

AUTONOMOUS DECISION- MAKING IN SMART FARMING: A LAYERED AGENTIC ARCHITECTURE FOR REAL-TIME PLANT STRESS MANAGEMENT

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ABSTRACT:

Sustainable plant growth reveals to be a critical challenge for life maintenance, especially given emerging environmental stress and demand for scalable agriculture. Concurrently, the rising attention to agentic paradigm – pro-active intelligent systems featured by autonomous reasoning, tools management and adaptive skills aggregation – provides

opportunities to enhance domain-specific fields as farming with decision-making architectures. This paper introduces “PlantLabSimulation”, a platform that investigates the use of Large Language Model (LLM)-driven agents within an agentic orchestration architecture to autonomously support plant growth for farmers, researchers, and general users. The system’s physics-driven plant growth simulation engine is integrated within a layered agentic structure. The simulation engine mimics the plant development through decoded biological processes including, biomass partitioning, light use efficiency, water balance, cumulative damage rate, seedling boost principles, nutrient dynamics and CO₂ flux across three presented plant species. As a decision unit – agentic architecture that encompasses monitor, reasoning and executor agents, enables continuous monitoring, reasoning and execution respectively. Unlike traditional rule-based systems, the proposed architecture leverages LLM-based decision-making and tool-augmented reasoning to dynamically handle interacting stressors and adapt interventions in real time.

KEYWORDS:

Agentic Orchestration, Plant Growth Simulation, Large Language Models, Autonomous Decision-Making, Physics-Driven AI, Tool-Augmented Generation (TAG), Smart Agriculture

Introduction :

The challenge of agricultural autonomy has been frequently highlighted due to emerging environmental concerns and human population expansion. The concept of Controlled Environment Agriculture (CEA) is dated back to mid-20th century, rapidly rising in 1960s to 1990s, following both scientific and machinery development. CEA historically aimed to cultivate crops within a highly controlled indoor environment, such as a greenhouses, vertical farms and plant factories, to optimize growth conditions and improve resource efficiency (Wilkinson, 2025; UNDP, 2025). This approach gained significant attention and commercial implementations, such as AeroFarms' aeroponic vertical farm, demonstrate the potential of CEA to provide year-round, high-density crop production while reducing dependence on external environmental conditions (Wilkinson, 2025). However, these systems expansion led to the impracticality due to requirement for human oversight. Attempts to address these aspects including construction of automated sensor networks and programmable logic controllers (S. Kumari, 2025) have led to operational efficiency, but they still lacked autonomy. The shift to the LLM paradigm with advanced tools definitions, including managing of physical tools, gathering data continuously provided significant Degree of Freedom (DoF) to the agentic frameworks. Central to this is Agent Orchestration (AO), the process of coordinating multiple specialized agents —such as monitors, planners, and executors—to achieve a unified goal through structured communication and task decomposition (A. Adimulam, 2026).

In order to explicitly study the plants growth patterns, several papers have extensively explored plant growth simulation process through experiments set with models like DSSAT (Decision Support System for Agrotechnology Transfer) and APSIM (Agricultural Production Systems Simulator). These models rely on fundamental physiological metrics such as Light Use Efficiency (LUE) – quantifier of amount of dry biomass produced per unit of absorbed photosynthetically active radiation (PAR), Vapour Pressure Deficit (VPD) – the difference between the pressure exerted by water vapor in saturated air and the actual vapor pressure at a given temperature (Al-Najadi R, et al., 2026). Critical driver to plant development is the Vapour Pressure Deficit (VPD), the difference between the pressure exerted by water vapor in saturated air and the actual vapor pressure at a given temperature. VPD is a primary determinant of transpiration rates and plant water stress (J. Kandasamy, 2023). The plant growth universally measured with Relative Growth Rate (RGR) – the ratio of biomass increase per unit of existing biomass over time (Xiao Y, et al. 2025).

Despite these advancements, a systematic investigation into the integration of LLM-based reasoning agents as an autonomous control layer atop a physics simulation remains largely unexplored. This paper filling this gap by focusing on application of Large Language

Model (LLM)-driven agents within a physics-based simulation environment and measuring its effectiveness and real-world applicability.

