Research Campaign - Artificial Intelligence for Autonomous Space Plant Production

Primary Author: Christine Escobar, 720-309-8475, Space Lab Technologies, LLC, chris@spacelabtech.com

Co-Authors:

Naeem Altaf, IBM

Richard Barker, University of Wisconsin Madison

Marufa Bhuiyan, Everest Innovation Lab

Melanie Correll, Agricultural & Biological Engineering Department, University of Florida

Ralph Fritsche, NASA Kennedy Space Center

Sara Humphrey, Environmental Horticulture Department, University of Florida

Pankaj Jaiswal, Oregon State University

Stephen Lantin, Agricultural & Biological Engineering Department, University of Florida

Emerick Larkin, Agricultural & Biological Engineering Department, University of Florida

Angela Price, IBM

Marshall Tabetah, Plane Space Design

Cristian E. Toma, Kalera

Space exploration and settlement of other planets will require production of fresh, ready-to-consume crops for a more sustainable and Earth-independent food system and supply chain. In addition, plants can provide multiple regenerative life support functions such as air revitalization and water recycling, further contributing to sustainable exploration. Communication time lags, limited crew time, and system complexity will prohibit human operation and maintenance of these systems, whether local or remote, making *autonomy* critical to their efficiency and success during deep space mission operations. Artificial intelligence can enable the safe, reliable, efficient, and autonomous production of healthy, high-quality crops and plant microbiomes, while reducing crew time, mass, volume, and power. Artificially intelligent agents can manage plant health through multiple life cycles by predicting, preventing, detecting, diagnosing, and responding to plant stress and system faults; and can optimize crop production by controlling the environment and scheduling crop or system maintenance. This paper discusses and recommends critical areas of research and development including sensor technology, data mining, machine learning, edge computing, robotics, and data and knowledge management, to realize space-viable autonomous controlled environment agriculture (CEA) in the next decade.

For semantic reference, **autonomy** is the ability of a given system or entity to achieve outcomes without direct control or intervention. **Artificial intelligence (AI)** is the ability of an artificial system or entity to rationally generate actionable insight that can be used to solve a problem or make a decision based on provided inputs. **Machine learning (ML)** is a subset of artificial intelligence (AI) that applies algorithms to data sets to rationalize and learn from the provided data and improve its accuracy or efficiency over time. **Automation** is the application of technology, programs, robotics, or processes to achieve outcomes with minimal human input. **Robotics** is the design and operation of robots, machines that perform programmed physical-mechanical tasks.

Goal 1. Autonomously Assess Plant Health & Safety

AI-powered plant growth chambers can recognize plant health and detect disease by taking advantage of data feeds from sensor networks, saving precious crew time. Important objectives for the next decade will be to A) use “the plant as a sensor” to inform automated control of the plants environment; B) incorporate data from novel sensors to better understand plant health and status; and C) monitor, understand, and manage the plant-microbiome interaction.

Objective 1A. Characterize Plant Health and Status from Available Data

Current and future space growth chambers will be heavily instrumented. A wealth of sensing technology exists or is emerging that can observe the health and status of plants, including metabolism, biomass productivity, growth, morphology, phenology, nutritional quality, stress, pathology, and environmental (shoot and root zone) conditions. Available and emerging sensing capabilities include structural imaging (ToF, lidar), spectroscopy (multispectral, hyperspectral raman, fluorescence, etc.), atmospheric sensors (CO_2, O_2, pressure, VOCs, etc.), water quality monitors (conductivity, nutrients, pH, dissolved gases), transpiration and water potential sensors, quantum sensors, and ‘omics platforms (nucleic acid, protein and metabolite sensing) (Patricio et.al 2018; Cho et al., 2018; Weng et al., 2018). Data fusion techniques and ML algorithms (e.g., regression, classification, ensemble learning) provide a more actionable picture or state estimate of plant health and status. Research is needed to determine how AI-powered CEA can use the ‘plant as a sensor’ to quickly, accurately, and consistently identify and diagnose abiotic or biotic stress, alert system operators, recommend interventions for crop loss avoidance, or recommend actions for enhancing performance, given plant and hardware models (*Objectives 2A and 2B).*

