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Dynamically Controlled Environment Agriculture: Integrating Machine Learning and Mechanistic and Physiological Models for Sustainable Food Cultivation

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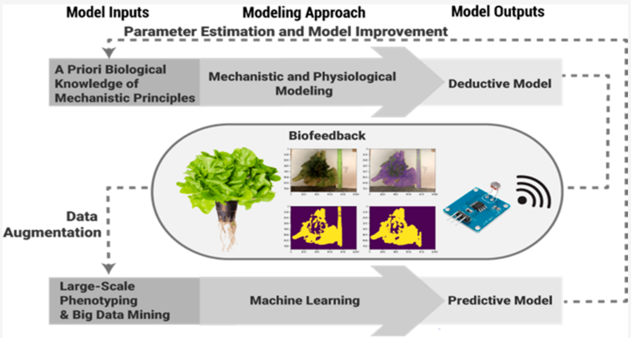

ABSTRACT: Inefficiencies and imprecise input control in agriculture have caused devastating consequences to ecosystems. Urban controlled environment agriculture (CEA) is a proposed approach to mitigate the impacts of cultivation, but precise control of inputs (i.e., nutrient, water, etc.) is limited by the ability to monitor dynamic conditions. Current mechanistic and physiological plant growth models (MPMs) have not yet been unified and have uncovered knowledge gaps of the complex interplay among control variables. Moreover, because of their specificity, MPMs are of limited utility when extended to additional plant species or environmental conditions. Simultaneously, although machine learning (ML) can uncover latent interactions across conditions, phenotyping bottlenecks have hindered successful application. To bridge these gaps, we propose an integrative approach whereby MPMs are used to construct the foundations of ML algorithms, reducing data requirements and costs, and ML is used to elucidate parameters and causal inference in MPM. This review highlights research about control and automation in CEA, synthesizing literature into a framework whereby ML, MPM, and biofeedback inform what we call dynamically controlled environment agriculture (DCEA). We highlight synergistic characteristics of MPM and ML to illustrate that a DCEA framework could contribute to urban resilience, human health, and optimized productivity and nutritional content.

KEYWORDS: *Artificial Intelligence, Phenotyping, Automation, Precision Agriculture, Plant Growth Modeling*

1. INTRODUCTION

Industrial agriculture contributes significantly to the environmental impact of human activity, which now dominates nearly all of Earth's biogeochemical cycles.[1−4] Industrial agriculture output, projected to increase 100−110% from 2005 to 2030,[5] requires sizable inputs of limited resources like fresh water, land with adequate sunlight and soil, and nonrenewable nutrients (e.g., phosphorus).[6−8] Consequences of modern intensive agriculture include deterioration of soils, aquifer depletion, and saltwater-intrusion, runoff and eutrophication, emissions (e.g., CO_2, N_2O, etc.), contributing to global warming and resource scarcity,[9] particularly because farmers often have insufficient measuring, modeling, and dynamic control mechanisms to optimize inputs for plant growth.[10,11] Moreover, due to lengthy supply chains, losses in the form of food waste from farm to fork can be as high as 40%,[12] furthering industrial agriculture's material and energy inefficiencies.

Whereas fertilizer overuse has resulted from farmers treating crops with uniform, rather than targeted, applications of fertilizer,[13] advancements in real-time nutrient monitoring can enable farmers to combat fertilizer overuse. Modern sensors have become more affordable and more precise, leading to increased implementation in the field and in greenhouses.[14−16] Precision agriculture, or "smart farming," a growing trend in efficient farming, is enabled through coordination of sensors and geographic planning tools, allowing farmers to treat cropland in a dynamic, tailored fashion rather than traditional blanket treatment.[17] These future improvements will likely be made possible via integrated user interactive models whereby

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Table 1. Comparison of Mechanistic and Physiological Models (MPMs) with Machine Learning (ML) in Agriculture

	mechanistic and physiological models (MPMs)	machine learning (ML)
model development	establishes mechanistic relationships between inputs (water, nutrients, light, etc.) and outputs (growth rate, yield, etc.) (e.g., Michaelis−Menten has been used to describe nutrient uptake kinetics using substrate nutrient concentration)	uses statistical analysis of data to predict outputs based on inputs
adaptability	extrapolation is limited to modeled parameters which may neglect plant genotype, environmental conditions, and plant species	can be adapted and generalized to a wide variety of species, environmental conditions, and variables with limited expert input
data requirement	parameter values can be found using relatively few growth trials	requires many growth trials and high phenotyping throughput to generate and validate
expert knowledge	requires *a priori* knowledge of mechanistic and physiological phenomena	can be generated with little to no *a priori* mechanistic foundation

farmers can selectively employ multiobjective optimization to maximize productivity, flavor, and nutrition and minimize environmental impact, cost, and resource intensity. Additionally, cyber-physical systems, data sharing, and open-source implementation will assist in resource coordination and improve computational models and machine learning algorithms,[18] further facilitating tighter resource use control.

Given the increasing threats to water and material resource availability in the face of both a changing climate and increasing population, emphasis has been placed on conserving water, energy, and material use in farming. Local, decentralized controlled environment agriculture (CEA) is one proposed approach to improving the sustainability of vegetable production,[19,20] due to the practitioners' ability to tightly control environmental inputs, such as the application of nutrients, water use efficiency, and lighting. CEA includes hydroponics or soilless farming, whereby the nutrients and water are delivered directly to plant roots using either recirculated (where a substrate is recycled in the system until a nutrient is depleted) or flow-through substrate (in which nutrient-rich water is continuously supplied at a constant concentration).[21−23] CEA can be used to produce vegetables and high-value products in any climate with high water, land, and nutrient efficiency, with local production enabling low transportation costs.[24,25] CEA reduces land use by as much as 80%[26] and water use and runoff by nearly 90% and enables more efficient use of nutrients[27] over conventional field agriculture[25]—an attractive characteristic given nutrient cycling's status as one of 14 Grand Challenges for Engineering for the 21st century.[4,28] Moreover, soilless farming is not constrained by soil quality, and the environment (e.g., light, temperature, humidity) can be controlled to maximize productivity while reducing non-point-source eutrophication, water use, and energy intensity.

Optimizing both resource inputs (e.g., minimizing water and nutrients) and output yields is a prerequisite to resource use efficiency and conservation. Resource optimization strategies for CEA have focused on water and nutrients, including conservation of water resources via irrigation procedures and water management.[29−31] Water use minimization for reducing negative drainage effects can also be achieved indirectly as a byproduct of minimizing drainage ion concentrations. Some works have considered nutrient utilization rate as a measure of the nutrient taken up by the plant as a percentage of the nutrient supplied (e.g., via fertigation),[32,33] leveraging mechanistic and physiological modeling (MPM) techniques from first-principles such as Michaelis−Menten enzyme kinetics.[34] A high nutrient utilization rate is desirable not only for resource minimization, but also for minimizing environmental damage from runoff. Nutrient use efficiency is increased when minimization objectives are placed on nutrient concentration in fertigation or drainage, though explicit constraints may be placed on the nutrient utilization rate for stricter adherence to conservation efforts or regulatory limits.

While CEA holds promise for more precise environmental control, control over input resource use (e.g., water, nutrients, energy for lighting, etc.) efficiency is, in part, constrained by technological limitations on monitoring substrate nutrient concentrations and plant nutrient uptake. These constraints limit the practical resource use efficiency benefits of CEA systems. For example, the high nutrient load from flow-through CEA systems can lead to hazardous soil, groundwater, and surface water contamination unless the leachate and runoff are physically captured or treated.[10] Proposed solutions often rely on recirculation[35] or the use of nonmineral nutrient streams that often have highly variable composition, like wastewater, aquaculture, and food processing.[36−43] Both recirculation and the use of variable nutrient streams introduce dynamism that necessitates increased levels of control via dynamic modeling and prediction.[44] To bridge this gap, practitioners have called for next generation CEA systems that leverage machine learning (ML) to facilitate dynamic control.[45] However, this approach has traditionally been costly due to the vast amounts of data required to train machines to take precise predictions[46] and a bottleneck in the speed at which plants can be observed and measured with respect to their growth and morphology (i.e., via phenomics or phenotyping).[47,48] Given these shortcomings, an integrative approach that leverages ML in conjunction with our mechanistic and physiological understanding of plant biology provides the opportunity to dynamically control the growth environment and better interpret the ML black box modeling.

