Precision Under Constraint

Focusing specifically on the evapotranspiration (ET) algorithm, this presentation details the adaptation of the complex Penman-Monteith equation for autonomous, low-resource environmental monitoring. This showcases our deep technical understanding and innovative approach to scientific modeling under severe real-world constraints.

From Theory to Application: Adapting Penman-Monteith for Autonomous Environmental Intelligence

The Evapotranspiration Algorithm of the Umbrella Project

Audience: Scientific and engineering reviewers, university admissions committees, and technical competition judges.

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Presented to Scientific Review Board

The Grand Vision: The Umbrella Project

A Self-Sustaining Micro-Ecosystem

The Umbrella Project is designed as an autonomous, self-sustaining system for environmental intelligence and enabling life in harsh environments.

- Purpose: Environmental monitoring, education, and resilience studies.
- Core Challenge: Operating autonomously for extended periods with minimal power and resource draw.
- **Critical Necessity:** Precise, real-time water management to maximize conservation.

The Critical Role of Evapotranspiration (ET)

Defining ET

Evapotranspiration is the combined process of water loss to the atmosphere via evaporation from the soil and transpiration from plant leaves.

ET as Water Demand

ET is the primary driver of water consumption and loss within the closed system, fundamentally determining irrigation scheduling requirements.

The Project Goal

Accurately estimating Reference ET (ET_0) directly on-device enables efficient, closed-loop, autonomous water rationing and management.

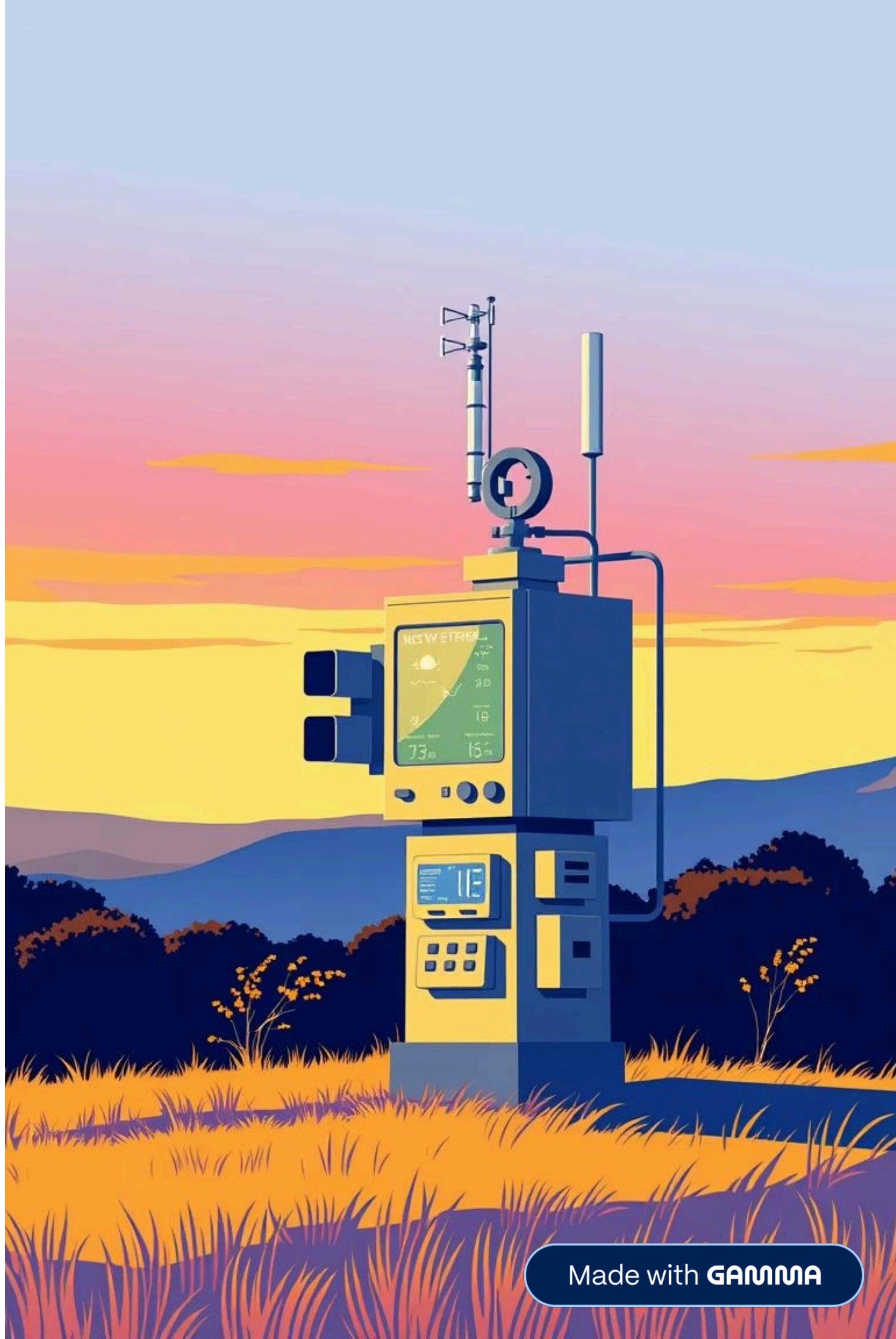
Introducing Penman-Monteith: The Gold Standard

