding [58]. Uncertainty of crop simulation models over large areas would be due to the spatial and temporal variability of weather conditions. Weather variables observed at weather stations and those provided by numerical weather prediction models are two important sources of weather variables that are often applied in crop models [59]. There are many mechanistic models developed to simulate crop growth in order to predict the yield and reaction of crops to stress phenomena. Some of the more important models and their applications are described below.

Mechanistic models and their applications in field management

Light interception and CO_2 assimilation is used as growth-driving processes in the world food studies (WOFOST) mechanistic CGM that describes plant growth based on its phenological development. Ways of using the model include: (1) a potential mode, where no growth limiting factors are taken into account and crop growth is purely driven by temperature and solar radiation; (2) a water-limited mode, where crop growth is limited by the availability of water and no other yield-limiting factors (nutrients, pests, weeds, and management decisions) are taken into account [59], and (3) a nutrient-limited mode, in which nutrient availability depends on the supply of nutrients to the plant roots [60]. Crop output indicators such as total biomass, leaf area index and yield prediction are outputs of the WOFOST for most crops [59,61]. The model simulates crop growth and development as a function of environmental conditions (soils and climate), crop characteristics, and crop management (irrigation and fertilizer application) [62].

Daily crop growth rate can be simulated in WOFOST by considering climatic conditions (solar radiation, temperature, relative humidity, wind speed, and rainfall), soil properties (soil depth, water holding capacity, and infiltration capacity) and crop characteristics (length of the growing cycle, photosynthetic characteristics, and distribution of dry matter) [63]. In a case study, to derive the

WOFOST model for predicting winter wheat yield in Hengshui district, China, the following data were collected: regional meteorological data (including daily maximum and minimum temperatures, rainfall, wind speed, and water pressure), soil characteristics (including field moisture capacity, wilting point, saturated water of soil), crop data (including temperature summation from sowing to emergence, temperature sum from emergence to anthesis, temperature sum from anthesis to maturity, sowing date radiation, and leaf area index) [60]. This is while [64] considered the phenological development stage (emergence, anthesis, and maturity), dry matter weight of leaf, stem and storage organ, and LAI in similar research as the parameters for adjusting WOFOST for winter wheat in North China. [63] simulated the sensitivity of potential yields and evapotranspiration of winter barley (as winter crop) and maize (as a summer crop) grown in Esfahan, Iran, using WOFOST. Soil–water–atmosphere–plant (SWAP) model, adapted from WOFOST, determines potential photosynthesis and biomass accumulation [65]. The soil and water assessment tool (SWAT), which is a physically-based, basin-scale, continuous-time model was developed by USDA-ARS (United States Department of Agriculture - Agricultural Research Service) to operate on a daily time step. This model serves as an interdisciplinary tool for simulating agricultural catchment management and has been used widely for designing water-related measures in agricultural catchments. To analyze the impacts of land-use change or agricultural management practices, recent studies have focused on the combination of both remotely-sensed products and SWAT [66].

The Decision Support System for Agrotechnology Transfer (DSSAT) is a collection of independent software describing weather, soil, experiment conditions and measurements, as well as genotype information for applying the model to different situations [67]. The model considers solar radiation, temperature, and precipitation as inputs to be used as a tool to improve land use planning and enhance profitability [2]. To reach their objectives, farmers use DSSAT to match the biological requirement of a crop to the land physical characteristics [68]. By assuming the uniformity of root length density distribution in each soil layer, the crop root water absorption rate is calculated by DSSAT. Crop-nitrogen interaction modeling is the major advantage of DSSAT over SWAP. Nitrogen dynamics of plant and soil is also feasible to be simulated by DSSAT, but it lacks capability in the case of other solutes. While, assuming nitrogen as a solute, SWAP is capable of simulating its movement and degradation. On the other hand, DSSAT requires weather variables including solar radiation, minimum, and maximum temperature, and rainfall, while in SWAP, wind and actual vapor pressure are also needed [61].