1.1 Research Objectives and Hypotheses

This paper aims to achieve three primary objectives:

1. To construct the architecture of a physics-based plant simulation engine, incorporation biological patterns of three defined plant species.
2. To present the design and workflow of an agentic system, which performs monitoring reasoning and tool application within a simulation environment.
3. To validate the simulation engine and agentic architecture through iterative test suites for plants behaviour and used generated data to train an XGBoost model that predicts plant stress conditions using features extracted from plant images.

It is hypothesized that an LLM-driven agentic system can autonomously detect and correct deviations in plants state environment (e.g., temperature, water, light) and anticipate impending plant stresses, offering adaptive approach to agricultural domain.

To evaluate the efficacy of the proposed agentic paradigm, this study follows a structured experimental approach and was organized according to the IMRAD structure. Firstly, in Section 2 (Materials and Methods) the development of the layered agentic structure was described and its integration with the biological processes. Followed by a demonstration of the system's ability to autonomously adapt interventions in real-time, in the Results (Section 3). Finally, the Discussion (Section 4) contrasts LLM-based reasoning with traditional rule-based systems to highlight its potential for scalable farming in the Discussion section.

2. Materials and Methods

2.1 Method description, Settings

System is developed as a modular plant growth simulation engine with connected autonomous agentic layer for monitoring and control. The system is implemented with a Flutter web frontend, a Flask + Gunicorn backend in Python 3.12, and deployed on Google Cloud Run. Firestore (Firebase) and Firebase Auth are utilized as a data storage and authentication service respectively. Sensor data insertion is mimicked through MQTT using Eclipse Mosquitto broker. The decision agent is empowered with Gemini 2.5 flash configuration that is utilized for both agentic decision-making process. Same Genimi model is used for vision-based reasoning with XGBoost for stress predictions. Three plant profiles were modeled: *Solanum lycopersicum* (tomato_standard), *Lactuca sativa* (lettuce_butterhead), and *Ocimum basilicum* (basil_sweet). These species were selected to represent distinct growth strategies and structural behaviours.

2.2 Plant Growth Simulation Framework

FIGURE 1 HERE

FIGURE 1 shows the 10 Layers of the proposed simulation framework architecture – sequential calculations that happen each hour simulation. Every node shows with variables are used to derived new metrics. The words highlighted with bold are used for the constant values. Plant stress and growth are modelled as continuous, time-dependent processes. Soil water balance considers the graduality of stress, which consequently leads to photosynthesis activity reduction and respiration growth that mimics the biologically accurate pattern of metrics restoring when the source of the stress is excluded. Photosynthetic efficiency varies based on current developmental stage and biomass accumulation reserve, following the pattern of logistic growth. A plant state is considered terminated when the physiological failure criteria are met, such as severe damage, biomass collapse, or sustained loss of growth or carbon gain. Importantly to mention, the plant state is instantiated with an initial biomass of 1.0 g and the seedling growth boost is applied at the start to allow early leaf area expansion, as subsequent physiological metrics and water-dependent processes in the simulation engine rely on this initial growth.

2.3 Environment Control Tools

A set of Seven intervention tools was developed and housed under the tools/ directory. Each tool is accessible by the agentic system. These tools supports environmental manipulations with environmental and plant state metrics consequentially, as summarized in TABLE 1.

TABLE 1 HERE

2.4 Agentic Orchestration

FIGURE 2 HERE

The demonstrated agentic system separated systems’ responsibilities between 3 agents – Monitoring, Reasoning, Executor, coordinated by Orchestrator agent. This multi-agent structure is a universal practice in control environments, especially in smart agriculture domain, where distributed operating and decision-making is effective for resource optimization and plant health (Kasaei S., et al.,2011). The Monitor agent activity can be configured to track plant state key variables each hour over 48-hour sliding windows, that includes VPD, PAR and growth rate for patterns monitoring. The result of the Monitor