Existing mechanistic modeling efforts have revealed gaps in our understanding of the complex interplay among numerous control variables[34,48]—complexity that machine learning can characterize without the explicit cause−effect relationships required for MPM. Simultaneously, the mechanistic models we do have can be used to construct the foundations of machine learning algorithms, reducing data requirements and validation costs. Machine learning algorithms, however, take tremendous amounts of data to construct and validate.[49] Given throughput limitations of existing plant phenotyping strategies, purely statistical methods remain expensive due to the number of replicates required to generate meaningful data.[47,48,50] Biologists have identified an opportunity to integrate MPM and ML into hybrid models to leverage the benefits of ML while capitalizing more efficiently on known mechanistic phenomena, but this hybridization has not yet been applied to controlled environment agricultural and plant growth modeling efforts. MPM and ML are compared and contrasted with

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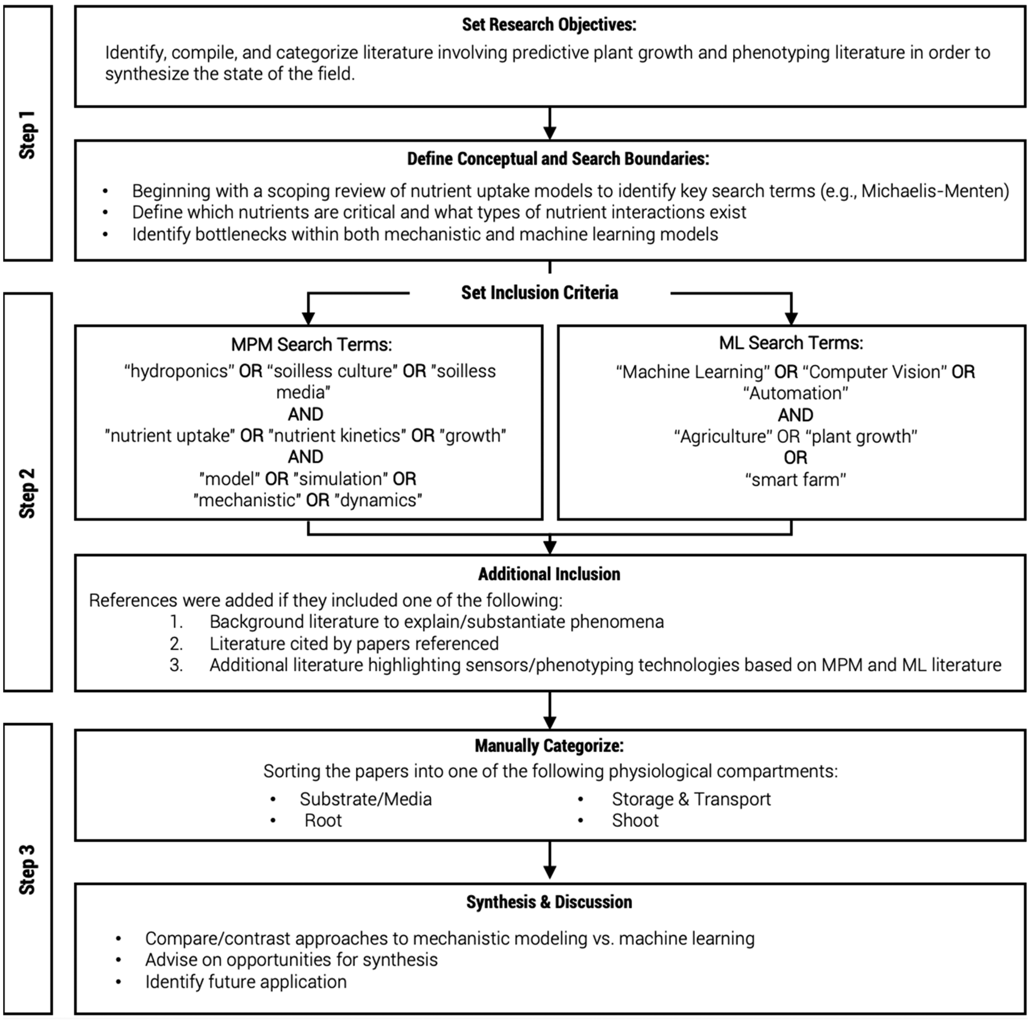


Figure 1. Methods diagram for literature review, synthesis, and discussion.

respect to plant growth in Table 1, which builds on prior work in other branches of biology[49] to describe plant growth model development, adaptability, data requirements, and expert knowledge requirements.

Synthesis of ML and MPM approaches has been demonstrated for several physiological applications in the medical communities.[51,52] These studies showed success for both type-2 diabetes phenotyping[53] and in the detection of brain tumors.[54] These successes in biomedical and human physiological studies suggest there is an opportunity to create hybrid models for use in CEA to model, predict, and optimize a wide range of plant growth objectives. Such hybridization has also been applied within the industrial sector, as evidenced by the increasing popularity of Digital Twins, high-fidelity digital models used to capture physical systems, first adopted in the industrial realm by NASA and the U.S. Air Force.[55] Digital Twins have been used to characterize manufacturing, urban, and livestock systems[56] and have been proposed for use in agriculture.[57] The objective of this critical review is to provide the basis for MPM-ML synthesis in CEA for sustainability by integrating literature on modeling, control, and automation in CEA within a novel framework we call dynamically controlled environment agriculture (DCEA). Specifically, we focus on the potential to improve the environmental sustainability of produce cultivation using CEA by integrating conventional MPM with recent advances in sensors, computer vision, and ML to perform prediction and control in real time. Such integration of physiological and machine learning techniques has potential to amplify existing efforts in sustainable material use in food production by facilitating the use of dynamic nutrient concentrations (e.g., from waste streams), recycled water, and tighter environmental control.

2. METHODS

In this critical review we synthesize the state of physiological, mechanistic, and machine learning literature to facilitate integrative work. The following section provides an overview of the methodology applied to this critical review.

2.1. Review Approach. First, an initial scoping of literature using Scopus and Web of Knowledge helped identify the key search terms, nutrients, and phenotyping bottlenecks (i.e., measurement and assessment of expressed traits like height, color, etc.) that are present in both MPM and ML models. These key search terms helped establish the inclusion criteria and search terms for both MPM and ML papers as shown in Figure 1.

2.2. DCEA Objectives. To integrate plant physiology with modern computing and optimize resource use, a DCEA framework will require plant growth models that are descriptive, flexible, and scalable. A number of academic and

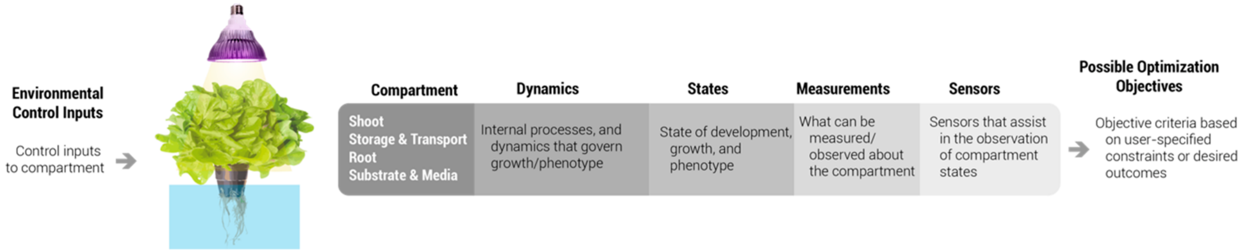


Figure 2. DCEA organizational approach, including environmental control inputs to individual compartments (substrate and media, root, storage and transport, and shoot), dynamics, states, measurements, sensors, and possible optimization objectives.

commercial software packages have been created for modeling the growth of whole plants, including CropSyst,[58] HortSyst,[59] Vegsyst, 3Bigs,[60] and many more. Most of these are analytical tools that run deterministic simulation models to aid in the management of crop systems, crop growth productivity, and the environment. While some existing softwares exhibit dynamic responses and accurate modeling under various factors (e.g., environmental, genomic, etc.), many are inflexible. Many such tools display predictions for a small set of control sequence rollouts or with very weak solvers and lack well-integrated optimization engines to derive optimal controls based on model predictions. For this reason, a dynamic, flexible modeling and control framework is called for that integrates mechanistic understanding of the dynamics that occur within and between individual plant compartments (e.g., roots, shoots, etc.) with modern computational techniques. This critical review provides an overview of state-ot-the-art modeling strategies found in literature with attention to integration opportunities for ML/MPM techniques to achieve these objectives.

