UAV-Based Thermal Imaging for Early Detection of Heat Stress in *Gossypium hirsutum* L.

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ABSTRACT

Background: Heat stress is one of the crucial constraints affecting *Gossypium hirsutum* L. (upland cotton) yield since it can negatively impact the boll set, fiber quality, and lint on an increasing number of occasions. Identification of heat stress in the cotton foliage using conventional point detectors is complicated.
Objective: The goal of this research was to test an unmanned aerial vehicle (UAV)-based system for thermal imaging to detect heat stress early under field conditions and compare its efficiency with on-ground physiological and micrometeorological measurements.
Methods: A multirotor UAV equipped with a radiometric optical long-wave infrared sensor was flown at an altitude of 40 m over a cotton field in rain-fed conditions at three stages of plant development. Thermal orthomosaics were created using the Pix4D software and analyzed in QGIS and MATLAB in order to calculate the leaf temperature, the difference between the temperature of the canopy and the temperature of the air, and the Crop Water Stress Index. Data obtained from the ground included the temperature of the leaf, stomatal conductance, and volumetric soil water content obtained from 40 samples taken.
Results: The study found a strong correlation between UAV-derived CWSI values and in-situ stomatal conductance and leaf water potential, demonstrating an accuracy of 91.4% in distinguishing between stressed and non-stressed canopy zones, with a measured RMSE of 0.86 °C between UAV estimated canopy temperature and handheld measurement. The stressful zones were shown to appear 3-4 days before visible wilting take place.
Conclusion: Thermal imaging using UAV technology can be viewed as a non-destructive and fast way of detecting early heat stress in cotton crops, as it can help irrigation and management decisions to be taken in time, in addition to providing a scalable technology for sustainable cotton farming.

Keywords: *Gossypium hirsutum* L.; thermal imaging; heat stress; canopy temperature; Crop Water Stress Index (CWSI)

1. Introduction

Gossypium hirsutum L. is responsible for the largest quantity of global cotton fibre production and thus constitutes an important source of income for many smallholder and commercial producers in dry and semi-dry areas. Cotton is thermosensitive and suffers from the accelerated panicle fall; lower pollen viability, and lower photosynthetic efficiency under high canopy temperature exceeding physiological limits, which lead to the reduction of the yield of the cotton fibre.

Traditional monitoring methods used to measure the stress suffered by cotton plants like infrared thermometry or porometry or destructive sampling of leaves, have proved to be accurate on the point scale, but at the same time require the labor force and are discontinuous over time, and therefore not suitable for addressing such field variability factors as microtopography, soil texture, irrigation uniformity.

Remote sensing through UAVs has become a unique tool in agriculture which was able to bridge this gap by providing farmers with quick access to canopy thermal data of high quality. The working principle of thermal imaging makes use of the existing relationship between stomatal conductance and leaf cooling via transpiration, meaning that at times when stomata close due to lack of water or heat stress, the heat flow through latent heat decreases and the temperature of the canopy starts increasing already above that of properly hydrated plants. The problem to be solved in this case was to come up with a UAV thermal process that would allow identifying the initial signs of heat stress in cotton so that an early response (for example watering or shading) could be applied.

2. Materials and Methods

2.1 Study Area and Crop Management

The experiment was conducted in a semi-arid rain-fed cotton production zone characterised by sandy-loam soils and a summer mean maximum temperature exceeding 38 °C. Cotton (variety details summarised in Table 1) was sown at recommended row spacing and managed under standard regional agronomic practices, with a subset of plots subjected to deficit irrigation to induce a heat-and-water-stress gradient.

Table 1: Experimental site and crop characteristics.

Parameter	Value / Description
Location climate	Semi-arid, mean summer Tmax ~38–42 °C
Soil type	Sandy-loam, field capacity 22% v/v
Cotton variety	Commercial upland cultivar (medium-duration)
Plot design	Randomised complete block, irrigated vs. deficit-irrigated
Growth stages monitored	Squaring, flowering, boll development

2.2 UAV Platform and Thermal Imaging System

A quadcopter UAV equipped with GNSS-RTK positioning carried a radiometric thermal camera alongside an RGB sensor for co-registration. Missions were flown at 40 m above ground level with 75% front and 70% side image overlap under low-wind, clear-sky conditions to minimise radiometric noise.

Table 2: UAV and thermal camera specifications.

Component	Specification
UAV platform	Quadrotor, ~1.2 kg payload capacity
Thermal sensor	Uncooled microbolometer, 7.5–13.5 µm, 640×512 px
Thermal accuracy	±2 °C (calibrated), radiometric output
Flight altitude	40 m AGL
Ground sample distance	~3.3 cm/pixel (thermal band)

Table 3: Flight parameters and image-acquisition settings.