agent activity is a structured JSON files with different levels alert: INFO for small deviations, WARNING for observed values inconsistency, CRITICAL for immediate life sustainability threats. The WARNINGS and CRITICAL alerts are sent to the Reasoning agent respectively. The Reasoning agent constructs a prompt from derived state metrics, passed by Monitor agent, including health flags, thresholds triggered. The prompt is sent to Gemini (gemini-2.5-flash), which returns a JSON response with analysis data and a set of recommendations approximately mapped to the tools. The application of LLMs to agricultural decision-making is a rising area of experiments, demonstrating significant potential for automated systems (H. Li, 2025). Finally, the Executor agent receives the actions list and applies it via mapping to the tools. The engine is accessed by Executor agent and it mimics physical manipulations with the plant, by that being a irreplaceable component in agentic AI framework for practical agriculture (P.N. Srinivasu, 2026). The Orchestrator agent is generally responsible for management of monitoring, reasoning and execution through supporting communication between these agents. Importantly to notice, only the Reasoning Agent is empowered with LLM.

2.5 Sensor Mapping and Validation

The engine of the PlantLabSimulation system incorporates a minimal set of sensors suite to monitor critical metrics required for autonomous control and relevant decision making regarding plants health. The mapping between sensors and simulated metrics are presented in FIGURE 3.

FIGURE 3 HERE

The selection of this mapping configuration is based on minimal set of environmental and physiological indicators in conducted agricultural research. Research has shown that VPD metric, that can be derived from air temperature and relative humidity is an accurate predictor of plant transpiration, thermal development progress and water stress than humidity itself (J. Kandasamy, 2023) and (Z. Lu, 2025). Soil temperature and moisture probes are sources are soil water and thermal state estimations, crucial for water balance calculations. PAR sensor provides light intensity, that is universally accepted metric for light energy available for photosynthesis (N. Buxbaum, 2022). Although the camera-based imaging systems usage for biomass and leaf area estimation has been proved to be a robust alternative to excessive sampling as in recent study, that utilized AI-powered computer vision and achieved the accuracy of 80% in estimating fresh biomass (P. Hemamalini, 2026), this research is utilizing the simulation of the biomass gain and leaf area relying on principles of seedling boost, environmental conditions wellness and root-first or lead-first strategy of the plant. Camera estimations for the biomass and leaf area

are only supplied during LLM-powered flow of stresses prediction. Finally, EC (electrical conductivity) sensor is widely recognized as a reliable source for nutrients availability Nitrogen (N), Phosphorus (P), and Potassium (K) and soil salinity in CEA, enabling automated nutrient monitoring and supply (Y. Faqir, 2024). Collectively, this setup provides a comprehensive DoF for the agentic orchestration framework to enable robust and continues state estimation.

2.6 Experimental Framework and Evaluation Metrics

This section illustrates the set of tests used for evaluating the physics-based plant simulation engine, focusing on its robustness, adaptability, and realism across various scenario-based tests. The terminology includes the definitions such as “acceptance criterion” representing the passing metric for the test, “scenario” signifying the unique configuration of the plant environment, “care regime” denoting the configuration of static schedule of the plant caring, that was developed to support plants life without decision-making unit functioning in optimal plant conditions.

2.6.1 Comprehensive Death Tests

TABLE 2 lists down a test group that evaluates the engine's ability to accurately simulate plant death under various critical stress conditions. The scenarios are configured to trigger insufficiency of different sources by that causing the chain effect of plant’s stress and consequential death. Importantly, there is a set of death thresholds that might be met by the plants during these tests, they are predefined and explained in FIGURE 1.

TABLE 2 HERE

2.6.2 General Simulation Tests

TABLE 3: Test Scenarios Definition. This tests set derived from relevant code file, validates the engine's overall performance under various conditions such as utilization of care regimes, reasoning layer and initial thermal conditions for different plant species. The scenarios aim to assess growth response, survival, and stress regulation, providing a comprehensive overview of the engine's adaptability and realism. In scenarios C1-D3 the daily regime is applicable to all simulation engine variables except of temperature regulation, meaning that no specific tool is applied to increase the temperature of the air purposely, however, due to biological dependences of the CO2 production by the plant

during its activity of any intensity, during scenario simulation temperature may rise gradually.