The goal of this review is to evaluate the roles nutrients and other environmental inputs play in plant growth, storage, and shoot dynamics and interactions, as more precise understanding could enable higher resource use efficiency, nutritional content, and productivity. For example, dynamic monitoring of photosynthetic status could enable optimization of lighting conditions to suit the dynamic needs of growth, providing adaptive lighting conditions and in turn reducing energy demands. Learning through graphical models and neural networks may help uncover insight to model the effects of nutrient content/stores more accurately on plant dynamics and thus provide growers with more control of outputs. It is generally accepted in the machine learning literature that single models trained end-to-end become increasingly difficult to design and less efficient as the system complexity increases.[61] Decomposing large systems into modules which can be optimized independently then modularly assembled has been a long-standing accepted approach to problem solving that we attempt to bring to this review. To these ends, we begin by presenting some compartment-specific mechanistic and physiological models to identify opportunities to integrate MPM and ML within our DCEA framework.

2.3. Organizational Approach. In the following sections we define a plant as a "system of compartments" to organize our review and contextualize our overall argument that integrating MPM and ML models can support our DCEA framework (Figure 2). Our "system of compartments" plant model that we use to categorize mechanistic models comprises four compartments commonly addressed by MPM: (1) substrate and media; (2) root; (3) storage and transport; and (4) shoot. As Figure 2 shows, each compartment is governed by specific dynamics and includes three categories of variables and their relationships, some of which can be measured using sensors: (un)controllable and/or (un)-observable inputs; (in)directly measurable or latent state variables; and how these compartments may relate to optimization objectives. Interactions between compartment states are identified as interaction ports (nutrient, starch, water, etc.). These ports are characterized by paired state variables that include molar flow and concentration gradient information.

We organized each of the reviewed modeling approaches based on environmental control inputs, dynamics, plant states, measurements, sensors, and optimization objectives into specific compartments (shoot, storage and transport, root, and substrate and media) based on initial findings that the mechanistic models in literature are grounded in physiological phenomena. These compartment sections are broken down into three subsections: (1) physiological basis and mechanistic models; (2) gaps, limitations, and sources of noise; and (3) sensor-mediated MPM-ML integration. This then provides a more flexible, adaptable framework for future integrative hybrid modeling approaches.

3. RESULTS AND DISCUSSION

There are two major thrusts in current plant growth modeling and prediction. Mechanistic models, grounded in first-principles such as Michaelis−Menten, have historically provided the foundation for the majority of such modeling efforts and thus provide a wealth of data and information to inform future modeling endeavors.[34] However, as discussed previously, these MPM approaches have their limitations. Recently, there has been a tendency to supplant this deeply rooted mechanistic knowledge with machine learning approaches that treat the plant as a "black-box," favoring sensors and visual learning techniques to train models. However, we have identified the opportunity to merge the mechanistic understanding of plant growth with modern computing techniques to build leaner, more adaptable models through a compartment-based, dynamically controlled environment agriculture (DCEA) framework. To these ends, plant growth modeling techniques in this section aim to detail methods used in related work to generate models of the plant growth cycle, to monitor changes in growth pattern affected by differing nutrient or environmental inputs. Offering selected examples of the benefits of consolidating machine learning and mechanistic models, this critical review suggests pathways for integration of visual and sensor monitoring with DCEA as a means of providing additional layers of biofeedback to elicit environmental or nutritional modifications that correct for or enhance growth and performance.

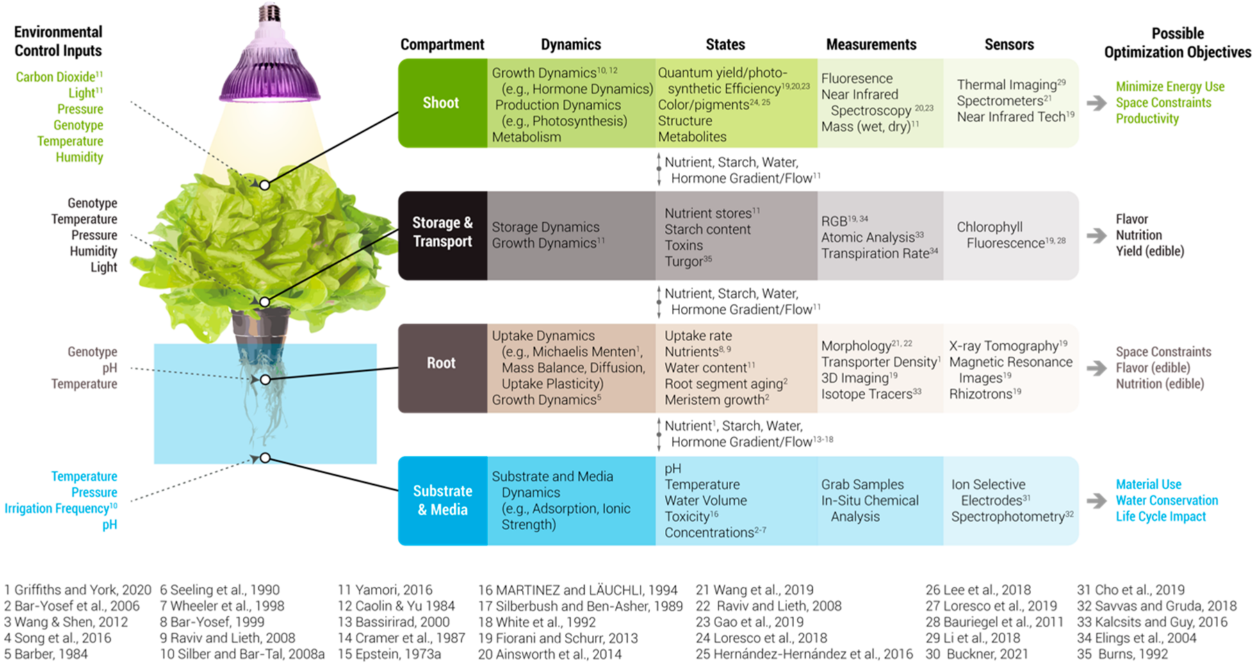


Figure 3. Organizational structure of plant growth models with examples of environmental control inputs, compartments, dynamics, state variables, measurements, sensors, and optimization objectives, which can be user-dictated or location-specific. Examples in each column (e.g., dynamics, states, etc.) are listed independently and do not necessarily correlate to subsequent columns (e.g., measurements, sensors, optimization objectives).

Recent advancements in sensing technology can obtain data of new types and with finer granularity than previously possible.[18] High-throughput phenotyping (HTP) uses a wide range of sensors to collect data and perform analysis on quantitative traits, accelerating phenotype discovery.[62] Some genotyping studies have quantified properties that are otherwise difficult to measure, such as root morphology.[63] Despite these advancements, gathering enough measurement data (i.e., phenotyping) to adequately train ML models is still costly,[47] implicating opportunities for leaner, hybrid models that leverage mechanistic understanding built on years of MPM research. The key capability that advances in sensors, when integrated with ML and/or MPM, provide is the ability to perform real-time monitoring, prediction, and control of plant states in a manner which is adaptive to varying environmental and genetic conditions using biofeedback, as well as offline model validation, parameter estimation, and data augmentation. In the following sections, we address each of these systems, describing both MPM and ML approaches that could facilitate DCEA. In particular, we review current understanding of causal pathways (through MPM) and the types of inputs required for ML to contextualize opportunities to integrate these approaches.

To aid in the development of a DCEA framework, Figure 3 provides an overview of the compartment-based approach we apply in this critical review. References are included with key terms to provide readers with reviewed literature and support a deeper understanding of the included dynamics, states, measurements, and sensors mentioned in each compartment subsection.

The organizational structure in Figure 3 facilitates the identification of MPM/ML model relationships and overlaps—creating an organizational schema that highlights the interactions of key model parameters. This allows for effective compartmentalization of ML/MPM areas that can be improved to better describe, predict, and facilitate control over dynamic plant systems.