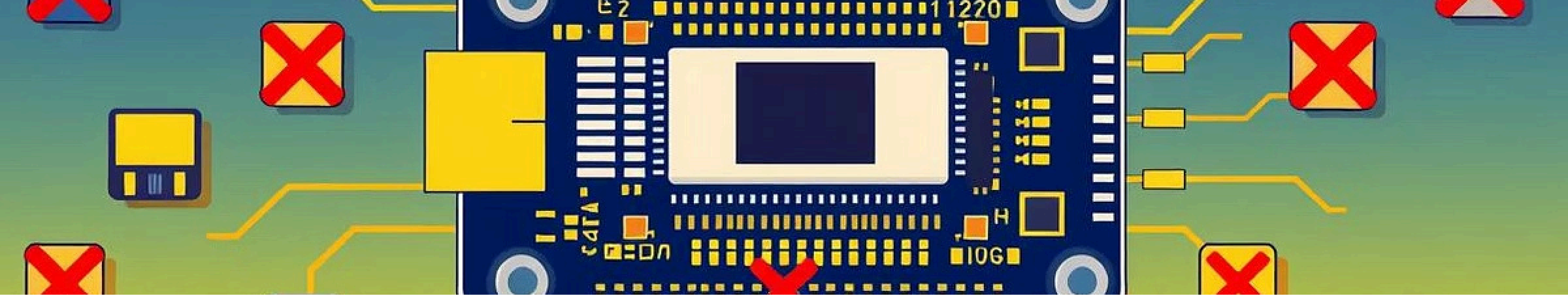
The FAO Penman-Monteith equation is the globally recognized standard for calculating reference evapotranspiration (ET_0) due to its strong theoretical basis in physics.

> **Theoretical Basis:** The equation rigorously combines the energy balance (radiation input) and aerodynamic resistance (wind and air humidity transport) approaches.

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T_{avg}+273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

While highly accurate, it requires a comprehensive suite of atmospheric and surface measurements.





The Constraint: Penman-Monteith's Data Demands

The rigorous nature of the Penman-Monteith model poses significant logistical challenges for a small, autonomous device operating under power limitations.

High Sensor Proliferation

The full equation requires sensors for net radiation, soil heat flux, air pressure, wind speed, temperature, and humidity, increasing cost and system complexity.

Increased Power Consumption

Operating and logging data from a high number of sensors significantly drains battery life, compromising autonomy.

Computational Load

Executing the full, iterative calculation imposes a heavy burden on the low-power microcontroller (MCU) selected for the system.

Our Approach: Intelligent Parameter Reduction & Derivation

Core Strategy: How can we achieve effective ET estimation with minimal, readily available on-board sensors?