TABLE 3 HERE

2.6.3 XGBoost Stress Prediction Tests

The validation of simulation engine architecture and agentic system, the plant check health pipeline includes 3 stages: the Gemini model (gemini-2.5-flash) extracts base physiological metrics of the plant, including estimated biomass, estimated leaf_area and yellowing, droop and necrosis metrics, which is then used by a boost model to predict stresses. The XGBoost trained model predicts stresses and its combination with plant's historical records is fed back to Gemini model to provide the plants health analysis and recommend the actions. The plant species – *Solanum lycopersicum* (Tomato). Two experimental scenarios were tested:

1. **Stress Persistence:** a sequence of Sick → Sick → Healthy → Sick. Objective: to verify that transient healthy appearances do not erase prior stress signals.
2. **Stress Memory:** a sequence of Healthy → Healthy → Sick → Healthy. Objective: to determine prior stress influence on later predictions.

Final stage health evaluation is supported by categorization of the mean of stresses metrics with combination of evaluation of LLM health analysis text as "Healthy", "Early Stress", "Moderate Stress", "Severe Damage", or "Inconsistent".

3. Results

The results of the Three (3) sets of tests were compiled and described in this section.

3.1 Results for Comprehensive Death Tests and General Simulations Tests

The simulation engine results demonstrated that terminal physiological failure was successfully achieved under the configured death conditions (Table 4). In the test_death_by_damage scenario, the plant died at hour 49 due to negative CO₂ uptake, while tests involving severe biomass depletion also reached the termination stage at hour 49.

The effectiveness of the autonomous care regimes was evaluated (Table 5) within a scope of three plant species as an opponent for predefined daily regime of tools application (Table 2). As a result, both the reasoning-only setup (A1-A3) and daily regime only control (B1-B3) presented successful maintenance of plants state as well as C1-D3 scenarios presented daily regime capability of plants life support. During E1-E6 scenarios the real-world behaviour of the plants was captured. All plants with disabled daily regime no matter of optimal environment died. Throughout 3 defined thermal value – 25 °C, 10 °C and 30 °C, the highest temp stress for tomato emerged on low temperature condition – temperature stress – 1.000, while for lettuce, highest stress for temperature was captured for high initial temperature configuration – 0.833.

TABLE 4 HERE

TABLE 5 HERE

3.2 Results for the XGBoost Stress Prediction Tests

The performance of the health-check pipeline was evaluating mainly by comparison between established flow in the system and pure Gemini model analysis (Table 6). In order to examine temporal dependency and stress memory both instances were fed the same images of tomato in the same order, following tracks S1 and S2. Track S1 has the sequence; Sick → Sick → Healthy → Sick. While Track S2 impose a different sequence; Healthy → Healthy → Sick → Healthy. Overall, both systems performed well in identification of the plant stresses for images separately, that supports the equality and validity of both approaches for single image classification and metrics extraction. Stresses levels were equally identified for all test cases.

TABLE 6 HERE

4. Discussion

This study presented PlantLabSimulation, a platform for evaluating LLM-driven agents in a physics-based plant growth environment. The results support the main objectives of the work: validating the simulation engine, testing the agentic control architecture, and assessing temporal stress handling.

During all scenarios during comprehensive death tests set (Table 4), the engine correctly triggered plant termination, indicating that all predefined objectives were met. Notably, in 5 out of 7 tests, CO₂ uptake below zero for the 48-hour threshold criteria was a satisfying threshold of the death condition. Only the test_death_by_zero_co2_uptake and test_death_by_negative_rgr scenarios met alternative death thresholds. These results confirmed that the designed engine effectively simulated plant mortality under extreme environmental conditions.

In general simulations tests (Table 5) both reasoning system and daily regime (A1-B3) managed to support stable growth, biomass gain and low stresses baselines. Importantly, it was observed that the numerical results were highly similar. Further investigation revealed that the agentic system primarily decided to set up a daily regime as a default schedule for sustaining plant viability. Due to the optimal environmental conditions, most activities from the daily regime plan influenced the plant state. Within the objective of maintaining plant survival, this behaviour is reasonable and can be considered a valid decision by the agents; however, future studies should evaluate the effectiveness of this system with the daily regime deliberately disabled and under stress condition.

