Real-Time Canopy Temperature Monitoring Using Infrared Sensors for Crop Stress Assessment

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ABSTRACT
Background: In the absence of any measures, crop water stress has adverse effects, such as the decrease of yield and water-use efficiency in irrigated agriculture. Canopy temperature is a well-known indicator of stomatal closure and transpiration reduction and infrared thermometry allows for the uninterrupted measurement of canopy temperature.
Objective: The study examines the development and performance of a cost-efficient method for real-time monitoring of canopy temperature, comprising features such as infrared sensing, environmental data fusion and an automatic decision-help system for irrigation.
Methods: The methods used for transmitting the data in the presented sensor network is in the form of an ESP32-based sensor network which integrates different elements such as a non-contact infrared thermometer, a temperature/relative-humidity sensor, a capacitive soil moisture probe, and a GPS module. It was seen that the Crop Stress Index (CSI), which was used to assess the importance of the canopy temperature readings obtained, is calculated by normalizing the difference between the temperatures of the canopy and the air with respect to the vapour pressure deficit. The method was carried out over the duration of 60 days and the results compared with the results obtained via handheld infrared guns and gravimetric sample tests.
Results: The results from the system show that the average absolute error amounts to 0.34°C with RMSE equal to 0.46 °C when compared to reference values with 94.6% of accuracy in detection of stress and 91.2% in irrigation decision making with lesser communications delays and technician’s involvement than in traditional monitoring systems.
Objective: Real-time information gathering regarding canopy temperature and decision making based on cloud technology can be considered as an efficient and economically viable approach for the modern automated irrigation systems.

Keywords: Precision agriculture; Infrared thermometry; Crop water stress; Crop Stress Index (CSI); LoRa; Wireless sensor network

1. Introduction
The purpose of precision agriculture consists in enhancing the effectiveness of the use of resources through meeting the irrigation and fertilization demands of crops not in accordance with rigid schedules but based on actual requirements of the crops caused by physiological processes [1, 2]. As a result of the increasing volatility of the climate, such as unpredictable rainfalls, high evaporation rate, and significant length of dry periods, the strain on irrigation systems has increased. It has become necessary to carry out the timely assessment of the moments of time when the crops suffer from a lack of water, which represents an important goal of agricultural practices [3, 4].
One of the most important physiological indicators that can be used to evaluate the water stress of crops is the canopy temperature. The closure of stomata due to the lack of water leads to the temperature increase [5, 6]. The greater is the difference between the air temperature and the canopy temperature, the higher its validity for predicting the stomatal conductance, leaf hydration, and crop losses due to drought [7, 8].
Infrared thermometry uses the above cited principle of measuring the longwave radiation of heat emitted from the surface of the canopy without having to physically engage with it, allowing obtaining temperature readings through non-contact and continuous observation [9]. When compared to measuring temperatures in leaves with the use of thermocouples or measuring humidity with the help of a psychrometer, infrared thermometry provides an advantage of measuring temperature without having any influence on the plants by not disturbing the boundary layer, combined with the ability to do it frequently and continuously [10, 11].
Traditional methods for measuring stress of crops include handheld infrared thermometry for assessing temperatures and visual observation, which require large labor inputs, are difficult to perform spatially, and vary according to observer competence and skill [12, 13]. Manual methods of monitoring temperature are unable to keep track of fast changes in temperature of canopy, like at peak stress times in the middle of the day, making them unfeasible for agricultural production on the commercial scale [14].

The development of inexpensive microcontrollers, wireless sensor networks and access to internet allows getting rid of periodic manual measurements and conduct continuous measurement of temperature in real-time [15, 16].
This need motivates the present study, which proposes and experimentally validates a real-time canopy temperature monitoring framework built on infrared sensing, multi-sensor environmental fusion, and an automated irrigation decision-support module. The specific objectives are to (i) design a low-cost sensor network capable of continuous canopy temperature acquisition under field conditions, (ii) derive a normalized Crop Stress Index that compensates for confounding environmental variables, (iii) evaluate the accuracy and reliability of the proposed system against conventional manual methods, and (iv) assess the scalability and practical deployment considerations of the framework for precision irrigation management [17, 18, 19, 20].