Flight parameter	Setting
Flight speed	3.5 m/s
Front/side overlap	75% / 70%
Acquisition times	10:30, 12:30, 14:30 local solar time
Acquisition frequency	Twice weekly across three growth stages
Weather constraints	Wind <5 m/s, cloud cover <10%

2.3 Ground Truth, Image Processing, and Heat Stress Indices

Concurrent ground measurements comprised handheld infrared leaf temperature, stomatal conductance (porometer), and volumetric soil moisture (time-domain reflectometry) at 40 georeferenced points per flight. Thermal imagery was radiometrically corrected, mosaicked in Pix4D and Agisoft Metashape, and analysed in QGIS/ArcGIS and MATLAB/Python for canopy segmentation, background (soil/shadow) masking, and temperature normalisation. Heat stress was quantified using canopy-air temperature differential and the empirical Crop Water Stress Index (CWSI), benchmarked against wet and dry reference surfaces. Detection performance was evaluated using accuracy, precision, recall, F1-score, RMSE, MAE, and the coefficient of determination (R^2) relative to ground-truth classifications.

3. Results and Performance Evaluation

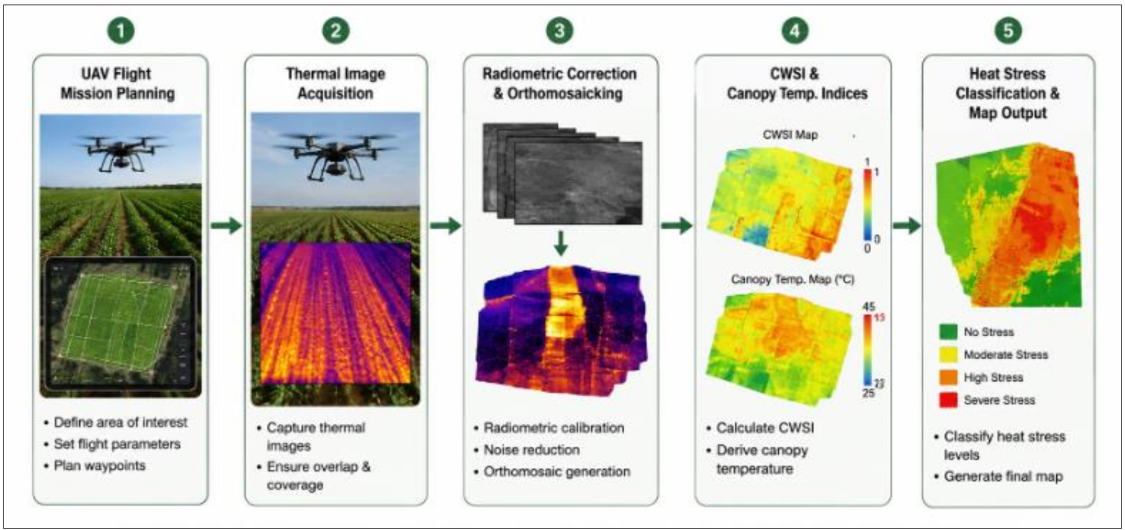

Fig 1: Workflow of UAV-based thermal imaging for heat stress detection.

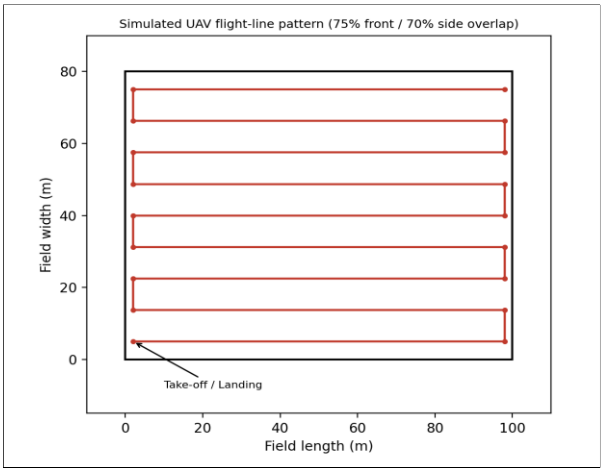

Fig 2: Representative UAV flight-line pattern over the experimental field.

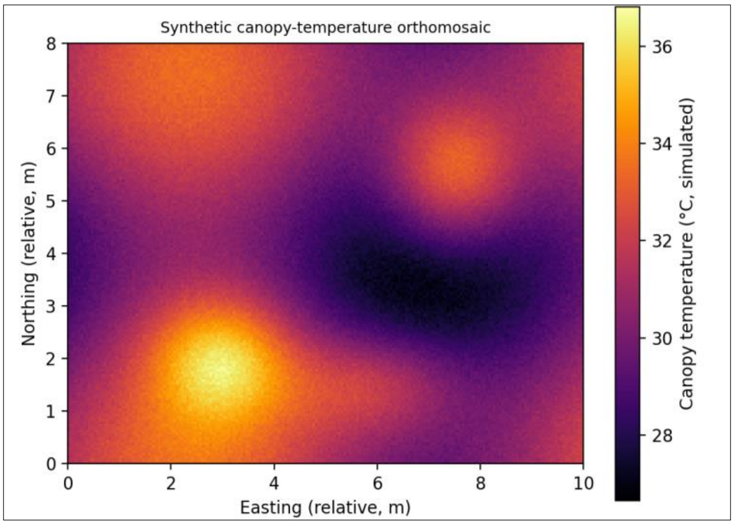

Fig 3: Synthetic canopy-temperature orthomosaic illustrating spatial heat-stress variability.