In the following scenarios: C1-E6 – the system demonstrated considerable robustness to initial thermal conditions. In C1-C3 scenarios with initial low air temperature the numerical representations of the biomass gain and stresses estimations are approximately the same as in case scenarios A1-B3 meaning that initial cold didn't result in plants death; nonetheless, important distinction should be highlighted, the pattern of biomass gain in first 100 hours during more precise investigation showed that plant tends to gain less biomass during lower temperature periods, when reaching suboptimal conditions, biomass gain returns to its trajectory. D1-D3 scenarios' plants with initial high temperature had successfully gained biomass growth during daily regime enabled, all stresses remained on approximately identical level. Importantly to notice, that these stress values are reflecting overall stress fluctuation during simulation, due to simulation time – 1440 hours, these metrics are approximated.

In conclusion for general simulations tests, plants objectively behaved accurately relatively to physiological stress and transition to phenological stage of termination. Overall, the simulated scenarios highlight critical necessity of daily regime or any caring procedures for the plants to survive. However future investigation is required to justify the sufficiency of agentic framework to handle all possible situations.

During examination of check-health pipeline (Table 6), since images were taken from the PlantVillage (Kaggle) dataset, specifically the tomato_healthy and tomato_early_blight classes, the detected stress were mainly associated with nutrients deficiency. Both developed flow and pure Gemini model accurately identified stresses of separated

images. The emerged difference in systems behaviour was observed regarding how these systems reasoned across the time. The pipeline system was able to recognise a sequential inconsistency of healthy plant surpassed straight after set of sick plants observations. The key phrase such as “The plant's condition appears similar to its state two minutes ago, suggesting that any recent brief recovery was temporary and the underlying nutrient problem persists, requiring urgent attention” was followed with recommendations of precise monitoring of the plants state. In other words, the pipeline turned to be more sensitive to chronological order and timeline resulting in flagging outstanding observations. By that XGBoost and temporal dependency showed the prevalence in logical reasoning regarding plants health compared to baseline Gemini model.

5. Conclusion

Developed Architecture – PlantLabSimulation has successfully validated the created plant simulation engine and the agentic system. Tests showcased accurate plants’ vulnerability to environmental constraints, while supporting sufficiency of specific tool application to support plant survival via default regime or agentic system. The historically-aware pipeline evaluated plants health patterns and calibrated decision-making process more consistently than the baseline Gemini Model. Overall, the results validated simulation engine and agentic architecture suitability for simulated plants life support, however future investigation and real-world experiments are required to justify its full suitability for real agricultural lab management.

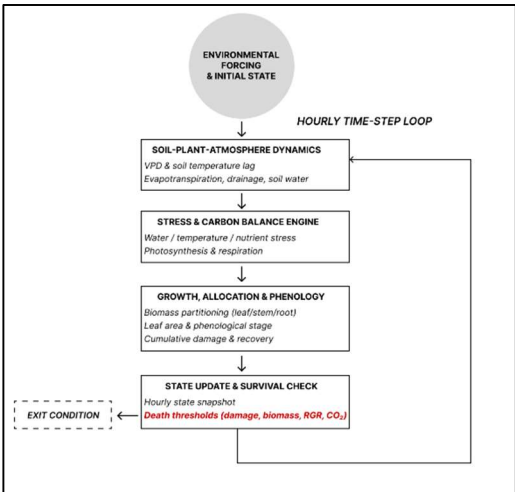


FIGURE 1: The Proposed Plant Growth Simulation Framework Architecture

TABLE 1: Summary of the Environment Control Tools.

Tool	ToolType	Primary Effect
Watering	WATERING	Adds water volume to soil; adjusts EC
Lighting	LIGHTING	Sets PAR level
Nutrients	NUTRIENT	Doses N, P, K into soil solution
HVAC	HVAC	Changes air temperature at maximum rate (°C/h)
Humidity	HUMIDITY	Sets relative humidity target
Ventilation	VENTILATION	Exchanges air at fan speed; affects CO2 and humidity
CO2 Control	CO2_CONTROL	Injects CO2 to reach target ppm