2. Materials and Methods

2.1 Experimental Site

Field trials were conducted on a 0.6-hectare commercial tomato (Solanum lycopersicum) plot in a semi-arid agro-climatic zone characterized by sandy-loam soil (bulk density 1.42 g/cm³, field capacity 24% v/v). The site experiences a mean daytime temperature of 28-36°C and relative humidity of 35-60% during the cropping season. Data were collected continuously over a 60-day period spanning vegetative growth through early fruiting, encompassing both irrigated and deficit-irrigation treatment strips.

2.2 Sensor System

The sensor network comprised a non-contact infrared temperature sensor (8-14 µm thermal band, field of view 10°, mounted at nadir 0.6 m above the canopy), a capacitive ambient temperature and relative-humidity sensor, a capacitive soil-moisture probe installed at 15 cm depth, a compact weather station recording solar radiation and wind speed, and a GPS module for spatial referencing. Each field node transmitted data to a gateway via a LoRa wireless communication module, chosen over Wi-Fi and ZigBee for its longer range and lower power draw across open field conditions.

2.3 Hardware Components

An ESP32 microcontroller managed sensor polling, onboard buffering, and LoRa transmission. Infrared and ambient sensors were factory-calibrated and cross-checked in situ against a certified blackbody reference and a mercury thermometer prior to deployment, with linear offset correction applied where deviations exceeded 0.1°C. Each node was powered by a 6 W solar panel with a 3.7 V lithium-ion buffer battery, sized for continuous operation through overcast periods. The data acquisition system sampled all channels every 5 minutes, a frequency selected to resolve diurnal canopy temperature dynamics without excessive power or bandwidth consumption.

2.4 Software Platform

Firmware was developed in the Arduino IDE. Time-series data were staged locally in a lightweight buffer and pushed to an MQTT broker for ingestion into a cloud IoT platform. Post-processing, statistical analysis, and model validation were performed in Python (pandas, NumPy, scikit-learn), with exploratory diurnal pattern analysis cross-checked in R. A web-based dashboard, built with a JavaScript charting library, rendered live and historical canopy temperature, soil moisture, and stress-index trends for field managers.

2.5 Experimental Procedure

Sensor nodes were installed at five representative locations spanning irrigated and deficit-irrigated strips. Canopy temperature, ambient conditions, and soil moisture were logged continuously, while irrigation events were scheduled according to two regimes: a full replacement of crop evapotranspiration (control) and a 60% deficit treatment (stress-inducing). Raw data were preprocessed through outlier rejection (values outside 3 standard deviations of a rolling 2-hour window), linear interpolation of brief transmission gaps, and time synchronization across nodes before stress index computation.

2.6 Performance Metrics

System performance was quantified using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) relative to a calibrated handheld infrared reference, the coefficient of determination (R^2) between predicted and observed canopy-air temperature differentials, classification accuracy, precision, and recall for stress/no-stress labeling, end-to-end response time from sensing to alert generation, and long-term sensor stability assessed through periodic recalibration drift checks.

3. Proposed Real-Time Canopy Temperature Monitoring Framework

The proposed framework follows a layered architecture spanning field sensing, edge aggregation, cloud processing, and decision support, as illustrated in Figure 1. At the field layer, each node fuses infrared canopy temperature with ambient temperature, relative humidity, and soil moisture, ensuring that a rise in canopy temperature is interpreted in the context of concurrent atmospheric demand rather than in isolation.