Objective 1B. Improve Sensing Capabilities
Improved sensing capabilities are needed to more readily and rapidly recognize and diagnose plant health and status, especially stress and pathology, microbiome health, root zone development, nutritional quality, and food safety. Visual symptoms that can be detected by crew may appear several days after stress begins (Kumar P. et al., 2021; Carillo, 2020), forfeiting the opportunity for early prevention or treatment of disease or injury. As novel sensing technologies emerge in the fields of optics, spectroscopy, electro- and biochemistry, electromagnetics, and multi-omics, they must operate within mission and spacecraft constraints (e.g., mass, volume, power, and bandwidth). Accurate, precise, and reliable sensors are needed that can observe plant canopies and root zones in small chambers; respond rapidly; operate autonomously with little to no crew time for sample preparation, operation, calibration, or maintenance; and operate with little to no consumables. In addition, novel sensors must be robust to the nominal and off-nominal spacecraft environment, characterized by high levels of radiation, high humidity and CO_2 levels, fluctuating pressures, variable gravity regimes, and intermittent power loss.

Objective 1C. Understand, Monitor and Manipulate the Plant-Microbiome
The plant-microbiome can support or hinder plant growth and health. Beneficial microbiomes will require active assistance, while serious infections require early detection and mitigation to avoid crop or yield loss. Research is needed to determine how machine learning and AI can understand, monitor, and manipulate the plant microbiome interaction throughout the plant life cycle (Marcos-Zambrano, et al., 2021; Carrieri, et al., 2021; Souza, Armanhi, & Arruda, 2020; Moreno-Indias et al., 2021). Specific research areas include:

- Recognition of the difference between "healthy" and "unhealthy" microbiomes,
- Determining the core members of a healthy plant microbiome (de Souza, et al., 2020)
- Quantifying the effects of plant genotype, phenotype, and environmental conditions on microbiome health and species composition and dynamics (Khodadad et al., 2020).
- Optimizing yield and quality (nutrient composition, bioavailability, digestibility, food safety).

Goal 2. Optimize Autonomous Growth Systems
Artificial intelligence can turn novice growers or autonomous systems into expert growers (Hemming et al., 2020). AI-powered systems can autonomously manage environmental control and maintenance activities for optimal crop and hardware performance (yield, quality, longevity, and efficiency) during nominal conditions and mitigate biotic or abiotic anomalies and faults during off-nominal conditions (e.g., plant stress or hardware failure). Important objectives for the next decade include the prediction and optimization of crop and growth chamber performance.

Objective 2A. Predict and Optimize Crop Performance
Considerable progress has been made in controlled environment space agriculture after decades of research and development (Zabel, 2016). In addition, advances in AI, edge computing, internet of things (IoT), and robotics have led to the automation of nearly all tasks in terrestrial indoor agriculture, from planting to harvest. These data-driven, AI-powered CEA systems can manipulate crops, manage nutrients and irrigation, and provide environmental control using a variety of sensors. AI affords autonomous crop selection and CEA resource management. As space plant habitat technology continues to improve, so must the predictive models of crop performance and growth chamber operation that inform growth chamber design and operation.

With accurate, robust crop performance models, data-driven, AI-powered CEA can provide decision support to an unskilled crew member or autonomous growth chamber, saving crew time, improving crop performance, mitigating crop loss, and reducing consumption of limited resources such as water and power. Examples of data-driven, AI-powered decision support tools include digital twins (DT), case-based reasoning, linear programming, or other optimization algorithms. Through data-driven analysis, an AI-powered CEA might recommend environmental setpoint changes, crop maintenance schedules, interventions to mitigate detected stress or disease (e.g., reducing humidity to prevent fungal infection), and the selection of plants and seeds with the greatest potential for successful growth in space (Langridge and Fleury, 2011; McCormick et al., 2021; Vos et al., 2010; Yu et al., 2019). Data-driven, AI-powered CEA can assist in making rapid, rational, and consistent decisions from learned knowledge, given unforeseen circumstances or novel data. It can also use models to forecast yields and growth stages (such as harvest readiness), predict disease onset (prognostics), or assess risk of crop loss (Abade et al., 2021). Finally, to maintain its value to the crew as missions evolve, the data-driven, AI-powered CEA should be capable of updating crop models as new data becomes available to accommodate changes in crop behavior, production goals, crew preferences, or other mission constraints.