3.1. Substrate and Media Dynamics.

3.1.1. Physiological Basis and Mechanistic Models. Understanding nutrient distributions in the growing substrate is important because nutrients enter the plant system boundary from the substrate and media compartment, as depicted in Figure 3. Mechanistic models of substrate−root interactions integrate chemical kinetics and ion diffusion within the growth medium with the physiological modeling of plant uptake phenomena, morphological transformations, and bioaccumulation at a molecular level.[64,65] In idealized MPM models, ion distribution in the nutrient media is affected by (1) boundary conditions, nutrient source by fertigation and sink to the plant uptake, and (2) differential equations, fluid dynamics including diffusion and mass flow.[66−69] One such common MPM strategy is with the advection-diffusion equation for modeling substrate and media dynamics as found in the Barber−Cushman model or the Porter diffusion model.[34,68,70,71]

3.1.2. Gaps, Limitations, and Sources of Noise. Many existing MPMs used to describe substrate and media dynamics have shortcomings including: complexity;[34,68,70,71] neglect of variable spatial and temporal scales;[72] applicability to situations with dynamic nutrient influent concentrations;[73−77] and consideration of key physiological considerations like active transport on the root surface or the effect of multiple ions on uptake.[34,41,78] Additionally, a number of confounding phenomena can make dynamic monitoring and control challenging in the substrate or grow media. For example, excess salinity can cause toxicity[74−77,79,80] but modeling salinity accumulation over the course of a grow-out requires accounting for input water salinity, evaporation, advective and diffusive flow, and interaction with the root uptake dynamics among other variables.[78] These shortcomings are reflected in existing software with complex models built-in, such as Visual MINTEQ,[81] MINEQL+,[82] and CHEAQS,[83] which are commonly used to manage chemical equilibria calculations.[18] Their complexities make it nearly impossible for end-users to understand and tune the often hundreds of parameters. Furthermore, complexity makes model verification difficult which in turn masks the omission of key unmodeled processes. Therefore, current MPM models and software tools alone are insufficient for the improved accuracy and reliability required for DCEA.

3.1.3. Sensor-Mediated MPM-ML Integration. The complexity of the dynamics involved with the modeling and control of nutrient substrate and media offers opportunity where ML may be of help. ML may be able to better capture complex and unknown/hidden interactions, as well as adapt to real-world data with less expert tuning. At the same time, existing MPM knowledge may be used to reduce the large data demands of ML and risk of overfitting. MPM can also help in fusing together different information streams and models, such as by integrating sensor data with the chemical equilibria to enable self-calibration, real-time monitoring, and dynamic feedback mechanisms. However, in order to fully leverage the opportunity, sensors and real-time data collection will be necessary.

In hydroponics, monitoring of nutrient salts is more straightforward than in soil agriculture,[84] making it more tenable to match supply to plant demand, but implementation and control depends on the type of hydroponic system. In flow-through systems (where substrate is continuously refreshed), farmers track electrical conductivity (EC) of substrates,[69,85] which is a cost-effective way to monitor the overall ionic strength of the substrate and can be useful when applying standard nutrient feeds at consistent dilutions as determined by growth phase and cultivation history; however, EC monitoring alone is unsuitable for recirculation and DCEA due to its inability to capture discrete ion concentrations,[86] which may individually require manipulation over time to maintain adequate nutrient supply.[78,87]

In practice, sensors placed in root-zones, supply/drainage measurement, and combinations of well-informed heuristics/empirical models and theoretical models can describe individual nutrient distributions and their dynamics through time-series models. Integration of ion-selective electrodes (ISEs) coupled with computer data management could also aid in the development of dynamic or adaptive modeling efforts, and in order to mitigate inaccuracies resulting from ion interference during in situ use, artificial neural networks (ANNs) have been recommended.[88] The application of ANN has been found to be most accurate when paired with a two-point normalization method (TPN) that compensated for signal drifts and interference in ion sensing capabilities, especially when monitoring NO_3^-, K^+, and Ca^{2+} ions.[88] Such differences should be considered when applying in-line sensing to different CEA configurations to more tightly control and regulate nutrient use and in turn conserving material inputs.

3.2. Root Uptake Dynamics and Structure.

3.2.1. Physiological Basis and Mechanistic Models. The uptake of mineral nutrients by plants is mediated by plant roots (Figure 3), making root activity and architecture (morphology) critical layers of study to guide our understanding of nutrient use efficiency[34] and dynamic system control. Root morphology and nutrient concentration have complementary effects, since uptake rate is the integral of the flux multiplied by root surface area (or length) in a given volume, over the total number of volumes in the substrate.[80,89] Leveraging simultaneous study of root morphologies and ionic transformations within growth media and biomass, successful models can predict plant growth.[90] Such models often evaluate nutrient flux across the root cell plasma membrane as a function of nutrient concentration, which is communicated through the substrate dynamics and root uptake dynamics ports.[64,91−95] The dynamics of this root uptake have direct implications for material use efficiency in agriculture and are predominantly modeled using enzyme reaction rate kinetics, as demonstrated by Michaelis−Menten (MM),[96] one of the most widely used MPM in plant nutrient modeling. Therefore, the control over root uptake dynamics can have long-standing impacts on both net nutrient addition over the lifespan of the crop and emissions to the surrounding environment by way of spent substrate effluents.

MM kinetics show that nutrient influx to root tissue is rate-limited and embedded in biomass growth.[34] MM kinetics model the effect of the probabilistic processes of enzyme transporters and have been used to describe plant uptake and growth given nutrient concentrations, where the flux J [mol $(\mathrm{m}^2\ \mathrm{root})^{-1}\ \mathrm{s}^{-1}$] of a given nutrient, i, through the roots' surface has been summarized as

$$J_i = J_{\mathrm{max},i}\frac{C - C_{\mathrm{min}}}{K_{\mathrm{m},i} + C - C_{\mathrm{min}}}$$

where K_{m} (μM) describes the substrate concentration at half maximal uptake, C (μM) is the concentration of nutrient i in the solution culture, and C_{min} is the minimum concentration at which nutrients are absorbed. Using this formulation, researchers have determined that the concentration of a given nutrient in the surround substrate (e.g., soil, hydroponic nutrient solution), especially nitrate, has a strong influence on the uptake of the nutrient[75,90,97]

Some more recent MPM, including the Barber−Cushman and Porter diffusion, partially overcome MM models' inabilities to generalize by combining elements of the substrate dynamics and root uptake dynamics compartments into a single model. The concentration of nutrients in the substrate and enzymatic activity in the root are neither spatially nor temporally uniform as assumed by traditional MM literature. In response, the Barber−Cushman model assumes the nutrient concentration in solution follows a spatial distribution given by mass flow and diffusion (advection-diffusion equation), with MM providing a Robin boundary condition.[65,70] The Porter diffusion model is similar, incorporating geometry into the substrate advection and diffusion equations.[68] Both models illustrate how independent models of the substrate and uptake dynamics can be combined to form more realistic plant models.[64,91−95]

3.2.2. Gaps, Limitations, and Sources of Noise. Embedded in all these examples of MPM lie inherent limitations that could be mitigated through use of ML. Complexities such as the interplay between geometry, competing or inhibiting nutrients, and additional physiological processes discussed later in this paper, simplified models such as MM alone are not dynamic or generalizable enough for DCEA. However, integrating ML with simplified models offer opportunities to learn and incorporate the implicit, hitherto unknown dynamics overlooked by MM models to form hyper-realistic plant models without having to explicitly define the underlying processes affecting uptake dynamics. Common assumptions in these models include homothetic behavior of the kinetic parameters at a range of biological scales (e.g., the epidermis cell, root segments, root axes, and the whole root system)[68] and isotropic, quasi-static (or constant) levels of ion concentration, water level, light, and salinity.[98] Furthermore, recent meta-analyses of nutrient uptake studies reveal a wide range of nitrate flux parameter values, due in part to the fact that uptake kinetic capabilities of a plant are highly dependent on the growth and measurement environments as well as temporal concentration dynamics.[34] In addition to a nutrient's concentration, uptake can also be dependent upon the concentration(s) of *other* nutrients.[41,78,99,100]

3.2.3. Sensor-Mediated MPM-ML Integration. ML could offer the opportunity to uncover more robust parameter values in MM and model more broadly generalizable extensions, when used in conjunction with conventional laboratory or field trials. Techniques developed for structure from motion (SfM) and simultaneous localization and mapping (SLAM) have more recently been applied to generate 3D spatial reconstructions and even 4D spatiotemporal reconstructions of plant growth to better understand local growth dynamics.[101−103] Reconstruction techniques have also been applied to root imaging in solution culture and aeroponics as well as in rhizotrons.[48] Noninvasive (i.e., those that do not require destruction of the plant) advances in root imaging best suited for biofeedback include magnetic resonance imaging (MRI) and X-ray computed tomography (CT).[48] Advanced computational tools for root classification include multiple instance learning, and the deep learning based U-Net, CNN (convolutional neural network), and transfer learning algorithms.[104] While these solutions provide insights into root system development, a community-wide database of images and learning models does not yet exist at a scale to provide sufficient data inputs for a purely ML-based approach, implicating hybridization opportunities.