Rezzoug et al. [69] used DSSAT to predict the growth and yields of wheat genotypes in Algeria. This method has been successfully used worldwide in a broad range of conditions and for a variety of purposes including: as an aid to crop management, nitrogen management, irrigation management, precision farming, climate change, yield forecasting, and sustainability. DSSAT has a huge database of detailed crop models which includes the CERES and CROPGRO families and other CGMs [61]. Scheduling of irrigation, determining the influence of water stress on plant growth and development, and the potential yield reduction caused by soil water are some of the capabilities of DSSAT [70].

CROPGRO predicts dynamic growth and composition of crops based on plant, soil, management and weather inputs giving it the capability to simulate soil water and nitrogen balances, soil organic matter, residue dynamics and pest/disease damage [71,72] as well as the maturity date, fruit number, fruit yield at harvest, LAI, and soil water content in the rhizosphere [73]. Originally, CROPGRO was developed to simulate the growth of legume crops [74] but has been used for other situations as well. In a case study, the suitability of environmental conditions to velvet bean physiological requirements was investigated by CROPGRO model and the performance of this model for phenology and nitrogen accumulation in different locations was evaluated. It was concluded that the model can be considered as a reliable tool for simulating velvet bean response to crop management and environmental conditions [75]. Rinaldi et al. [73] calibrated CROPGRO for processing tomato in Southern Italy to evaluate the economic aspects of 23 different interactive irrigation and/or nitrogen management scenarios. In another study, the CROPGRO cabbage model, included in DSSAT software, was calibrated and evaluated in the Hawaiian climate for white cabbage [74].

AquaCrop is a user friendly, simple, accurate, robust model requiring only a small number of input parameters [76]. It stimulates the development of green crop canopy cover, crop transpiration, above-ground biomass, and final crop yield variables as functions of water availability and consumption, field management parameters, plant physiology, soil water, and salt budgeting concepts [77]. The model simulates the balance between soil and water and the processes related to crop growth as a function of the crop, soil, weather, and management as input data parameters, on a daily time step. In AquaCrop, (1) expansion of canopy, instead of LAI, is simulated in terms of proportional green canopy cover; (2) in comparison with other water-driven crop models, a broader range of water stress impact on transpiration is considered; (3) it accounts for the dynamic effects of a range of environmental stress factors, especially water [78]. Rinaldi et al. [76], used AquaCrop to simulate the effect of climate change and other parameters on the growth and yield of paddy. In another study, based on the dataset of a 6-year experiment, with several irrigation treatments including full irrigation, different levels of deficit irrigation, and no irrigation, AquaCrop model was calibrated and validated in Shiraz, Iran [79].

AquaCrop can be used to generate an irrigation schedule [80]. The model is also employed for determining the crop response to water stress, develop schedules with deficit irrigation, improve irrigation management in the farm, assessing the potential rise in crop production and field management, evaluate crop production under climate change effect and to develop decision support tools for farm operations [77]. AquaCrop was utilized to simulate cabbage yield and irrigation water use in south-western Burkina Faso [81]. Under variable irrigation and nitrogen levels, maize yield was forecasted by this model with acceptable accuracy in New Delhi, India [82]. Based on Seven years (2007–2013) of rainfed field experimental data, AquaCrop was calibrated and its ability to simulate the cumulative grain yield of rainfed maize for different soil fertility levels was evaluated in the northern Guinea Savanna zone of Nigeria [83].

There are many other CGMs that have been used in various research works. Light-use-efficiency-based CGM's ability was tested to simulate biomass accumulation in wheat and weeds to understand the effect of weeds on wheat early-season crop growth and grain yield loss [54]. They realized that modeling the weed community biomass accumulation based on the amount of radiation is possible. Wheat growth was also modeled, successfully. In a case study, ORYZA2000 was used by [84] to simulate the growth, development and water balance of rice crops (*Oryza sativa*). To simulate plant fertilizer demand, the USDA Environmental Policy Integrated Climate (EPIC) model was used [85]. Liang et al. [86] developed an integrated soil-water-heat-carbon-nitrogen simulator (WHCNS) as CGM to assess water and nitrogen management in North China. Based on soil-water balance, crop phenology, root growth, crop water production function, and irrigation management model, a field crop irrigation management decision-making system (CropIrri) was developed. This model (1) utilizes the mean meteorological data of several years to develop an irrigation schedule before sowing, and utilizes the forecasted weather data to manage real-time irrigation; (2) uses crop phenology simulation to determine the compatibility of different varieties in different regions, and to simulate the period of crop development stages; (3) simulates root growth and elongation, by applying root growth model; (4) sets custom irrigation schedules in different stages for certain irrigation plans and estimates the crop water productivity function for evaluating yield losses; and (5) simplifies input parameters to ensure smooth system running [87].