Full Penman-Monteith Complexity

High accuracy, high data demand (multiple sensors).

Intelligent Reduction

Selective parameter retention and empirical derivation.

Simplified Algorithm

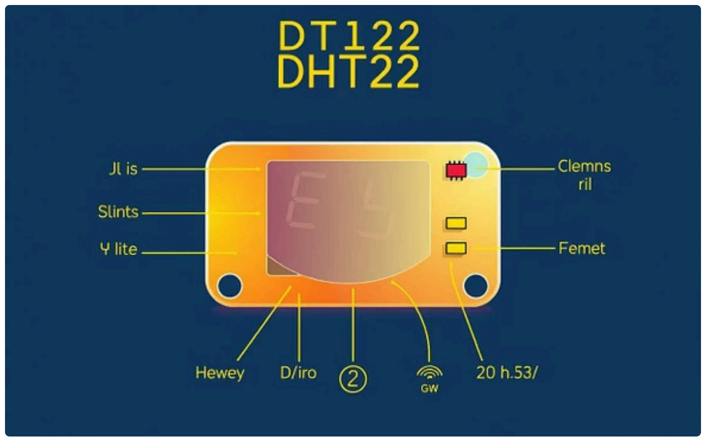
Low sensor count (T, RH), low power draw.

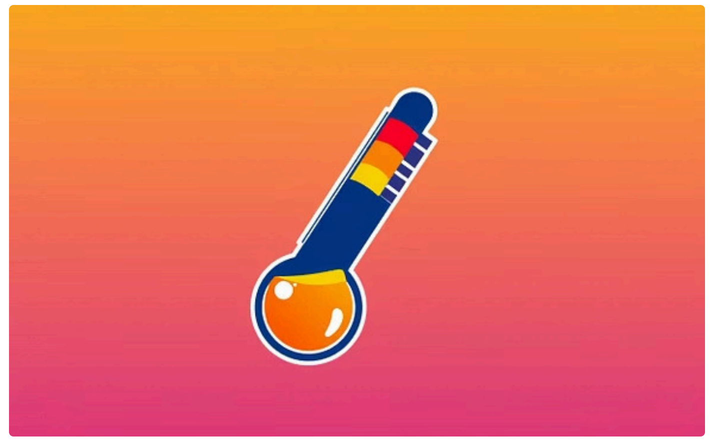
Effective ET Scheduling

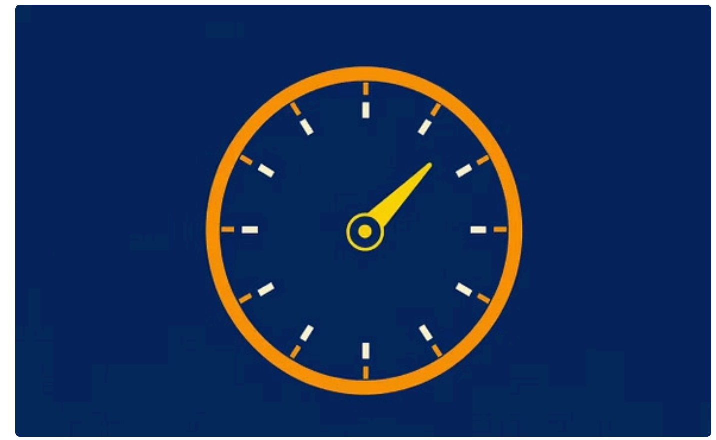
Enables optimal water rationing and conservation.

Key Retained & Directly Measured Parameters

We focus on the most influential variables that can be reliably and economically measured using a single, robust, low-power sensor.







Temperature (T)

Directly measured. Crucial for determining saturation vapor pressure (e_s) and the slope of the vapor pressure curve (Δ).

Relative Humidity (RH)

Directly measured. Essential for calculating the actual vapor pressure (e_a), which informs the critical vapor pressure deficit (VPD).

