Low-Cost, Multi-Sensor Automation for Hydroponic Lettuce & Microgreens in CEA

2.0 Methodology.

2.1 System Overview

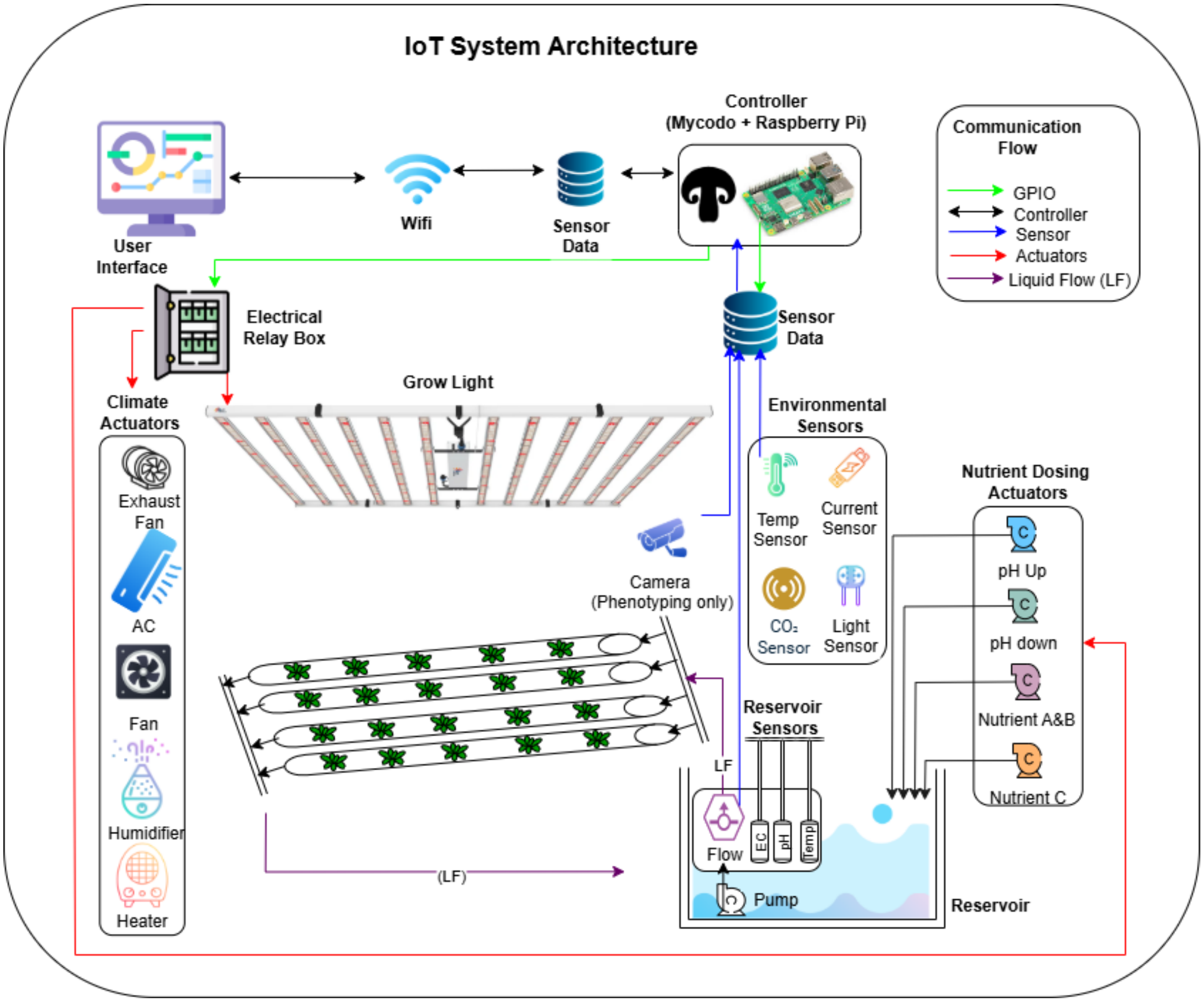
A low-cost, modular automation framework was developed to evaluate adaptive environmental and nutrient management for hydroponic lettuce in Controlled Environment Agriculture (CEA). The system maintained stable setpoints for pH, electrical conductivity (EC), and climate variables, while enabling EC steering to meet defined growth targets under energy and nutrient efficient conditions.