ML and computer-mediated feedback development could assist in uncovering complex interplays as they relate input and output quantities. For example, it has been found that nutrient uptake plasticity can have impacts on uptake rates. Roots previously subjected to pretreatment under nutrient deprivation can subsequently exhibit significantly reduced uptake rates compared to roots from the same plant previously exposed to higher concentrations under pretreatment.[105−107] Such plasticity could have far-ranging impacts on predictive models for setups that rely on variable nutrient influx (e.g., waste-derived, or input-dependent circular-economy setups), where dynamic conditions could significantly alter adherence to predetermined parameter values or isotherms. In such cases, ML and biofeedback mechanisms could be particularly useful in predicting and controlling conditions to suit desired yields.

3.3. Transport and Storage. *3.3.1. Physiological Basis and Mechanistic Models.* The dynamics mediating the transportation and storage of water, nutrients, and energy between the root and shoot are critical in modeling the overall growth of a plant, but current approaches largely rely on incomplete MPM. Section 3.2.1 described supply driven models of nutrient uptake in which uptake is a function of the substrate availability, but demand-driven models, which model uptake as a function of plant dry mass by organ and growth stage, have also been proposed and imply the demand for nutrients by plant masses dictates nutrient uptake substrate.[69,108] However, both supply and demand affect nutrient uptake, and the nutrient gradients and flows between different plant compartments is dependent upon dynamic effects (e.g., resistance due to gravity and stem geometry), which are necessary to understand for generalizing MPM models to DCEA.

Similarly, energy in the form of carbon, ATP, and redox equivalents is produced and consumed by different plant organs. Thus, energy transport throughout the plant is also dependent upon both supply by shoot dynamics and demand by growth, maintenance, and root uptake.[109] Many factors such as age, light, and temperature all affect the energy demand of various plant organs.[109] Energy is also stored in large quantities for future use by many plants (e.g., tubers).

Plant water status is another physiological attribute that influences many aspects of plant dynamics such as mass transport, photosynthesis, osmotic pressure, and turgor pressure, as well as having direct implications for resource management and use efficiency. Water content is affected by inflow from the uptake dynamics and storage and shoot dynamics port and outflow due to transpiration. Transpiration rate can be mechanistically modeled with the Penman−Monteith equation.[110] Water flow is regulated by demand to the uptake dynamic and storage and shoot dynamics port and regulation of transpiration via stomata.[111,112]

3.3.2. Gaps, Limitations, and Sources of Noise. Understanding the dynamics of energy transport and storage throughout the plant is imperative for real-time plant modeling in DCEA and involves combining well-understood MPM with ML models for less-understood processes. Specifically, the trajectories of energy transportation and storage in a *typical* plant can be well measured, but the factors which mediate these dynamics and modify them in response to various stimuli need further study. Because transport and storage depend strongly on so much hidden information (e.g., hormones), ML may be particularly well suited to uncovering latent states and dynamics.

Phytotoxicity is also relevant for DCEA because toxins can gradually build up in plants, giving them a dynamic state. Many nutrients, such as Na, Cl, K, Mn, phenolic compounds, terpenes, organic acids, and fatty acids, can cause phytotoxicity if applied in excess.[78] Thus, these nutrients need to be controlled within specified parameters to avoid mismanagement or detrimental effects. Moreover, dynamic monitoring of uptake can further mitigate risk, but models alone tend to be insufficient. Nitrate accumulation in leaves is another cause for control in CEA which not only impacts nutrient use efficiency, but also has adverse effects to human health if consumed.[108,113] Nitrate accumulation has been shown to be affected both by substrate and atmospheric conditions[114] illustrating the need for more comprehensive models in DCEA. Like energy dynamics, nutrient and toxin dynamics may benefit from ML due to the abundance of unobservable variables.

Nutrient concentrations in the plant, especially freely available nutrient concentration in storage (e.g., vacuoles), are latent variables, meaning concentrations are not easily observed in real time. This makes the roles various nutrients play in the storage and shoot dynamics challenging to characterize without offline analysis. In dynamic models especially, effects are often inferred indirectly through nutrient uptake. For example, photosynthetic rate, stomatal conductance, and transpiration rate show dependence on nitrogen uptake,[115] and others have demonstrated the applicability of near-infrared spectroscopy in the measurement of carbohydrate storage.[116] Even so, nutrients have different concentrations in different organs,[69] which makes developing mechanistically accurate models from indirect inference even more challenging.

3.3.3. Sensor-Mediated MPM-ML Integration. Atomic analysis, isotope tracers, and other analytical chemistry techniques are irreplaceable tools for better understanding the roles nutrients play in storage and shoot dynamics in addition to interactions between storage and shoot dynamics and growth dynamics.[117] Spectral reflectance has also shown promise in predicting nutrient deficiencies.[118,119]

As mentioned above, plant water status has implications for numerous other plant systems, thus providing another key opportunity to integrate physiological understanding with sensors for dynamic biofeedback and control. Water content can be measured using NIR reflectance sensors and has been used to identify water-stressed crops.[119] Transpiration rate can be estimated through thermal measurements of leaves.[120−122] By combining dynamics equations with measurements of transpiration, irrigation, evaporation, and NIR water content, water content in the plant can achieve good observability when used in a factor graph estimator or sensor fusion.[123−125]

3.4. Shoot Phenotyping and Classification. *3.4.1. Physiological Basis and Mechanistic Models.* Accurate shoot models are integral for practical application of plant growth modeling, as this compartment largely predicts the crop yield. The shoot compartment in Figure 3 encompasses many of the dynamics associated with carbon production and use, including both the photosynthesis mechanics and shoot geometry or structure.

The type and direction of shoot growth, which influences plant efficiency and crop yield, are affected by various factors including genotype, forces, and resource directions. Growth is primarily fueled by photosynthetic activity and the foundations of many growth models assume growth rate to be proportional to mass or area, though the parameters differ appreciably species-to-species and even experiment-to-experiment.[34,68] Environmental forces such as gravity and wind impact the direction of growth by promoting primary growth in the corresponding directions or by asymmetrically promoting secondary growth causing bending.[126−128] Reactions to grow toward resources such as light or higher nutrient concentration pockets can be expressed as the differential demand for growth by different shoot or root segments.[126,129] Finally, growth may also be accelerated or inhibited by resource surpluses or shortages. For example, root growth may be slowed when nutrient content in the storage and shoot compartments is sufficient.[130] Feedback interactions with various nutrients and organ-specific growth behavior have been shown to correlate growth rate to the dynamics of other compartments,[131] making growth a particularly interconnected modeling component.

Dry mass (DM) accumulation has been found via statistical methods to follow predictable stages across plant species which, in our review framework, can be explained by the interaction of multiple mechanistic models. Initial vegetative growth exhibits exponential growth followed by linear growth and a possible senescence phase depending on season or other environmental changes. Fruiting growth exhibits linear DM accumulation.[69] The initial exponential growth can be interpreted as a feedback loop between the uptake dynamics and growth dynamics because photosynthetic activity generates carbon proportional to leaf area (source) and uptake-enabled growth increases leaf area proportional to carbon flow (sink). The linear growth rate is typically explained by diminishing returns due to leaf overlap causing projective leaf area to not scale linearly with leaf area. In this phase, more accurate modeling incorporating the interplay of production and growth mechanistic models may be investigated. It is also claimed that hormonal signals inhibit leaf growth during this period,[68] possibly to actively prevent self-overlap, which could be supported or refuted using computational learning techniques and plant geometry data. The possible senescence phase is explained by environmental changes reducing photosynthetically active radiation (PAR), an input to the photosynthetic dynamics of the storage and growth dynamics compartment. Finally, linear DM accumulation during fruiting is expected because growth dynamics direct growth toward fruit instead of toward leaves so leaf area does not change during this phase. Thus, we can see that dry mass accumulation stages during vegetative and fruiting growth can be easily explained as indirect relationships naturally arising from existing mechanistic models in isolated compartments.