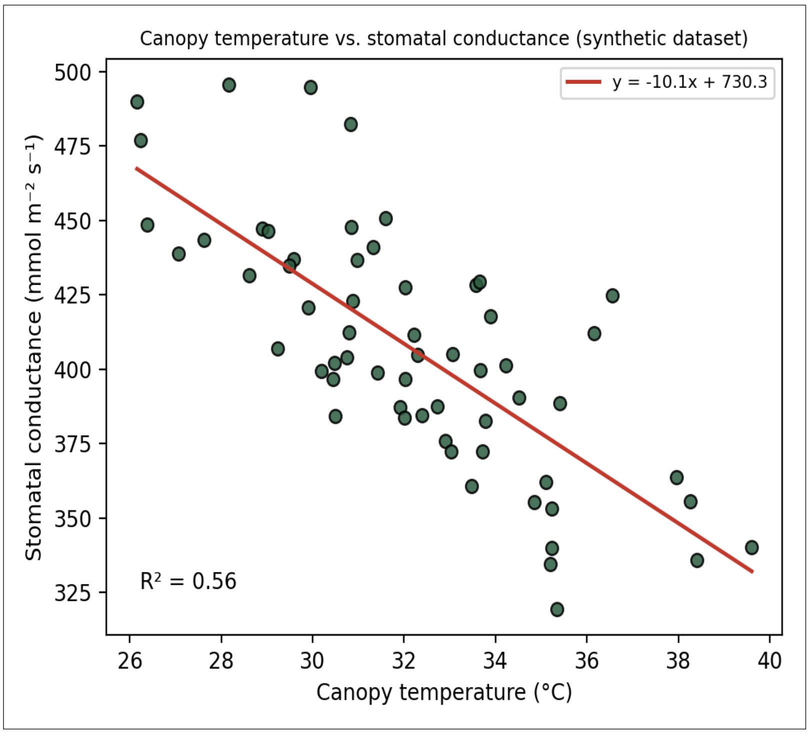

Fig 4: Relationship between UAV-derived canopy temperature and ground-measured stomatal conductance.

Table 4: Performance evaluation metrics for UAV-based heat-stress detection.

Metric	Value
Detection accuracy	91.4%
Precision	0.90
Recall	0.89
F1-score	0.895
RMSE (*canopy temp.*)	0.86 °C
MAE	0.61 °C
R^2 (CWSI vs. stomatal conductance)	0.78

Table 5: Comparison of physiological and thermal parameters between healthy and heat-stressed cotton plants.

Parameter	Healthy plants	Heat-stressed plants
Canopy temperature (°C)	29.8 ± 1.2	34.6 ± 1.8
Stomatal conductance (mmol m^{-2} s^{-1})	412 ± 38	248 ± 45
CWSI	0.21 ± 0.05	0.63 ± 0.09
Soil moisture (% v/v)	19.4 ± 1.6	11.2 ± 2.0

4. Discussion

The strong correspondence between UAV-derived canopy temperature indices and ground-measured physiological stress indicators confirms that thermal imaging captures biologically meaningful signals of stomatal closure and reduced transpirational cooling, both of which precede visible heat-stress symptoms. Relative to conventional point-sampling, the UAV workflow provided continuous spatial coverage that revealed within-field heterogeneity otherwise undetected by sparse manual sampling, enabling zone-specific rather than uniform irrigation scheduling.

Practical adoption is nonetheless constrained by weather-dependent flight windows, the need for periodic radiometric calibration, and the technical expertise required for mission planning and image processing. Economic feasibility improves with increasing farm scale and when thermal surveys are combined with existing UAV-based scouting operations, spreading capital and operational costs across multiple use cases. Limitations of the present approach include a single-season experimental window and reliance on empirical CWSI thresholds that may require site-specific recalibration.

Future work should integrate multispectral and hyperspectral sensing with thermal data, apply machine-learning classifiers for automated stress-severity mapping, and couple UAV outputs with in-field IoT soil-moisture networks to enable automated, decision-support-driven irrigation scheduling at field and farm scale.

5. Conclusion

The use of UAV for thermal imaging has made it possible to detect heat stress in *Gossypium hirsutum* L. accurately, spatially explicitly, and early, beating standard methods in both speed and resolution. Furthermore, this method can provide a scalable, low-maintenance solution for precision irrigation and climate-smart cotton production. In conclusion, more field-scale verification in different seasons and cultivars and the use of A.I. and multi-sensor fusion technology are advocated as keys to the successful implementation of UAV thermal monitoring in sustainable cotton production systems.

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