A Raspberry Pi 5 running the open-source Mycodo platform (Kizniche, 2025) served as the central controller for sensor acquisition, actuation, and data logging. Mycodo supported modular input-output mapping, rule-based and PID control, and data recording.

Reservoir sensors measured pH, EC, solution temperature, and flow rate; environmental sensors tracked air temperature, relative humidity, vapor pressure deficit (VPD), and CO_2 concentration. Analog readings were converted via an ADS1115 ADC, and all data were time-stamped in Mycodo for analysis of control precision and resource use.

Mechanical Relays were driven by the raspberry Pi's GPIO pins, and operated peristaltic pumps for nutrient and pH dosing, the NFT recirculation pump, LED lighting, and climate devices (fans, humidifier, heater, exhaust fan and air conditioner). Control functions combined feedback rules and PID loops, with all events automatically logged.

The NFT lettuce system operated under continuous nutrient recirculation with dynamic EC control. Collected datasets on environmental conditions, actuator duty cycles, and energy use formed the basis for evaluating open-source automation as a cost-effective strategy to enhance productivity and sustainability in CEA.



2.2 Hardware

2.2.1 Sensors

Reservoir and environmental sensing were implemented using Atlas Scientific EZO circuits (pH, EC, RTD, CO_2, Flow) and Adafruit modules (BME280, ADS1115, YF-S201C), selected for low cost, modularity, and compatibility with the Raspberry Pi 5 controller (Atlas Scientific, 2024a–e; Adafruit Industries, 2023a–c; Bosch Sensortec, 2018).
These sensors provided real-time feedback for automated management of nutrient solution and microclimate. The EZO-pH, EZO-EC, and EZO-RTD PT-1000 circuits monitored solution pH, conductivity, and temperature in the nutrient reservoir with their probes, while the EZO-CO_2 NDIR sensor measured canopy-level CO_2 concentration.

A YF-S201C turbine sensor coupled with the EZO-Flow circuit quantified the recirculation flow rate. Air temperature, relative humidity, and vapour pressure deficit were recorded by a BME280 sensor, and data were recorded in Mycodo. Subsystem energy use was tracked by a split-core current transformer interfaced through an ADS1115 16-bit ADC, allowing device-level energy partitioning. All sensors communicated via the I^2C bus, except for analog signals routed through the ADS1115.Measurements were sampled every 60 s, time-stamped, and stored in the Mycodo database for subsequent evaluation of control stability and resource-use efficiency. Calibration procedures and installation specifications are summarized in Table 1.

2.2.2 Actuators and Electrical Loads

System actuation consisted of nutrient dosing, NFT recirculation, lighting, and climate conditioning (Table 2). GPIO-driven mechanical relays on the Raspberry Pi provided on/off control for all loads. Four peristaltic pumps dispensed acid, base, and nutrient solutions under Mycodo rule-based logic and routines linked to pH and EC feedback. A submersible pump maintained continuous nutrient film flow within the NFT channels. LED panels were relay-switched to a 16 h light / 8 h dark photoperiod (05:00–21:00). Temperature was regulated by conditional activation of a resistive heater and portable air-conditioning unit, while humidity control employed an ultrasonic humidifier and inline exhaust fan to maintain VPD between 0.8–1.2 kPa (day) and 0.5–0.8 kPa (night). All circuits were fused and GFCI-protected, with current monitored for energy-use analysis.

2.2.3 Integration Context

The assembled hardware formed the physical framework for the adaptive control logic (Section 2.3) and experimental design (Section 2.4). Integrating multi-sensor feedback with relay-based actuation through Mycodo enabled autonomous maintenance of hydroponic setpoints and facilitated quantitative assessment of automation precision, responsiveness, and energy demand under realistic NFT lettuce-production conditions.