3.4.2. Gaps, Limitations, and Sources of Noise. Crop yield, which is strongly dependent upon photosynthesis, is an important attribute for measurement and control that involves complex dynamics that MPM often fails to adequately predict. Dry matter (DM) accumulation in the shoot has potential ramifications in material input efficiency. DM accumulation is primarily attributed to photosynthesis as opposed to nutrient uptake on account of biomass stoichiometry, whereby 40−50% of dry matter is carbon, derived from CO_2.[69] Photosynthesis is well described by chemical models through several genotype and environmentally dependent pathways and has strong correlation to plant geometry since shoot irradiance depends on geometry, while growth is also directed as a function of light. However, mechanistic photosynthetic models are limited in capturing the interconnected nature of plant growth. The photosynthetic rate, in turn, is primarily dictated by light, CO_2, and water content but may also depend upon other atmospheric conditions and nutrient availabilities if there are deficiencies.[109]

Modeling of shoot structure, pathways, and the subtle relationships between nutrient deficiencies and photosynthetic production all present opportunities for ML to improve upon the power of MPM. These pathways are particularly salient to DCEA due to their dependence on so many environmental and genetic factors. Photosynthesis pathways have been well studied, with Farquhar's early C3 model being the basis for many C3, C3−C4, and C4 models.[132] The basic C3 model for photosynthesis involves CO_2 diffusion from the atmosphere to the chloroplasts and Rubisco carboxylation and oxygenation rates which are light-dependent, but a number of improved models can be made by considering additional diffusion and reaction dependencies.[109,132] The C2 pathway, used for photorespiration, is also often used at a rate of 25−50% that of photosynthesis depending on CO_2 stress conditions.[109] Although it is less efficient, it is thought to be related to nitrogen uptake and accumulation thereby affecting the nitrogen port from the root compartment. Despite powerful MPM, the complex interplay between nutrient stores, environmental conditions, and photosynthetic processes could benefit from ML in attaining better adaptability and robustness for DCEA.

3.4.3. Sensor-Mediated MPM-ML Integration. Photosynthesis is one of the better understood plant dynamics in part because it has several nondestructive and accurate measurement techniques. PAR sensors can accurately measure the radiative power available to the plant. Together with leaf geometry measurements, the radiative power available for photosynthesis can be measured. CO_2 sensors can also monitor for gas-related deficiency and closed-chamber or highly controlled environments, such as is common in photoautotrophic micropropagation studies, can even be used to measure photosynthetic rate with even greater precision and rigor.[133] Temperature, which also affects photosynthetic rate, can also be measured. Finally, chlorophyll fluorescence, thermal imaging, and imaging spectroscopy can be used to measure parameters such as quantum yield, chlorophyll A density, radiation absorption, and photosynthetic efficiency.[119,134,135] Spectral reflectance can even be used to estimate photosynthetic parameters in remote sensing applications (i.e., from air and space).[118] Once platforms provide significant biofeedback integration, this data can be translated into learning outcomes for future automation.

Imaging techniques for measuring plant geometry have been increasingly used for noninvasive data collection on plant geometry and growth,[136] enabling farmers and researchers to track and monitor growth without damaging plants, and in turn validate models, control inputs, and predict outcomes. Imaging technologies include red/green/blue (RGB) imaging, IR-based depth imaging,[48,137] time-of-flight (ToF), and LIDAR which can be used at scale and in situ, as well as MRI, PET, and CT scans which are primarily for research purposes.[48,136] Indeed, highly significant linear or polynomial correlations have been found between calibration of part area based on total leaf area and fresh and dry mass, via single-view RGB imaging.[138] RGB imaging, though, lacks robustness to lighting-related variability such as shadow and inconsistent lighting.[136] An increase in precision can be achieved by digitally reconstructing leaf area and growth rates.

Sensors that provide depth, such as RGB stereo imaging,[139−141] IR-based depth imaging (e.g., Kinect, Realsense),[142−144] time-of-flight,[141] and LIDAR,[145,146] appear to be capable of creating significantly more detailed and precise plant geometry reconstructions but are primarily used for topology measurement from a single or few views for LAI or canopy analysis.[136] Tomographic imaging technologies including MRI, PET, and CT scans have also been applied for studying plant growth and geometry, but their throughput is too low for widescale application.[136]

Classification, or segmentation, based approaches are majorly classified into classical segmentation approaches and ones that use neural networks to augment their methods. Such approaches allow algorithms to be geared toward identifying disease in plants, in addition to growth stage analysis. Multiple phenotypes (e.g., leaf area, stem diameter) can be estimated through images, when additional scale information is provided. Conventional ML strategies, such as support vector machines, have been used to estimate leaf area, stress effects, crop growth, and genetic association.[104] Additionally, genetics have strong correlations to both overall growth factors and stage-specific growth factors, and low cost, high throughput techniques have been developed to correlate growth properties with specific genetic markers, many of which have been studied using ML.[63]

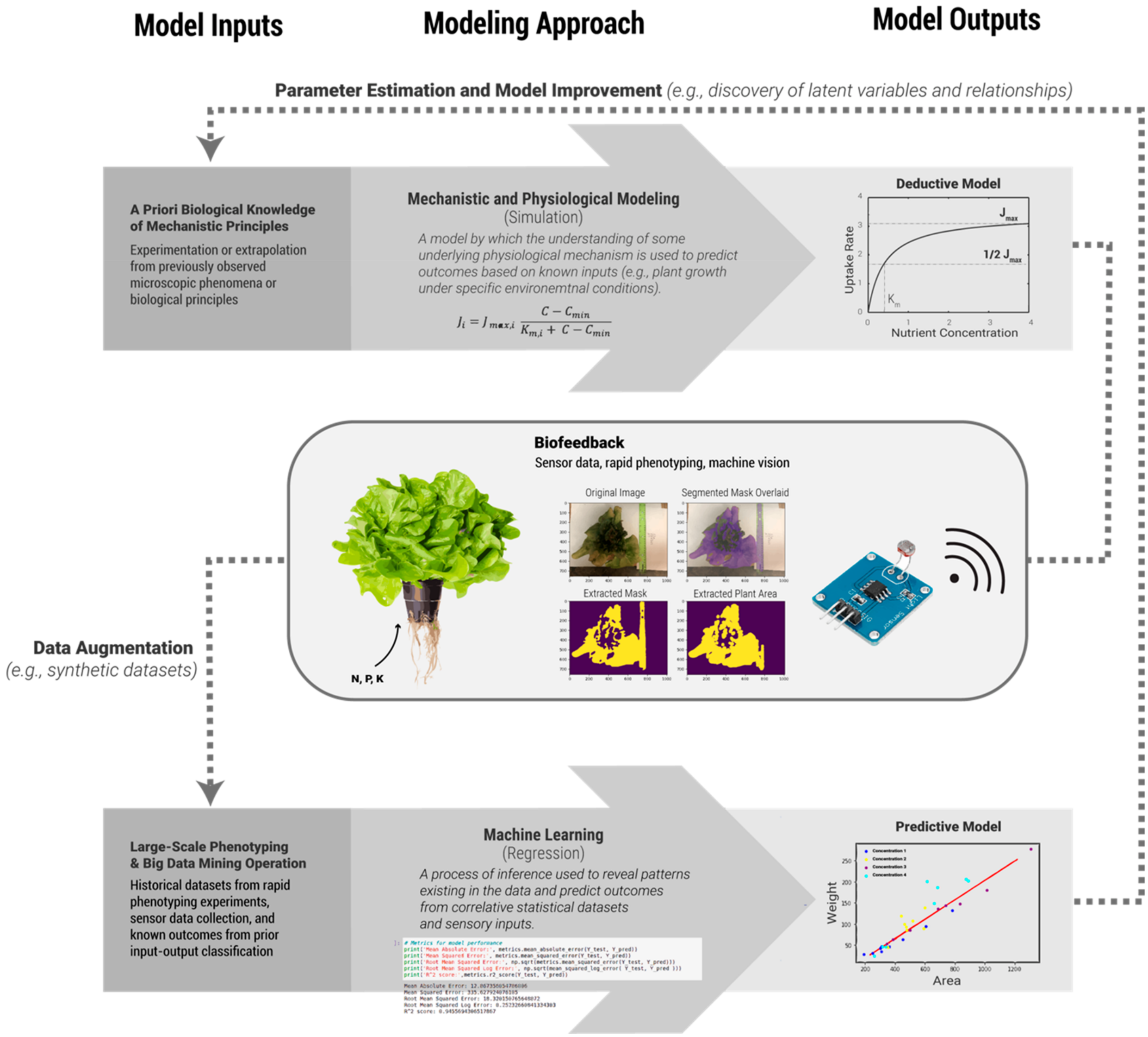
One approach has been to use feature extraction to classify plant canopy. Multiple weak classifiers can be combined to build a strong classifier, such as the Viola−Jones classifier. This can be used in conjunction with a marker of known size to accurately measure the leaf area index.[147] From a performance comparison of multiple classifier types (support vector machine (SVM), multilayer perceptron (MLP), and random forest (RF)) for plant segmentation, it was observed that random forests afforded the highest precision; however, the choice of hyperparameters for each classifier greatly affects the resulting performance.[148]