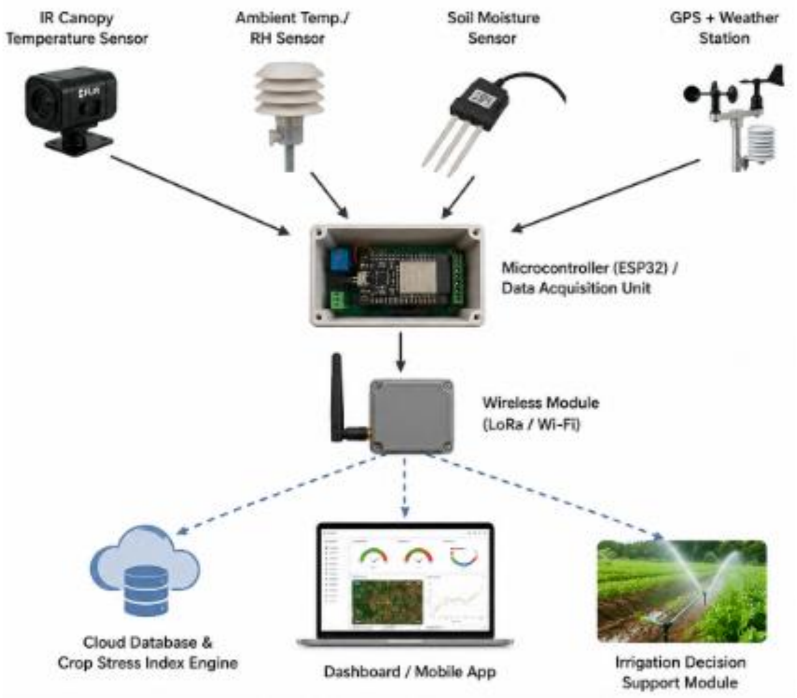

Fig 1: Overall architecture of the real-time canopy temperature monitoring system, from field sensor nodes through cloud processing to the irrigation decision-support module

Signal conditioning at the microcontroller applies noise filtering through a moving-average window, followed by temperature normalization that adjusts for sensor emissivity assumptions and view-angle effects. Environmental compensation then expresses the canopy-air temperature differential relative to vapor pressure deficit, yielding a Crop Stress Index that remains comparable across varying weather conditions and times of day.

The complete information flow, depicted in Figure 2, proceeds from raw acquisition through filtering and normalization to CSI computation, after which a rule-based and threshold-calibrated classifier determines whether canopy conditions indicate incipient water stress. When the CSI exceeds a site-calibrated threshold, the decision-support module issues a real-time alert to the dashboard and mobile application and, where an actuated valve is present, can directly recommend or trigger an irrigation event.

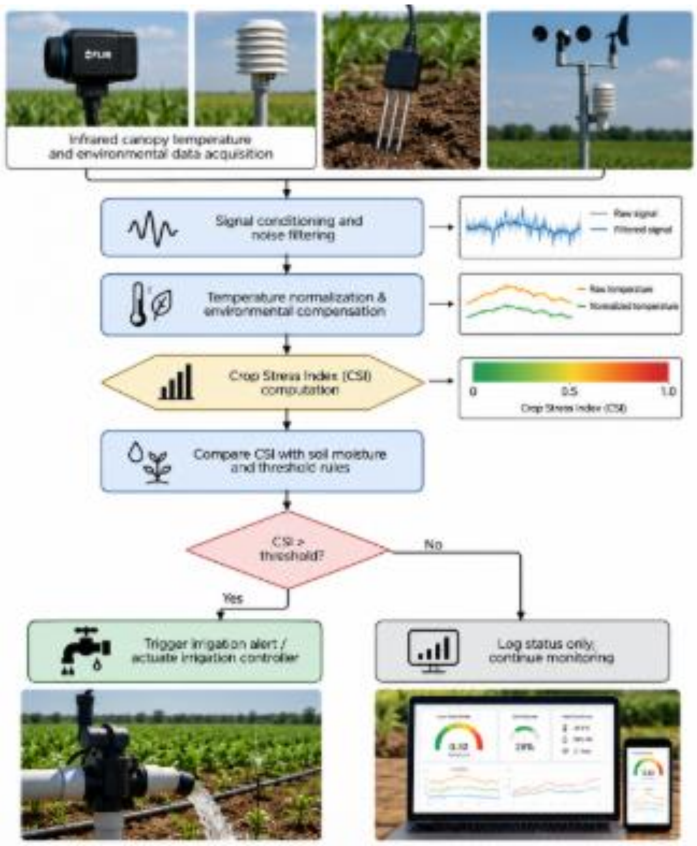

Fig 2: Flowchart of data acquisition, preprocessing, crop stress estimation, and irrigation decision-making within the proposed framework