Data-driven, AI-powered decision support requires real-time knowledge of plant-environment state and predictive models of crop performance, as a function of available state parameters. The relationships between crop performance, controllable growth conditions and interventions, and uncontrollable factors throughout developmental stages (e.g., germination, vegetative, flowering, fruiting), off-nominal growth, and periods of CEA inactivity or dormancy are complex and dynamic. Important crop performance metrics (or responses) for multi-objective optimization include seed viability, germination rate, growth rate, yield, harvest index, calorie content, nutritional density, palatability, safety, stress tolerance and resource consumption (especially water and energy). Controllable factors that influence crop and microbiome performance include plant genotype, growth conditions (e.g., temperature, humidity, light intensity, photoperiod, fertilizer composition, pH, air flow, CO_2/O_2 partial pressure, dissolved O_2, root moisture, vapor pressure deficit, etc.), and maintenance schedules (e.g., planting, fertilizing, watering, pruning, pollinating, or harvesting). However, crop performance might also be affected by uncontrollable factors such as cabin temperature and pressure, changes in the microbiome, VOC contamination, abiotic or biotic stress, or hardware anomalies (e.g., loss of water pressure). Thus, the 'optimal' growth conditions and maintenance schedule will likely change but can be managed with data-driven algorithms such as model predictive control (Piñnon, 2005).

Robust learning models require the application of data mining and machine learning tools (see *Objective 1A*) to large training and testing datasets collected from plant growth experiments in space relevant conditions. The creation of specific datasets for space relevant environments is a critical area of future research.

Objective 2B. Predict and Optimize Growth Chamber Performance
The need for robust life support systems increases with mission duration and distance from Earth. Hardware and software robustness, achieved through reliability, resilience, and survivability across a wide range of usage conditions, will be a critical area of research and development as growth chambers transition from research platforms to operational crop production systems (Escobar et al., 2017; Escobar et al., 2019).

Growth chamber components need to have a sufficient life under normal conditions (reliability) but also the ability to maintain performance in unanticipated conditions (robustness) and recover from degradation or failure (resilience). In addition, mass constraints limit the ability to carry spare parts. Thus, the development of rugged, reusable, resilient, and repairable space CEA components must be prioritized. Validated system performance models and reliability analyses predicting performance degradation and time to failure are needed to inform hardware architecture design, component selections, operations and resource management protocols, and hardware maintenance schedules. Prior to mission deployment, significant hardware reliability and robustness testing in relevant environments must also occur to verify chamber performance.

Terrestrial advances in autonomous technology for CEA, including robotics, sensors, data-driven, AI-powered analysis, data processing, and automation technologies are rapid and are outpacing space technology development (Fountas, S, 2020). Terrestrial robots can reduce human labor for seed sowing, grafting, transplanting, spraying, pest control, weed removal, thinning, pollination, and harvesting (Kumar R. et.al, 2021). Most of this technology is too massive for a volume constrained space habitat, too energy intensive, or intolerant of the high vibration loads and radiation exposure inherent in space travel. Research and development are needed to miniaturize and ruggedize state-of-the-art terrestrial CEA robotics, sensors, and data handling for space use (Monje, 2019). In addition, autonomous CEA equipment must be interoperable with spacecraft computing and communications infrastructure.

In flight, data-driven, AI-powered system health management can detect, isolate, compensate, and recommend mitigation for off-nominal events and anomalies, such as environmental excursions, and faults, such as sensor or pump failures, providing needed resilience. In addition, isolated spacecraft cabins present a particularly 'fertile' environment for pathogen growth and outbreaks, presenting a unique challenge for space agriculture. This is especially the case for dormant periods when hardware is not in use. Chambers will need to be restored to their initial state prior to starting new growth cycles. Robust chambers that can manage waste, autonomously clean, and disinfect soiled, wetted surfaces, and manage transitions between dormant and active use are particularly needed for system longevity.