Hidden Markov models (HMM) are system models which are assumed to evolve (discretely in time) as a function of only the current system state and inputs, where the former may be hidden and only indirectly observable. Probabilistic approaches like HMM work well due to their robustness in dealing with imperfect plant data. For example, HMM has been used to find correspondences between sets of stem and leaf scans separated temporally, estimating correspondences as the hidden states of the model. It, however, requires a minimal representation to be computed explicitly beforehand.[103]

Graphical models have seen great success modeling HMMs and other systems in fields such as robotics and machine learning, and have recently gained popularity for use in agricultural modeling and automation.[149−151] Bayesian Networks (BNs), graphs in which directed edges indicate causal dependencies of the target variable nodes on the source variable nodes, are particularly common graphical models in agricultural modeling due to their natural ability to handle uncertainty and learn from incomplete information.[152] BNs can also incorporate varying degrees of learned vs expert-supplied information, with several technique available for learning the structure of the graph itself from data in addition to the parameters.[152] Recent applications using sensors have further increased the utility of BNs, but BNs still tend to be too highly reliant on unknown or as of yet undiscovered environmental parameter values due to variable microclimate effects.[20]

One of the main challenges in segmentation-based approaches is the initial step of accurately segmenting the plant from the background, due to sensitivity to lighting changes, camera resolution, and scale.[147] Analyzing different color spaces effectively performs this segmentation; however, the variability and complexity of images in a hydroponic environment limit the applicability of simple color-based segmentation. An augmentation to this approach is iterative thresholding based on color information and subsequently clustering into spatially coherent segments based on color similarity and pixel proximity. This approach has reported increased robustness to illumination changes.[153,154] Lee et al. built on this by incorporating a random forest classifier,[148] leading to high performance plant segmentation even in the presence of noisy data.

Deep learning-based frameworks can increase the accuracy and robustness of segmentation tasks with uncertain size, low resolution, or complicated background. Contrary to conventional ML approaches, which are sensitive to image variation due to changes in lighting, deep learning methods instead rely on feature extraction to directly perform plant phenotyping tasks from input images without the need for preprocessing. Region-based convolutional neural networks (CNNs) have been used to perform semantic segmentation of crops in real-time.[155] While the current approaches are currently designed to segment crops and weeds from soil in robotic farming, the premise can be extended to hydroponic setups with controlled background environments. Techniques such as long−short-term memories (LSTMs) have proven to be particularly useful in modeling the dynamic nature of plant growth, encoding temporal information in classification. Combined with CNNs, this type of framework lends itself well to phenotyping over the



Experimentation or extrapolation from previously observed microscopic phenomena or biological principles

A model by which the understanding of some underlying physiological mechanism is used to predict outcomes based on known inputs (e.g., plant growth under specific environemntal conditions).

$$J_i = J_{max,i}\frac{C - C_{min}}{K_{m,i} + C - C_{min}}$$

Historical datasets from rapid phenotyping experiments, sensor data collection, and known outcomes from prior input-output classification

A process of inference used to reveal patterns existing in the data and predict outcomes from correlative statistical datasets and sensory inputs.

```
]: # Metrics for model performance
   print('Mean Absolute Error:', metrics.mean_absolute_error(Y_test, Y_pred))
   print('Mean Squared Error:', metrics.mean_squared_error(Y_test, Y_pred))
   print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(Y_test, Y_pred)))
   print('Root Mean Squared Log Error:', np.sqrt(mean_squared_log_error( Y_test, Y_pred )))
   print('R^2 score:',metrics.r2_score(Y_test, Y_pred))

   Mean Absolute Error: 12.867358654706806
   Mean Squared Error: 335.627924076105
   Root Mean Squared Error: 18.320150765648872
   Root Mean Squared Log Error: 0.25232660841334383
   R^2 score: 0.9455694306517867
```

Figure 4. Proposed opportunities for synthesis in mechanistic and physiological modeling (MPM) and machine learning (ML) to improve model efficiency and performance.

growth stage of a plant.[156] Multiview approaches can be combined with deep learning techniques to segment and build a 3D point cloud of the plant. Such 3D point clouds offer higher precision when segmenting plant parts into stem and leaves, including individual instances of leaves, when compared to 2D segmentation, which can occasionally classify similar-looking background pixels as foreground (plant).[103,157,158] Magistri et al. extended the advantages of a 3D point cloud to a temporal association, by using semantic segmentation via an SVM to extract correspondences between point clouds, allowing for phenotype tracking over plant growth.[159]

To summarize, more sophisticated models which tightly couple shoot dynamics with other components are needed for DCEA. Growth modeling directly affects many other dynamic processes throughout the plant since most processes are geometry dependent, such as the dependence of nutrient uptake and photosynthetic activity on root surface area and leaf area index respectively. Conversely, production and uptake directly affect growth in spatially and temporally dynamic processes, making ML (e.g., computer vision) a particularly useful tool in modeling such complex interactions.

3.5. Integrating ML and MPM into DCEA.

MPM rely on empirically derived parameter values that are specific to plant varietal, growth environment, light intensity, and a host of additional variables, so empirical calibration is required to determine the validity and applicability of the mechanistic models derived for plant growth. Techniques such as regression have long been used to empirically derive the parameters required for mechanistic models.[160] The intent is that empirical parameters are generalizable across plants, but in practice this is rarely the case with wildly different parameters found in different environments, laboratories, and even among different growth cycles in the same laboratories under the same controlled conditions.[69,151,160] When the same measured inputs create different outputs, it becomes clear that there are unmodeled variables such as genetic, human, or environmental variability that are insufficiently measured and accounted for.

Meanwhile, advancements in modeling, such as ML-based techniques, can better make use of such vast amounts of data. For example, contemporary data assimilation approaches, such as the PEcAn framework, use Bayesian modeling to derive

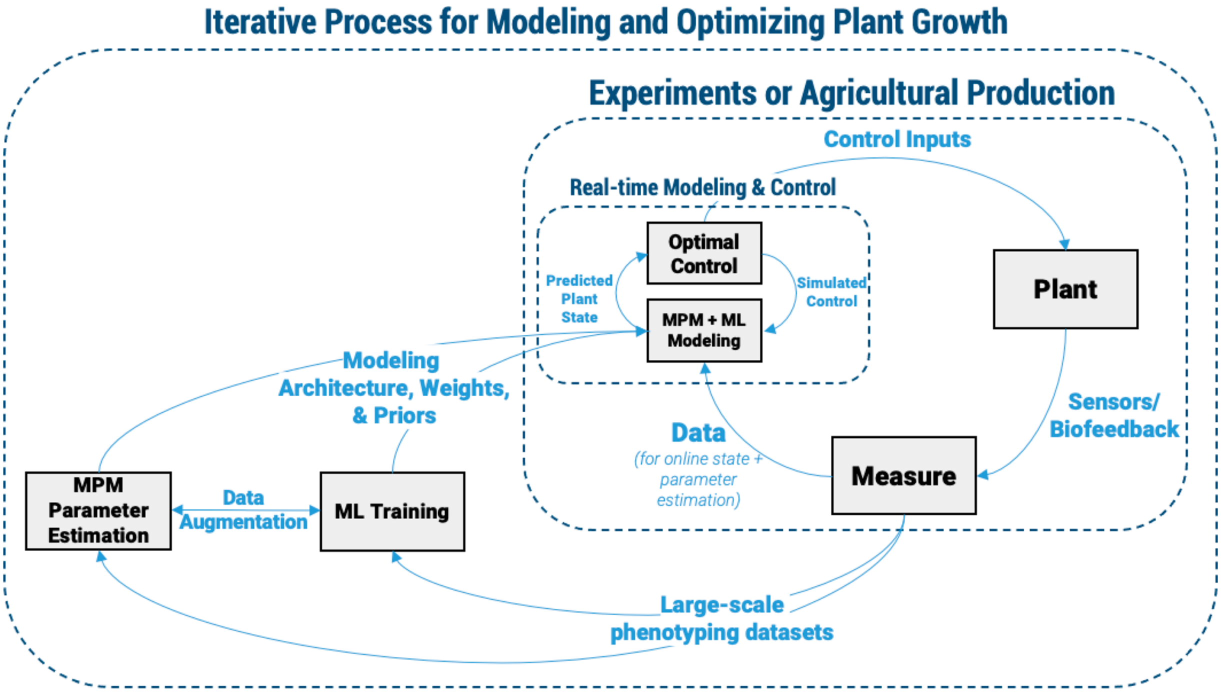


Figure 5. High-level model refining process which illustrates how ML + MPM can be integrated both within the plant model and also for offline analysis/optimization. In real-time modeling and control, data from biofeedback can be used not only for plant state estimation, but also online model parameter estimation using machine learning (e.g., dynamic Bayes nets).

parameter values efficiently from large data sets. Data assimilation has been used to characterize very large-scale vegetation changes to improve ecological modeling efforts.[161] However, this highlights a shortcoming, as ML strategies are inadequate if data are not prolific. Without sufficient usable training data, the ML methods often return incorrect estimates of the underlying relations driving processes or produced results that are unusable. Given the "hidden states" nature of ML models, this could result in drastically different predictions for nutrient uptake or phenotypic expressions for given input variables.