Processed data and derived indices are stored in a time-series cloud database, enabling historical trend analysis, seasonal comparison, and retrospective irrigation audit. Figure 4 (Section 4) details the corresponding IoT communication and dashboard architecture that delivers this information to end users in near real time.

4. Results and Performance Evaluation

Diurnal canopy temperature patterns diverged clearly between irrigation treatments (Figure 3). Under full irrigation, canopy temperature remained 1.5-2.8°C below ambient air temperature throughout the midday period, consistent with active transpirational cooling. Under the 60% deficit treatment, canopy temperature exceeded ambient air temperature by up to 2.0°C during peak radiation hours (11:00-15:00), reflecting reduced stomatal conductance.

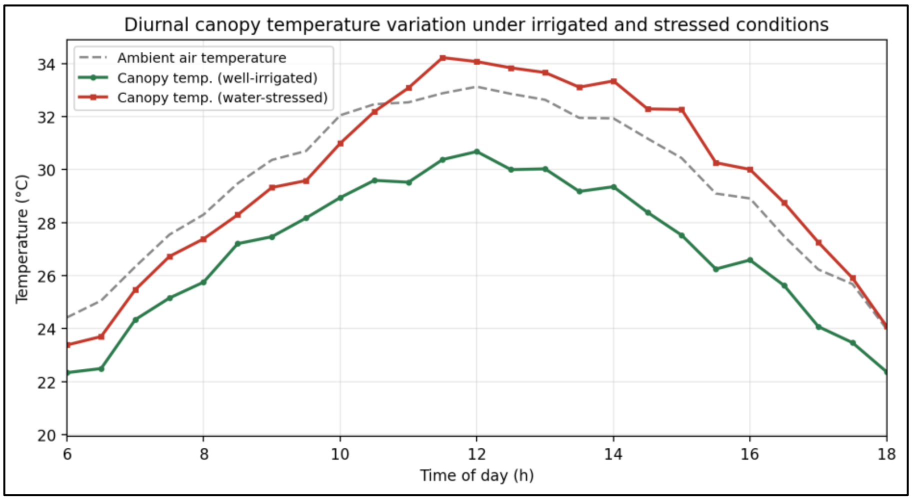

Fig 3: Diurnal canopy temperature variation under well-irrigated and water-stressed conditions relative to ambient air temperature

Table 1 summarizes the hardware specifications and measurement performance of the deployed sensors, while Table 2 compares the proposed system against the conventional handheld-thermometer and manual soil-sampling approach across key performance metrics.

Table 1. Specifications of Hardware Components and Infrared Sensors.

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Component	Model/Type	Measurement Range	Accuracy	Purpose
Infrared temperature sensor	Non-contact IR thermometer (8-14 µm)	-20°C to 80°C	±0.2°C	Canopy surface temperature
Ambient temp./RH sensor	Capacitive digital sensor	-40°C to 80°C / 0-100% RH	±0.3°C / ±2% RH	Air temperature and humidity
Soil moisture sensor	Capacitive soil probe	0-100% VWC	±3% VWC	Root-zone moisture
Microcontroller	ESP32 dev module	N/A	N/A	Sensor control and LoRa transmission
Wireless module	LoRa transceiver, 868/915 MHz	Up to 5 km line-of-sight	N/A	Long-range low-power data link
GPS module	u-blox NEO-6M	Global	±2.5 m	Node geolocation