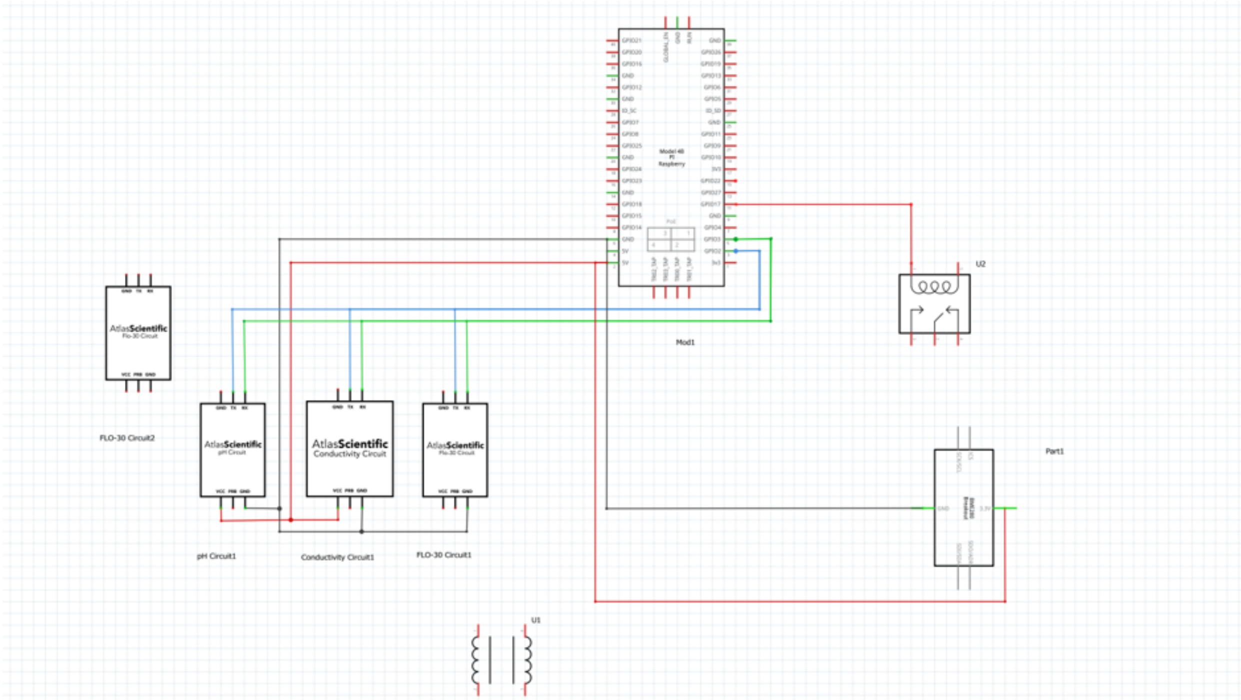


Figure.. (Circuit Diagram)

2.3 Software & Control Logic

2.3.1 Interfacing Sensors with Mycodo

The automation system operated on a Raspberry Pi 5 running Raspberry Pi OS (64-bit, Debian Bookworm) with Mycodo v8.16.2 (Kizniche, 2025) as the central control environment. Mycodo provided unified interfaces for sensor data acquisition, actuation, and data logging through the Pi's GPIO and I^2C buses.

All sensors were registered as inputs including Atlas Scientific EZO circuits (pH, EC, RTD PT-1000, CO_2, Flow) and the BME280 for atmospheric monitoring. Analog signals from the split-core current transformer were digitized via an ADS1115 ADC. Each device was configured with its I^2C address, calibration coefficients, and 60 s sampling interval. Actuators were mapped as outputs to GPIO pins driving mechanical relays for nutrient dosing, lighting, NFT recirculation, and climate regulation.

Control logic combined Conditional Controllers, On and Off Triggers and PID loops, enabling rule-based responses for pH and EC adjustment, photoperiod scheduling, and temperature–humidity regulation. Control evaluations executed every 30 s to balance responsiveness and data stability. All sensor readings and actuator events were time-stamped and stored in Mycodo's SQL database. Automated CSV exports supported validation and external analysis.

Data integrity was maintained through layered version control. Raw data resided locally on the microSD card and were mirrored to an external SSD for redundancy. Configuration files (*.json), calibration logs, and control settings were archived at the start and end of each crop cycle and version-tracked in a private GitHub repository containing custom Python scripts and calibration datasets.

Full I^2C address assignments, GPIO mappings, and power-channel designations are listed in the I/O Address Map (Table 3) to ensure reproducibility of both hardware and software integration across experiments.

2.3.2 Nutrient and pH Control

Automated nutrient and pH regulation were implemented in Mycodo through conditional control functions processing real-time data from Atlas Scientific EZO-pH and EZO-EC sensors. The system maintained a pH range of 5.8–6.2, with corrective actions triggered below 5.6 or above 6.4. Four peristaltic pumps, acid (pH-down), base (pH-up), nutrient A+B, and nutrient C were configured as independent relay-controlled outputs.

Each correction operated as a time-based pulse to simplify calibration and reduce cost: nutrient pumps dispensed for 10 s per event, and pH pumps for 5 s. After each pulse, a mixing dwell of 360s was enforced before acquiring new readings.