This dual-measurement approach, enabled by the low-cost DHT sensor series, provides the foundation for deriving all other necessary thermodynamic variables.

Deriving Unmeasured Parameters: The Ingenuity

We mathematically derive high-demand parameters from the basic Temperature (T) and Relative Humidity (RH) inputs, minimizing hardware complexity while maintaining physical fidelity.

Derived Moisture Parameters

Delta (slope)
Derivative of es vs T

Temperature (T)
Primary input

Vapor pressure deficit (VPD)
es minus ea

Relative Humidity (RH)
Primary input

Actual vapor pressure (ea)
From T and RH

Saturation vapor pressure (es)
Computed from T

1

Saturation Vapor Pressure (e_s)

Derived from T using empirical functions (e.g., Tetens' equation), estimating the maximum moisture capacity of the air at that temperature.

2

Actual Vapor Pressure (e_a)

Calculated as $e_a = e_s \times (RH/100)$, representing the true moisture content.

3

Vapor Pressure Deficit (VPD)

The difference $(e_s - e_a)$. This is the driving force of transpiration, directly linked to plant water stress.

4

Psychrometric Constant (γ)

We assume a standard atmospheric pressure based on fixed deployment altitude, negotiating the need for a pressure sensor.

Strategic Assumptions & Simplifications

To overcome the stringent data demands of the full Penman-Monteith equation within our low-resource constraints, we employ a strategy of intelligent simplification and parameter derivation. This allows us to achieve effective ET estimation with minimal, readily available on-board sensors.

Net Radiation (Rn)

Direct measurement of net radiation is highly impractical for a low-power device. We address this by either utilizing a constant value derived from regional average solar radiation data or implicitly handling its influence through our adaptive irrigation logic, which responds to observed plant water needs.

Soil Heat Flux (G)

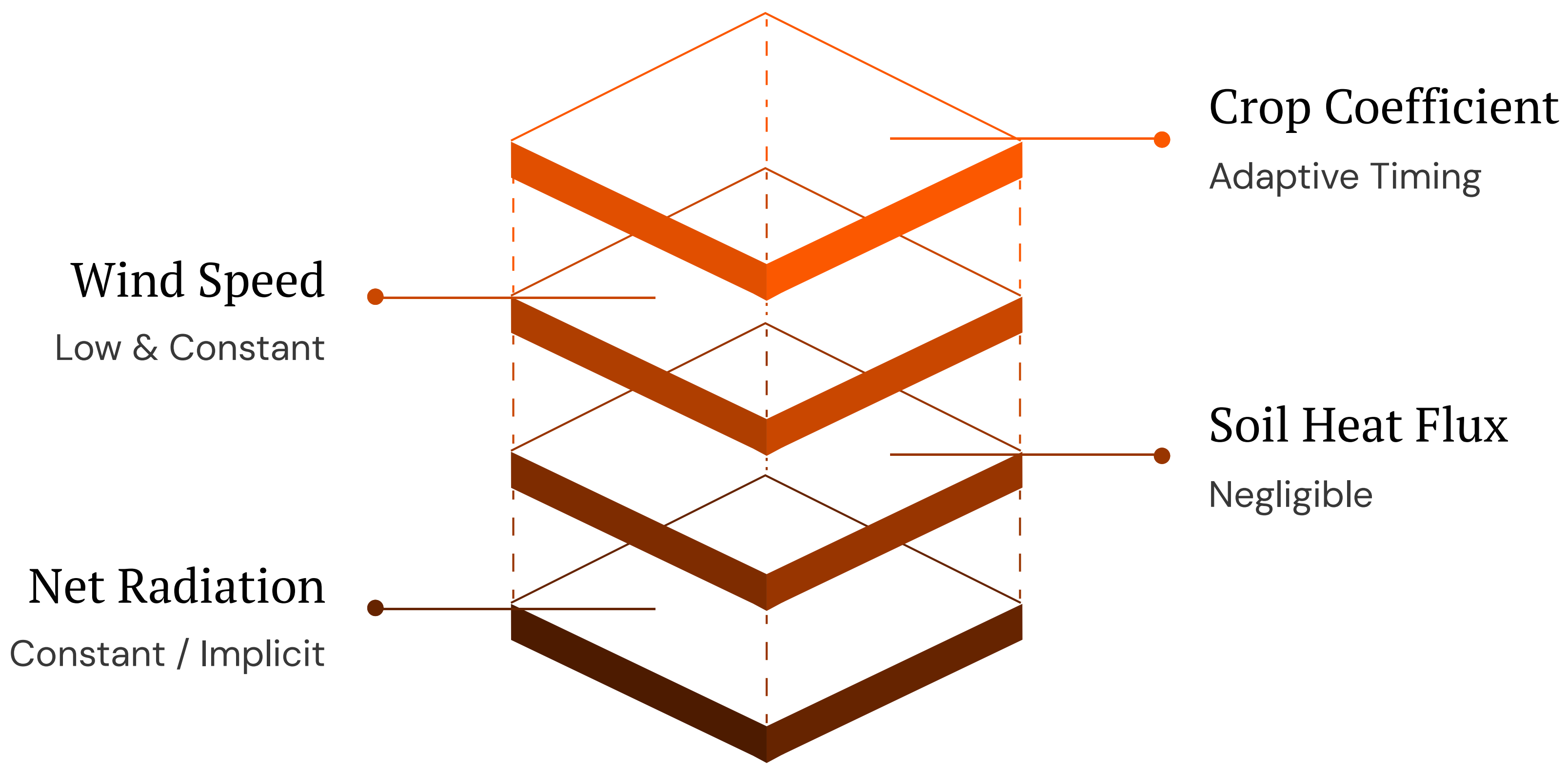
In most agricultural applications, for daily or longer time scales, soil heat flux (G) is typically assumed to be zero or a small, negligible fraction of net radiation (Rn), particularly during the daylight hours when ET is most significant. We adopt this standard simplification.