The yield variability of rainfed cultivation significantly depends on the total rainfall and its temporal distribution during the growing season, while variability would be reduced in the fields with assured water supply [88]. Crop growth patterns usually reflect the spatial and temporal variability of the factors affecting crop yields. Therefore, monitoring the pattern helps farmers to manage the field site-specifically [89]. Meanwhile, precision agriculture includes site-specific management of crop production based on variable (temporal/spatial) field conditions [90].

To reduce the input of water, fertilizer and crop protection chemicals for maize, vine, kiwi, asparagus and pomegranate in Greece and Bulgaria, a project was set up to manage farms site-specifically to protect the environment by spatial and temporal control of the inputs [91]. The temporal effect of crop stress factors, such as drought, nutrient deficiency, pests, and diseases, on crop yield, accounts for more than 50% of crop yield variability across years and sites [89]. Managing these factors may lead to sufficient profit, while it is a major challenge for farmers and, thus, simplified approaches should be developed [89]. The availability of nitrogen, as a mobile nutrient, as well as soil-immobile nutrients may be influenced by weather and its impact on soil nutrient supply and plant demand. These parameters result in temporal variability in nutrient availability throughout the field [92].

As long as the soil water content is between field capacity and critical soil water content (within the optimum range), there is no limiting factor to reduce daily growth rate and the soil is considered sufficiently wet; but, as soon as the soil water decreases below a critical point, evapotranspiration is reduced with a factor from 1 to 0 corresponding to the soil water content depletion between the critical point and wilting point [59].

Temporal management of agricultural practices has to be taken toward PA aims, which has not been sufficiently investigated in previous research works. However, crops during their growth and development need sufficient irrigation, fertilization, environmental microclimatic control and protections which can be simulated using CGMs. Crop growth models can provide decision-makers and agricultural producers with a road map to plan the timetable of farm operations based on crop temporal requirements.

These models, can both simulate crop growth and development as well as estimate the plant requirements during its lifetime. Therefore, a farmer can estimate the final yield based on current climatic conditions, inputs, treatments and operation timetable. On the other hand, CGMs enable the farmer to implement the right practices with the right intensity at the right time in the right place to provide the optimized conditions for crop production. This helps to achieve high efficiency while reducing environmental impacts.

4. Conclusions

Crop growth models are mathematical descriptions that stimulate plant growth and development. CGMs are typically empirical (also called descriptive, statistical, or regression) or mechanistic (also known as explanatory, dynamic, or process-based). The empirical models are not generalizable, while, the mechanistic models are global and simulate the growth and development processes as a function of crop phenology, climatic conditions, soil characteristics, irrigation, and field management parameters. Furthermore, the mechanistic models include a large variety based on the purpose of the application, required data, and the crop in question. These models predict crop yield and biomass production. At the same time, they are capable of scheduling the application of inputs (fertilizers and protective chemicals as well as irrigation water) during crop growth and development based on the region where the crop is cultivated. Due to the importance of temporal management of agricultural practices and the prediction capability of the CGMs, it is suggested to use them as the governing control systems to plan farm operations, temporally.

Since, precision agriculture entails spatial/temporal management of agricultural practices in the right place at the right time to obtain the highest achievable yield, the least environmental impact, and better economy of crop production, the linkage between PA and CGMs, which have similar goals, promises the potential of achieving very beneficial results.

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