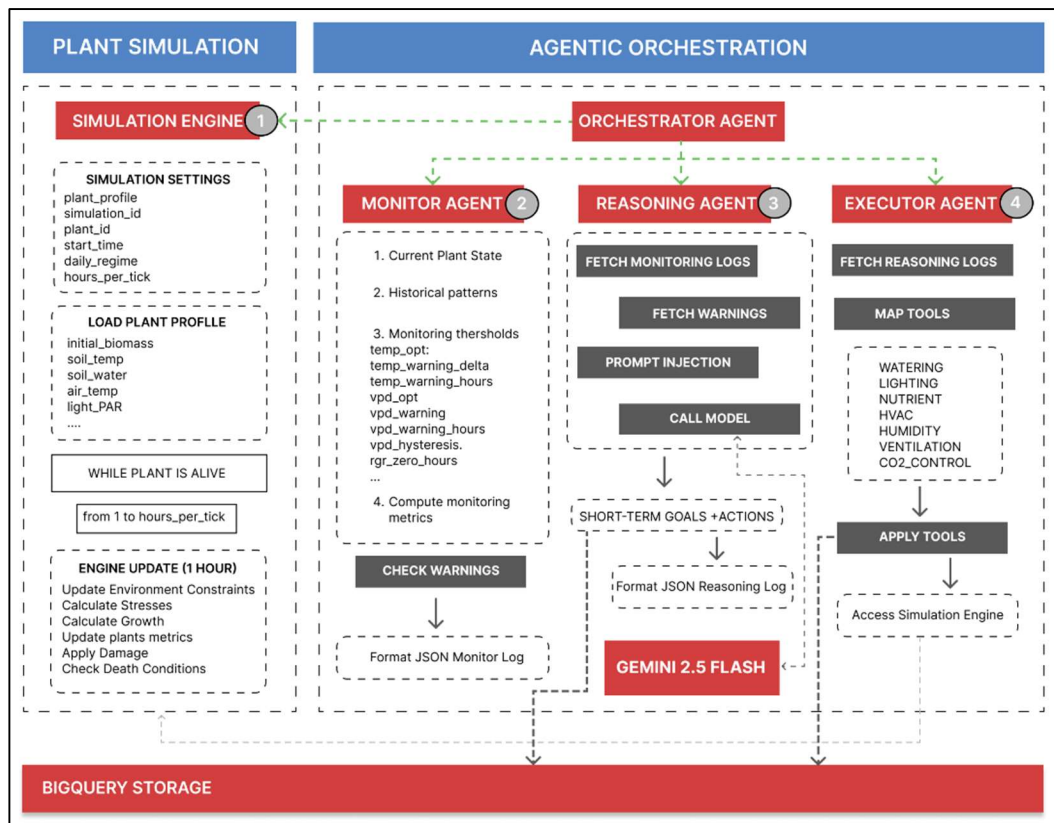


FIGURE 2: The Proposed Agentic Layer Representation

Sensors and Metrics Mapping

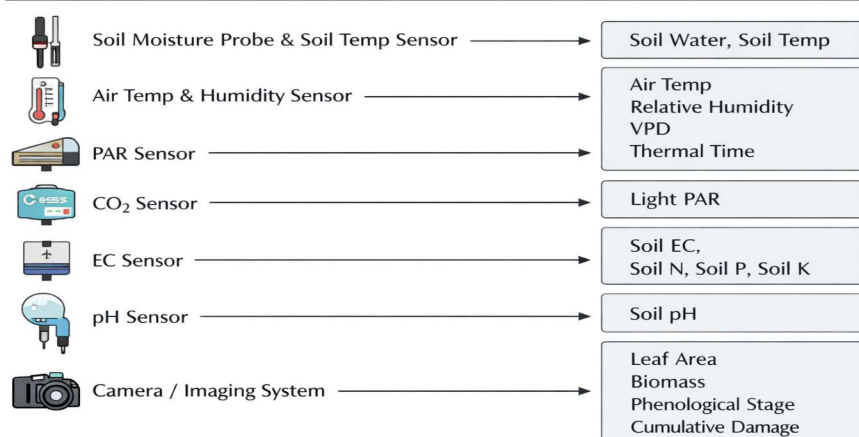


FIGURE 3: Minimal sensor configuration and its mapping to simulated plant and environmental variables

TABLE 2: Summary of Plant Mortality Validation Scenarios and Acceptance Criteria.