Wind Speed (u2)

Accurate, continuous wind speed measurement is challenging for a small, integrated device operating in a sheltered microclimate. We assume a low, constant average wind speed appropriate for the enclosed environment created by the Umbrella Project, reflecting the reduced airflow within.

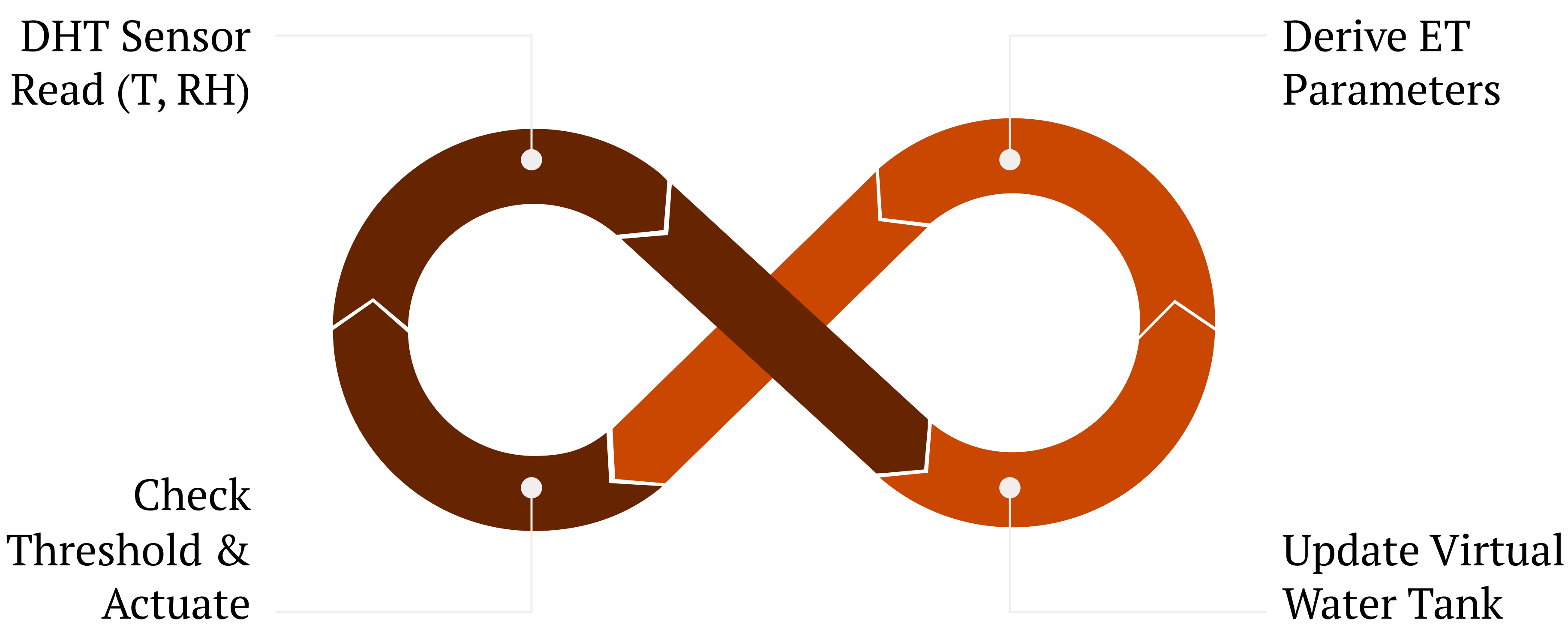
Crop Coefficient (Kc)