Table 2: Performance Evaluation of the Proposed Monitoring System

Metric	Proposed System	Conventional Method	Improvement (%)
MAE (°C)	0.34	0.71	52.1
RMSE (°C)	0.46	0.89	48.3
R^2 (canopy-air ΔT)	0.93	0.78	19.2
Stress-detection accuracy (%)	94.6	81.2	16.5
Irrigation-decision accuracy (%)	91.2	76.5	19.2
Response time	< 2 min	> 4 h (manual round)	N/A
Labor time per hectare per day	5 min	45 min	88.9

Sensor calibration drift over the 60-day trial remained below 0.15°C, confirming acceptable long-term stability without recalibration. Average communication latency between field node and dashboard update was 38 seconds, well within the operational requirement for near-real-time alerts. Power consumption analysis indicated that solar-buffered nodes sustained continuous operation, including through three consecutive overcast days, without data loss. The layered architecture, in which additional field nodes register with the existing gateway and cloud pipeline without modification to the processing logic, indicates favorable scalability toward larger commercial farms.

5. Discussion

The observed canopy-air temperature differentials and their divergence between irrigation treatments corroborate earlier findings that stomatal closure under water deficit produces a measurable, rapid rise in canopy temperature relative to ambient conditions [5, 7]. The magnitude of separation recorded here (up to 2.0°C under deficit irrigation) falls within the range reported for other row crops under comparable evaporative demand [8], supporting the generalizability of the proposed Crop Stress Index across cropping systems.

Relative to prior infrared-based monitoring studies, the present framework's accuracy gains stem primarily from environmental compensation using vapor pressure deficit rather than raw temperature differentials alone, a refinement consistent with recommendations in recent literature on stress-index normalization [9, 11]. The substantially lower MAE and RMSE compared with handheld measurement reflect both the elimination of operator-induced variability and the benefit of continuous rather than episodic sampling [12, 13].

Practical deployment nonetheless faces constraints. Direct sunlight, dust accumulation, and wind-induced sensor movement can introduce transient readings that require robust outlier filtering [10, 14]. LoRa communication, while power-efficient, is susceptible to attenuation in densely vegetated or topographically complex fields, motivating careful gateway placement [16]. From a cost perspective, the hardware bill of materials remains modest relative to commercial agricultural IoT packages, positioning the framework as an accessible option for smallholder and mid-sized operations, though initial setup expertise remains a barrier in some contexts [17].

The scalability of the cloud-based architecture supports extension to larger farms through additional node deployment without redesigning the processing pipeline, aligning with broader trends toward modular IoT-enabled smart irrigation systems [15, 18]. Integration with machine learning classifiers, rather than fixed thresholds, represents a promising direction for improving stress detection under heterogeneous soil and canopy conditions [19]. Complementary integration with UAV-based thermal remote sensing could further extend spatial coverage between fixed ground nodes, combining the temporal resolution of continuous ground sensing with the spatial resolution of aerial thermal imagery [20]. Collectively, these findings reinforce the role of real-time canopy temperature monitoring as a practical and scalable component of climate-resilient, water-efficient precision agriculture.

6. Conclusion

In this research, a canopy temperature monitoring system based on infrared technology has been presented and validated experimentally in real time for the automatic assessment of crop water stress. The system works with less than 0.5°C in terms of measurement error resulting in the stress detection accuracy of more than 94% and lowered labor requirement compared to conventional manual observation and proved its reliable performance and low latency during a 60-day field experiment. The findings demonstrate the ability of inexpensive infrared sensing technologies accompanied by environmental compensation and cloud-based decision-making to provide timely and valuable irrigation recommendations at a reasonable cost for different types of farms. Some of the limitations observed are the sensitivity to environmental impacts and dependence on fixed-point temperature measurements which make the analysis of inter-nodes areas impossible. The authors suggest studying the possibility of applying adaptive machine-learning water stress classification and integrating the proposed technology with UAV-derived thermal imaging in future research.

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