To prevent overdosing and oscillation, multiple safeguards were embedded:

- Deadbands and hysteresis: No action occurred within 5.8–6.2; fine-tuning pulses were applied for minor deviations (5.6–5.8 or 6.2–6.4), and corrective doses for larger excursions (<5.6 or >6.4).

- Mutual exclusion: Acid and base pumps were locked out for 10–15 min between activations and interlocked with the circulation pump to prevent localized pH gradients.

For NFT-grown lettuce, EC followed a staged trajectory, beginning near 1.2 mS cm^{-1} and increasing in 0.2 mS cm^{-1} increments to 2.0 mS cm^{-1} toward harvest. When EC dropped below the target band, nutrient pumps delivered 10 s pulses; when exceeding the band, Mycodo issued an alert recommending dilution or RO-water addition. EC readings were temperature-compensated to 25 °C using RTD PT-1000 data, and EC dosing was automatically paused if temperature input was unavailable.

All dosing events were automatically logged with pre-/post-event pH and EC, pulse durations, dwell times, and outcome status, ensuring full traceability. These feedback loops underpinned later analyses of control responsiveness and nutrient-use efficiency, demonstrating that low-cost automation can maintain hydroponic solution stability with minimal operator input.

Dynamic EC setpoints were later adjusted throughout the 28-day growth period based on median plant-weight checkpoints (see Section 2.4), allowing crop response to guide nutrient concentration over time.

2.3.3 Irrigation Control

Irrigation for the NFT lettuce system operated under a continuous recirculation regime. A submersible pump delivered nutrient solution from the reservoir through NFT channels, maintaining a constant thin film along the root zone. Flow rate was monitored in-line using a YF-S201C turbine sensor interfaced with an Atlas Scientific EZO-Flow circuit, with data logged in Mycodo at 60 s intervals.

Although the pump operated continuously rather than through relay-based switching, real-time flow data provided diagnostic validation of system performance, enabling detection of pump failure, line obstruction, or reservoir depletion. This ensured reliable water and nutrient delivery throughout the 28-day period of growth.

Continuous flow also stabilized root-zone oxygenation and nutrient availability, supporting uniform growth and minimizing thermal or concentration gradients along the channel. Flow monitoring further allowed estimation of cumulative water circulation and pump duty for resource-use analysis.

By coupling constant flow with sensor feedback, the irrigation control strategy exemplified how low-cost, open-source automation can maintain precise hydraulic conditions while generating traceable data for efficiency assessment in hydroponic NFT production.

2.3.4 Lighting Control

Lighting for photosynthesis was automated in Mycodo using two Daily Trigger functions assigned to the lighting relay (GPIO 22). A Span Trigger defined the ON window and a Point Trigger enforced OFF at the end of the photoperiod. The schedule provided a 16 h light / 8 h dark cycle (05:00–21:00, America/Los_Angeles), optimized for lettuce growth.

Lighting control operated as a relay-based ON/OFF system, with fixture intensity manually adjusted through onboard dimmers and mounting height to maintain target photosynthetic photon flux density (PPFD) at canopy level. All switching events were logged automatically for performance validation and reproducibility.

The Daily Light Integral (DLI) was estimated from measured PPFD and the 16 h photoperiod, offering sufficient precision for this proof-of-concept study. Although closed-loop PAR feedback was not implemented, the configuration provides a scalable basis for future integration of automated dimming and spectral control in low-cost CEA systems.

2.3.4 Climate Regulation

Climate control within the grow tent encompassed temperature, humidity (via VPD), and CO_2 concentration, maintaining stable environmental setpoints synchronized with the photoperiod (day: 05:00–21:00; night: 21:01–04:59). These automated functions ensured physiologically appropriate conditions for lettuce growth and generated high-resolution datasets for assessing control precision and energy efficiency.

2.3.4.1 Temperature Control

Temperature regulation employed conditional logic in Mycodo using feedback from the BME280 sensor positioned at canopy height and shielded from direct light. Day and night profiles followed the photoperiod through Daily Triggers. During the day, the cooling relay (AC) activated at ≥24 °C and disengaged below 21 °C, while the heating relay engaged below 20 °C and deactivated at 21 °C. At night, cooling initiated at ≥22 °C and stopped below 19 °C, with heating engaged below 18 °C and off at 20 °C.