Instead of explicitly calculating a crop coefficient, our adaptive irrigation timing implicitly accounts for the specific water needs of the plants and the unique microclimate conditions created by the Umbrella Project, making direct Kc calculation unnecessary.



The Algorithm in Action: Adaptive Irrigation Logic

The core of our autonomous system lies in translating derived ET values into actionable irrigation decisions. This intelligent logic ensures optimal water delivery, reacting dynamically to plant needs and environmental conditions.



Virtual Water Tank Concept

We maintain a digital representation of the available water volume in the soil within the device's microclimate. This "virtual water tank" is conceptually filled by rainfall/manual irrigation events (which can be externally logged) and depleted by the calculated ET_0.

Irrigation Trigger

An irrigation event is triggered when the calculated ET_0 causes the virtualWaterVolume to drop below a predefined threshold. This threshold is dynamically adjustable and represents the point at which plant water stress would begin.

Irrigation Duration/Volume

The required irrigation duration and volume are determined by how far the virtualWaterVolume has fallen below the threshold, combined with the simplified ET demand for the upcoming period. This ensures precise replenishment, avoiding over- or under-watering.

Data Logging & Validation

Key parameters, including derived ET values, dayProgress (daily ET accumulation), and allTimeIndex (cumulative ET), are continuously logged. These arrays provide a robust dataset for system validation, performance monitoring, and future algorithmic refinements.

Validation & Future Directions

Validation Methods

- Comparison with actual water usage in controlled environments
- Plant health and growth as proxy indicators for effective irrigation
- Long-term data logging for seasonal trend analysis

Future Enhancements

- Integration of simplified solar radiation sensor
- Machine learning for dynamic adjustment of assumptions (wind speed factor, etc.)
- Remote calibration capabilities for the virtual tank
- Potential for multi-device network data sharing

Precision Under Constraint: Impact & Implications

Core Achievement

Effective, autonomous evapotranspiration estimation and precision irrigation on a low-power, low-resource device.

Scientific Rigor

Methodical approach to simplifying complex models for real-world application while maintaining physical fidelity.

Broader Implications

Environmental Restoration

Scalability for environmental restoration projects.

Democratizing Tech

Democratization of precision agriculture technology.

STEM Education

Educational applications in STEM learning.

Resource-Scarce Environments

Potential for deployment in resource-scarce environments.

Next Steps: Join Our Mission

We invite collaboration for further research and implementation to expand the reach and impact of this innovative technology. Together, we can cultivate a more sustainable future.