Scenario ID	Care Regime	Initial Conditions	Species	Duration (h)	Objective	Acceptance Criterion
test_death_by_damage	No care	Tomato (standard profile)	Tomato	240	Validate plant death due to cumulative damage or CO2 zero uptake	Cumulative damage percentage (cumulative_damage) reaches or exceeds 95% or Sustained CO2 uptake ≤ 0 for more than 24 consecutive hours
test_death_by_biomass_depletion	No care	Tomato; biomass = 0.02 g, leaf_area = 0.0001 m², light_PAR = 0	Tomato	100	Validate plant death due to severe biomass depletion	Biomass decreases to 0.01 g, or Sustained CO2 uptake ≤ 0 for more than 24 consecutive hours
test_death_by_negative_rgr	No care	Tomato; biomass = 5.0 g, light_PAR = 0 (darkness)	Tomato	72	Validate plant death due to sustained negative relative growth rate (RGR)	Sustained RGR ≤ 0 for more than 48 consecutive hours, or Sustained CO2 uptake ≤ 0 for more than 24 consecutive hours
test_death_by_zero_co2_uptake	No care	Tomato; biomass = 10.0 g, light_PAR = 0	Tomato	48	Validate plant death due to prolonged absence of CO2 uptake	Sustained CO2 uptake (co2_uptake) ≤ 0 for more than 24 consecutive hours
test_variable_tick_rates	No care	Tomato; biomass = 5.0 g, light_PAR = 0	Tomato	72	Validate consistent death within range of different simulation tick rates	Death occurs at all tested tick sizes (1h, 6h, 24h) with timing within ±1 tick of expected death., or Sustained CO2 uptake ≤ 0 for more than 24 consecutive hours

TABLE 3: General Test Scenario Definition

Scenario ID(s)	Care Regime	Initial Conditions	Species	Duration (h)	Objective	Acceptance Criterion
A1 / A2 / A3	Reasoning-only orchestration	Initial Air Temp: 25.0 / 20.0 / 24.0 °C	Tomato / Lettuce / Basil	1440	Evaluate reasoning-based orchestration capabilities	Survival, stable growth
B1 / B2 / B3	Daily regime enabled only	Initial Air Temp: 25.0 / 20.0 / 24.0 °C	Tomato / Lettuce / Basil	1440	Evaluate the basic caring regime efficiency	Survival, stable growth

C1 / C2 / C3	Daily regime enabled + low initial temperature	Initial Air Temp: 10.0 °C	Tomato / Lettuce / Basil	1440	Evaluate robustness under initial cold stress	Survival, stress adaptation
D1 / D2 / D3	Daily regime enabled + high initial temperature	Initial Air Temp: 30.0 °C	Tomato / Lettuce / Basil	1440	Evaluate robustness under initial heat stress	Survival, stress adaptation
E1 / E2 / E3	Daily regime disabled and low initial temperature	Initial Air Temp: 25.0 / 10.0 / 30.0 °C	Tomato	1440	Assure reaching termination stage with unfriendly environment	Natural activity decrease, leading to death or severe stress
E4 / E5 / E6	Daily regime disabled and high initial temperature	Initial Air Temp: 25.0 / 10.0 / 30.0 °C	Lettuce	1440	Assure reaching termination stage with unfriendly environment	Natural activity decrease, leading to death or severe stress

TABLE 4: Simulation Results for Comprehensive Death Tests

Scenario	Survived	Failure Description (Quantitative Trigger)	Outcome
test_death_by_damage	No	Plant terminated at hour 49 due to 48-hour zero/negative CO ₂ uptake condition, final biomass 0.410 g	PASS
test_death_by_biomass_depletion	No	Plant terminated at hour 49 after 48 consecutive hours of zero/negative CO ₂ uptake; biomass reduced to 0.020 g	PASS
test_death_by_negative_rgr	No	Plant terminated at hour 49 due to sustained negative carbon balance (CO ₂ uptake ≈ -0.00443 g) over 48 hours; biomass 5.009 g	PASS
test_death_by_zero_co2_uptake	No	Plant terminated at hour 49 after continuous zero photosynthesis and respiration-driven CO ₂ loss (-0.00884 g) for 48 hours	PASS
test_variable_tick_rates (1h)	No	Death occurred at hour 49 under 1 h timestep due to 48-hour zero/negative CO ₂ uptake condition	PASS
test_variable_tick_rates (6h)	No	Death occurred at hour 54 under 6 h timestep due to 48-hour zero/negative CO ₂ uptake condition	PASS
test_variable_tick_rates (24h)	No	Death occurred at hour 72 under 24 h timestep due to 48-hour zero/negative CO ₂ uptake condition	PASS