Dynamic environments, complex confounding relationships, and poorly understood processes present several challenges for MPM, where combining ML with MPM may help. Several confounding attributes of plant nutrient uptake, use efficiency, and growth provide opportunities for synthesis between ML and MPM. Other, less well-understood drivers of nutrient uptake such as transporter efficiency and density which have complex interactions between genotype, environment, and phenotypic expression, make accurate per-plant modeling difficult.[34] Learning via a hybrid model would incorporate the knowledge of underlying dynamics via mechanistic modeling while also allowing for predictions of hidden quantities that influence the plant state.[52]

In addition to dynamic concentration considerations, a host of other factors can confound predictive MPM, providing opportunities for ML integration. For example, the use of simplified mechanistic models to describe nutrient uptake in an entire plant system can undermine the concatenation of systems involving multiple ion transporters, assimilation mechanisms, uptake into vacuoles, and organismic transformations.[34] When molecular-scale mechanisms of nutrient uptake are broadly classified as phenotypic traits, resolution can be lost. As such, mechanisms and patterns of activity in the intermediate layers that result in physiological regulation and in phenotypic manifestations at the macroscopic level may be needed when building more robust predictive models.[48] ML has been used successfully to relate phenotypical parameters to plant genotypes,[119,162] further implicating ML as a tool that could improve the MPM.

Whereas over-reliance on MPM requires expert knowledge and considerable research resources to expand models to make use of additional sensor modalities, ML and other approaches that are less reliant on MPM can more easily scale to include the ever-growing modalities and quantities of measurement data. Figure 4, which builds on conceptual frameworks proposed for human biology,[49] provides an overview of some proposed opportunities to create hybrid ML-MPM models using sensors.

The integration of various modeling efforts coupled with real-time monitoring of plant states could afford practitioners the ability to control and optimize growing conditions depending on desired outcomes, which can include sustainable material management, energy use, and waste generation, or even plant nutritional value. Through sensor integration and computer vision, biofeedback can be introduced as a real-time mechanism to dictate appropriate actuation at the plant-level, farm-scale, or urban network scale, where nutrient demands, as measured by visual or sensory cues, can dictate supply routing and network organization. Augmenting the approach with real or synthetic data from mechanistic models integrates the biofeedback mechanism, placing constraints on the predictive functions of machine learning. This could serve to reduce the dependence on input data quantity.[51] Noninvasive techniques, including methods from computer vision, can be used to confirm, validate, and augment mechanistic models experimentally by building visual models. These models, when integrated with machine learning, can monitor, quantify, and predict phenotypes and physiological conditions highly accurately, thus improving upon our understanding and determination of mechanistic models.

3.6. Future Perspectives for DCEA.

Hybrid MPM-ML models could provide profound opportunities to improve nutrient, energy, and water use efficiency. Moreover, DCEA could enable pathways to optimize nutritional content of produce, making possible designer produce and medicinal food options for public consumption.

For such integrative work to become truly powerful to optimize growth in DCEA, there is a need for scientists to test and compare different models with different crop types to identify the model components that are most well-suited in a variety of scenarios. Once this work is done, a simplified MPM that is more generalizable could be developed and augmented using ML for parameter adjustment and the discovery of latent variables. Figure 5 depicts the plant modeling process and illustrates two high-level directions where ML and MPM can complement each other. In the first, the whole-plant model can be composed of both ML and MPM models, using the each in the plant compartments where they excel. The division of a plant model into four compartments, substrate, root, transport, and shoot, allows a modular architecture in which any suitable model can be used for each compartment. Referencing Figure 3, the only invariant a model must satisfy is to use the same nutrient/starch/water inputs/outputs to the adjacent compartments, but any MPM or ML model can be used for each compartment using whatever choice of dynamics equations, states, and feedback measurements apply for that model. The second area where ML and MPM can complement each other is in offline data analysis. MPM may be able to create synthetic data or perform data augmentation to amplify small data sets for training ML models. The hybrid whole-plant model can also be used to estimate latent variables or be optimized end-to-end to improve both ML and MPM model parameter/weight priors using data that could not otherwise be measured.

Another exciting application for ML-MPM integration in DCEA is the translation of graphical models to hierarchically scale a single plant model to many plants, rows, farms, and even cities by connecting subgraphs. Connecting multiple plants in a greenhouse, for example, can be achieved through interaction ports by first creating many plant models by following the following procedure: (1) matching their environmental inputs (i.e., temperature, humidity, etc.) to one common set of variables representing the greenhouse's environmental condition; (2) connecting their nutrient solution input ports to the total irrigation and fertilizer input port; and (3) summing their crop yield ports into a total crop yield port. By combining many plants into a single graph, practitioners will have the ability to optimize for the total resource consumption and yield. This is a powerful step toward broader resource conservation and agricultural material use efficiency, especially given the variability in requirements among individual plants. Similarly, the resource input and yield output ports of each greenhouse can be summed to obtain the total inputs and outputs of a farm, and the input and output ports of each farm can be summed to obtain the total inputs and outputs of a city. Furthermore, the graphical models are flexible enough to also model food consumption, waste generation, and waste processing. These relationships are not necessarily directional: demand drives supply just as much as supply drives demand.

Sensor technologies can also provide feedback of plant phenotyping on an agricultural scale. Both conventional machine learning and deep learning strategies can be applied to computer vision segmentation techniques to measure plant stress effects. To capture high-throughput data at large scales, multispectral, hyperspectral, visible, and thermal cameras can be used for remote sensing.[104]

Sparse, nonlinear incremental optimization algorithm based on Bayes trees[163] also naturally provides an efficient means for distributed computing by intelligently relinearizing compartments only when necessary. For example, city-level resource management, food supply chains, and distribution networks can be optimized using linearized farm models, with relinearization "requests" to farmers made only when necessary. Representing sparse, modular plant growth models using factor graphs naturally scales to efficient distributed optimization of multilevel hierarchies for resource management and food supply.

While DCEA holds promise for more precise, dynamic control of the growing environment, there still exist several limitations requiring further research. For example, current approaches to CEA are restricted to a select few crops (e.g., leafy greens, herbs), limiting applicability of local CEA. Additionally, energy use in a strictly controlled environment is typically higher than field-grown produce. Because of these potential limitations, to facilitate the proliferation of a sustainability oriented DCEA protocol, more work is needed to broaden the applications of CEA to include additional crops and reduce energy consumption in indoor growing environments.

4. CONCLUSIONS

Nutrient cycling, resource conservation, and sustainable agriculture are major 21st century problems.[164−166] CEA is a proposed solution, but current approaches largely assume complete environmental control,[24] which can become problematic when recycled water and nutrient sources are applied.[21] Our review shows that integrating MPM and ML approaches into what we call DCEA can likely address these problems by incorporating real-time biofeedback to handle variable nutrient concentrations and dynamic environmental inputs. Several pathways are outlined to integrate modeling and estimation with sensing, latent state monitoring, and DCEA technological interventions with the goal of successfully applying environmental control to optimize a given user-driven objective function such as maximal resource use efficiency.

Recent advances in sensor technologies will enable efficient plant tracking and sharing of data to inform more accurate and adaptable plant growth models, which can be incorporated at a variety of food system scales. However, given the high cost of operating machine learning systems, which require a lot of data to properly train machines to take precise predictions, incorporating mechanistic and physiological models as a source of synthetic data inputs at the outset could help reduce data requirements and thus cost.

Because of the high complexity of the plant system, future research should focus on establishing causal relationships between dynamic environmental parameters and phenotypical outcomes. The high level of control and optimization afforded by hydroponics and other forms of DCEA coupled with emerging agriculture technology interventions afford practitioners and scientists alike many opportunities to ask new questions and devise novel solutions that maximize food production, while minimizing economic costs and environmental externalities.

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Notes

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