A 2 °C hysteresis band (21–23 °C day; 19–21 °C night) prevented relay chatter, and mutual-exclusion logic blocked simultaneous heating and cooling. All switching events were logged automatically with timestamps, enabling calculation of response time and duty cycle. Periodic cross-validation with a reference thermometer confirmed sensor accuracy, ensuring reproducible and energy-efficient thermal regulation within the controlled environment.

2.3.4.2 Humidity and VPD Control

Humidity regulation was based on vapor pressure deficit (VPD) rather than relative humidity alone. VPD was computed automatically in Mycodo from BME280-derived temperature and humidity data and expressed in kilopascals (kPa). Separate daytime (05:00–21:00) and nighttime (21:01–04:59) control functions were synchronized with the photoperiod to maintain climate consistency.

During the day, the target VPD range was 0.8–1.2 kPa, optimal for lettuce transpiration and gas exchange. When VPD < 0.8 kPa, the exhaust fan activated and the humidifier paused; when VPD > 1.2 kPa, the humidifier engaged and the exhaust deactivated. At night, the control band narrowed to 0.5–0.8 kPa to match reduced evaporative demand.

A ± 0.1 kPa hysteresis margin and mutual-exclusion logic prevented rapid relay cycling or simultaneous actuator operation. All switching events were logged automatically in Mycodo with timestamps for traceability.
This configuration allowed dynamic stabilization of canopy-level VPD, achieving energy-efficient humidity control and demonstrating reliable low-cost automation for CEA climate management.

2.3.4.3 CO_2 Monitoring

CO_2 concentration was continuously measured using an Atlas Scientific EZO-CO_2 nondispersive infrared (NDIR) sensor (I^2C address 0x69). Data were logged in Mycodo at one-minute intervals and visualized on the system dashboard for real-time diagnostics. The sensor was installed at canopy height to capture crop-relevant air composition within the grow tent.

No active CO_2 enrichment or feedback control was implemented in this proof-of-concept study. Monitoring served primarily as a diagnostic measure to evaluate air-exchange efficiency and to contextualize environmental stability for subsequent analysis of automation performance and resource-use efficiency.

2.4 Integrated Control Architecture

All automation functions were coordinated within Mycodo through a unified control hierarchy linking sensors, actuators, and data logging. The photoperiod defined the primary timing layer, synchronizing day–night transitions across temperature, humidity (VPD), and lighting subsystems.
Rule-based condition logic, On/Off Triggers, and PID controllers operated concurrently but independently, each maintaining its assigned setpoint while respecting interlocks and hysteresis constraints to prevent conflict or relay chatter.

Nutrient and pH regulation functioned as continuous event-driven loops, while environmental modules followed diurnal profiles governed by daily triggers. Dynamic EC setpoints were coupled to median plant-weight checkpoints (Section 2.5), enabling feedback between crop response and nutrient concentration.

All system states, including sensor values, relay actions, and controller responses, were time-stamped in Mycodo's SQL database, forming a unified dataset for evaluating control precision, responsiveness, and energy demand. This architecture illustrates how low-cost, open-source hardware can achieve multi-variable feedback coordination typical of commercial environmental controllers.

2.4 Experimental Design

2.4.1 Design Logic and Aims

This proof-of-concept study evaluated whether a low-cost, multi-sensor automation framework could (i) maintain prescribed environmental and nutrient setpoints, (ii) steer lettuce growth toward a marketable fresh weight of 0.5 lb (227 g) within 28 days through adaptive, median-based EC control, and (iii) quantify resulting effects on resource-use efficiency (RUE) for energy, water, and nutrients.

The design was structured around three complementary objectives:
(a) *Automation reliability*: determine the proportion of time pH, EC, temperature, and vapor pressure deficit (VPD) remained within defined tolerance bands;
(b) *Growth steering*: evaluate the ability of the adaptive algorithm to align observed fresh-weight progression with a modeled Gompertz trajectory through 4-day feedback checkpoints; and
(c) *Resource-use efficiency* – assess how EC and photosynthetic photon flux density (PPFD) modulation influenced yield per unit of energy, nutrient, and water consumed.

The Gompertz growth model $L_t = Ae^{-e^{(b-kt)}}$ (Putra et al., 2025) was parameterized with A=227g, b=3.2 and k=0.20k to generate 4-day fresh-weight targets forming the experimental baseline. All sensors and actuators were managed by Mycodo on a Raspberry Pi 5, which logged pH, EC, temperature, humidity, and actuator states. The operator's role was limited to implementing EC adjustments at each checkpoint and applying a single mid-cycle lighting correction if growth deviated from the modeled curve. This human-in-the-loop framework functioned as a semi-autonomous testbed for validating feedback-based environmental control.