TABLE 5: Simulation Results for General Simulation Tests

Scenario ID	Survival	Final Biomass (g)	Peak Biomass (g)	Final Stage	Water Stress	Temp Stress	Cumulative Damage (%)	Outcome
A1	Survived	129.459	144.382	flowering	0.050	0.000	0.0	PASS
A2	Survived	134.895	135.050	vegetative	0.035	0.042	0.0	PASS
A3	Survived	97.471	98.498	mature	0.072	0.138	0.0	PASS
B1	Survived	129.459	144.382	flowering	0.050	0.000	0.0	PASS
B2	Survived	134.895	135.050	vegetative	0.035	0.042	0.0	PASS
B3	Survived	97.471	98.498	mature	0.072	0.076	0.0	PASS
C1	Survived	129.459	144.382	flowering	0.050	0.000	0.0	PASS
C2	Survived	134.895	135.050	vegetative	0.035	0.042	0.0	PASS
C3	Survived	97.471	98.498	mature	0.072	0.138	0.0	PASS
D1	Survived	129.459	144.382	flowering	0.050	0.010	0.0	PASS
D2	Survived	134.895	135.050	vegetative	0.035	0.042	0.0	PASS
D3	Survived	97.328	98.485	mature	0.072	0.138	0.0	PASS
E1	Died	0.501	0.501	dead	0.900	0.200	22.0	PASS
E2	Died	0.500	0.500	dead	0.000	1.000	28.0	PASS
E3	Died	54.087	54.087	dead	0.000	0.500	12.3	PASS
E5	Died	0.050	0.050	dead	0.900	0.131	22.1	PASS
E6	Died	0.050	0.050	dead	0.000	0.625	15.3	PASS
E7	Died	0.184	0.184	dead	0.000	0.833	20.4	PASS

TABLE 6: Simulation Results for XGBoost Stress Prediction and Temporal Consistency

Sim	Model	Step	Biomass (g)	Leaf Area (m²)	Necrosis	Water Stress	Nutrient Stress	Temp Stress	Overall Stress	Qualitative Health
S1	Pipeline	1	0.0	0.0000	0.30	0.050	0.509	0.036	0.224	Moderate Stress
S1	Pipeline	2	0.3	0.0055	0.08	0.054	0.600	0.012	0.187	Moderate Stress
S1	Pipeline	3	3.0	0.0021	0.00	0.051	0.004	0.023	0.020	Healthy
S1	Pipeline	4	8.0	0.0400	0.28	0.083	0.450	0.012	0.206	Moderate Stress
S1	Model	1	0.50	0.0020	0.65	0.30	0.50	0.10	0.367	Severe Damage
S1	Model	2	0.45	0.0018	0.25	0.10	0.20	0.05	0.142	Moderate Stress
S1	Model	3	0.48	0.0022	0.00	0.00	0.05	0.00	0.017	Healthy
S1	Model	4	0.52	0.0021	0.65	0.30	0.30	0.10	0.280	Moderate Stress
S2	Pipeline	1	15.0	0.0070	0.00	0.059	0.018	0.011	0.022	Healthy
S2	Pipeline	2	0.15	0.0015	0.00	0.048	0.017	0.019	0.021	Healthy
S2	Pipeline	3	0.20	0.0050	0.15	0.055	0.664	0.011	0.220	Moderate Stress
S2	Pipeline	4	1.5	0.0042	0.00	0.051	0.007	0.012	0.018	Healthy

S2	Model	1	0.50	0.0020	0.00	0.10	0.20	0.00	0.075	Healthy
S2	Model	2	0.45	0.0018	0.00	0.20	0.25	0.00	0.113	Early Stress
S2	Model	3	0.40	0.0015	0.30	0.20	0.60	0.00	0.275	Moderate Stress
S2	Model	4	0.50	0.0020	0.00	0.00	0.10	0.00	0.025	Healthy

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