Goal 3. Manage Data and Knowledge Repositories at Scale

To effectively infuse AI into autonomous plant growth systems, collected data and knowledge obtained must be properly managed, ensuring accessibility, usability, integrity, security, and adaptability over time and across systems. Thus, two key objectives are to (A) create plant data and knowledge repositories, and (B) create information architectures for space plant production. A solid information architecture designed specifically with space plant growth use cases in mind is key to creating AI-powered systems with lasting and continued value. This architecture must contain a knowledge repository from which intelligent agents can generate actionable insight. Over time, new behaviors, environmental factors, model drift or changes in mission context will alter the effectiveness and value of initial training sets. Autonomous plant growth systems will need to compensate for change by refining knowledge contained in the information architecture. Learned information should be catalogued in a knowledge and solutions repository which is documented, accessible, usable, and explainable. AI-powered plant growth systems must also operate with limited computing power and storage by utilizing technologies like edge computing. Finally, proper data governance policies must be in place to maintain the security, integrity, and effectiveness of the data, learning model and system over time.

Objective 3A. Establish Information Architecture and Create Knowledge Repositories

The quality and organization of data upon which AI systems rely is critical for efficient analysis and the generation of useful, actionable insight. Building and maintaining a robust collection of standardized reference data, supplemental 'learned' knowledge and solutions repository is key in maintaining the value of an AI-powered system. Collection and utilization of large training and operational data sets and complex predictive models prior to and during autonomous space crop production will require a sound knowledge repository and information architecture, data standards, and ontologies (Cooper et al., 2018; Davidson, 2003). First, system developers must understand *what* data, metadata, and knowledge (e.g., models) need to be collected and stored, and with what granularity, frequency, and quality, for it to have value over time. Next, system developers need an information architecture that includes standards for organizing and storing data, metadata, and knowledge. How do scientists capture data and models such that they can be integrated and used across different data types, experiments, or platforms, such as the NASA GeneLab? How do CEA developers capture and integrate the horticultural knowledge of expert growers in a language an AI can understand, apply, and update? How do they reduce data for limited storage and processing availability (e.g., edge computing)? Finally, CEA operators must have access to visualization and data mining tools to assist in the interrogation and exploration of data, metadata, and knowledge. While many groups such as AgMIP (www.agmip.org) and Planteome (www.planteome.org) are developing metadata standards, space CEA relevant knowledge repositories, information architectures, and data standards are still needed.

Objective 3B. Develop & Integrate AI-Powered Architectures at Scale

Standardization of data architectures, data organization methods, data governance and retention policies will enable uniform development and deployment of data and models across multiple systems, environments, and interoperable platforms. Tools are needed for combining, modeling, and visualizing complex data sets in-situ from vast and often discrete data sources with limited computing resources and storage, using space-viable edge computing technology.

Data-driven, AI-powered space CEA architectures must be reliable, effective, robust, and interoperable with other spacecraft subsystems, such as life support. Architectures must accommodate human intervention when needed (or desired), using adjustable autonomy, and provide useful, timely information to their human users. The underlying architecture for the hardware, machine learning pipeline and other associated systems should be uniform, re-usable, modular, scalable, resilient, secure, able to operate concurrently, and adaptable (able to adjust in real time). Monolithic design and patterns should be avoided in favor of scalable modularity and flexible processes where appropriate. Techniques such as software containerization, microservices, event driven architectures, and coding/programming languages that natively support concurrency enable fault-tolerance, high availability, and hot-swapping if necessary.

Digital twins (virtualized models of a physical system or entity) for both the controlled environment (growth chamber) and plants themselves can aid in assuring nominal process behavior and allow closed-loop control and decision support. Digital twins can deploy and integrate with physical systems in real-time, leveraging live data feeds from sensor networks and other real-time data sources. Several fields have successfully adopted DTs, including the chemical processing, pharmaceutical, and aerospace industries (Glaessgen & Stargel, 2012; Datta, 2016); however, realization in biological systems, particularly for space, has remained at a conceptual/proof-of-concept technology readiness level (TRL 2-3). Recent advancements in wireless and biosensor networks, increases in computing power, and real-time analytics with machine learning and edge computing has paved the way for more advanced DT research and development in support of autonomous space plant production systems.

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