2.4.2 Plant Sampling and Adaptive EC Adjustment Protocol

Lettuce (*Lactuca sativa* L., cv. 'Salanova Red Tango'; Johnny's Selected Seeds, USA) was used as the model crop for the nutrient film technique (NFT) experiment. Seeds were germinated in rockwool cubes under a 16 h light / 8 h dark photoperiod at 22 ± 2 °C and 60–70 % relative humidity. After 12 days of nursery growth, uniform seedlings (3–4 g average fresh weight) were transplanted into net pots fitted within NFT channels. Each channel received a continuous recirculating film of nutrient solution supplied from the main reservoir. The NFT configuration provided a stable hydroponic baseline for automation testing and feedback control of nutrient and environmental variables.

The trial began with an initial nutrient solution conductivity of 1.2–1.4 mS cm^{-1} during establishment (Days 0–4). Subsequent EC setpoints were adjusted at 4-day intervals based on performance relative to Gompertz-derived fresh-weight targets.

At each checkpoint, ten representative plants were sampled along the NFT channel to minimize positional bias. The same plants were re-sampled throughout the cycle. Median fresh weight (W_{median}) was computed as:

$W_{median}=W_{(5)}+W_{(6)}/2W$

where $W_{(5)}$ and $W_{(6)}$ are the 5th and 6th ranked values from the 10 sampled plants.
The median served as the decision variable for EC control according to the following rules:

- If W_{median} fell within the target band, EC was maintained.
- If W_{median} fell below the target band, EC increased by 0.2 mS cm^{-1}.
- If W_{median} remained above the band for two consecutive checkpoints, EC reduced by 0.1 mS cm^{-1}.

All EC changes and median weights were automatically logged in Mycodo.
By Day 12, growth lagged significantly behind the modeled trajectory, prompting a one-time

PPFD increase from ≈ 200 to ≈ 445 μmol m^{-2} s^{-1} (daily light integral ≈ 25.6 mol m^{-2} d^{-1}). This new PPFD level was maintained for the remainder of the experiment, while EC continued to adapt. At harvest (Day 28), plants were evaluated for fresh weight, leaf number, and visual quality (colour uniformity, tip burn). Measurements were taken between 18:00–19:00 h to reduce diurnal variability.
This feedback protocol established a closed monitoring adjustment loop directly linking plant performance with environmental control inputs.

2.4.3 Data Processing and Analysis

All sensor and actuator data were logged at 15-min intervals in Mycodo and exported as CSV files for analysis in MATLAB R2025a. Recorded variables included pH, EC, nutrient temperature, air temperature, relative humidity, VPD, CO_2 concentration, and actuator states (pump runtime, lighting cycles, and electrical current).

Data processing involved:

1. **Integrity checks:** identification and interpolation of missing or out-of-range data.
2. **Noise reduction:** 15-min averaging of high-frequency sensor signals.
3. **Temporal alignment:** synchronization of system logs with 4-day sampling data.
4. **Correlation analysis:** linking median FW, EC and PPFD trajectories, and system stability metrics.

Analyses performed in MATLAB included:

- Time-series visualization of setpoint tracking and system response.
- Regression modeling of EC and PPFD effects on biomass accumulation.
- Setpoint stability for the percentage of time each controlled variable remained within tolerance.
- Actuator duty cycle and power consumption derived from current-sensor data.

Resource-use efficiency (RUE) was expressed as:

RUE=Y/R

where Y is fresh biomass (g FW) and R represents total resource input, energy (kWh), nutrient (mL), or water (L).

Derived metrics included:

- **EUE** (Energy Use Efficiency): g FW · kWh^{-1}
- **NUE** (Nutrient Use Efficiency): g FW · mL^{-1}
- **WUE** (Water Use Efficiency): g FW · L^{-1}

Comparisons were made between the baseline phase (low PPFD) and the enhanced-light phase (445 μmol m^{-2} s^{-1}) to quantify efficiency trade-offs.
Statistical analyses (Pearson correlation, one-way ANOVA) were conducted in SPSS v31 for cross-validation.
System schematics and data-flow diagrams were created in Draw.io and refined in Adobe Illustrator for publication.