



DTSM: A UAV-based framework for temporal rice stress detection and growth analysis

Muhammad Nasar Ahmad^{a,b,c,*}, Xiaohui Yuan^{a,d}, Shuai Yang^{a,b,c}, Lichuan Gu^{a,b,c}, Hui Peng^{a,b,c}, Rana Waqar Aslam^e, Md. Enamul Huq^f, Akib Javed^e, George D. Bathrellos^g

^a School of Information and Artificial Intelligence, Anhui Agricultural University, Anhui, Hefei, 230036, China

^b Anhui Provincial Engineering Research Center for Agricultural Information Perception and Intelligent Computing, Hefei, China

^c Key Laboratory of agricultural electronic commerce of the Ministry of Agriculture, Hefei, China

^d Department of Computer Science and Engineering, University of North Texas, Denton, TX, USA

^e State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing, Wuhan University, Wuhan, Hubei, 43007, China

^f Department of Geography and Environment, Faculty of Human Sciences, Sultan Idris Education University, Tanjong Malim, 35900, Perak, Malaysia

^g Department of Geology, University of Patras, Greece

ARTICLE INFO

Keywords:

Agriculture
Rice
Spatiotemporal analysis
Vegetation indices
Remote Sensing

ABSTRACT

Timely detection of crop stress is important for precision agriculture and agroecosystem resilience, particularly in environments where ground calibration data are limited or environmental conditions change rapidly. Traditional stress detection approaches often rely on single-date imagery or external calibration, which can limit temporal interpretation and transferability across heterogeneous fields. This study presents the Dynamic Temporal Stress Method (DTSM), a data-driven framework for monitoring and quantifying vegetation stress patterns in rice fields using multi-temporal UAV observations. DTSM integrates four vegetation indices, namely NDVI, NDRE, GNDVI, and MSAVI2, derived from UAV imagery acquired at three phenological stages (July 17, August 1, and August 12, 2024). The framework combines binary thresholding for initial stress mapping, temporal differencing to track stress change, and a Stress Persistence Index (SPX) to quantify repeated stress occurrence over time. Spatial patterns of stress were further evaluated using zonal statistics and Getis-Ord G_i^* hotspot analysis to identify persistent stress clusters. Results showed clear temporal variation in crop stress, with stress intensity peaking on August 1, when NDRE-based mapping indicated 41.4% of the field under stress. Approximately 15.7% of the study area exhibited persistent stress across all observation dates. Spatial analysis identified Zones Z3, Z4, and Z8 as recurring stress hotspots. These findings indicate that integrating temporal change detection, multi-index analysis, and spatial persistence assessment can improve the interpretation of crop stress dynamics and support precision management in UAV-based agricultural monitoring.

1. Introduction

On-time and precise identification of crop stress is the building block of precision agriculture, particularly in climate fluctuation, resource scarcity, and sustainable intensification of food production systems. Crop stress refers to conditions that negatively affect plant growth, development, or yield. It is generally classified into abiotic stressors, such as drought, salinity, temperature extremes, and nutrient deficiency, and biotic stressors, including pests, pathogens, and weeds [1–3]. Rice, a major crop consumed by more than half the world's population, is

impacted by these stressors (Fig. 1) and requires exact monitoring instruments to determine the health of the plant during the decisive phenological phases [4,5]. Among the crops prone to abiotic stresses, rice (*Oryza sativa* L.) [6]. is especially sensitive at critical phenological phases like tillering, panicle initiation, and grain filling [7]. Remote sensing methods [8,9], specifically targeting vegetation indices (VIs) such as the Normalized Difference Vegetation Index (NDVI) have been used extensively to evaluate crop health in a non-destructive manner over large scales [9,10]. However, traditional approaches often rely on single-date observations, which can miss subtle or evolving stress signals

* Corresponding author.

E-mail addresses: mnasarahmad@ahau.edu.cn (M.N. Ahmad), xiaohui.yuan@unt.edu (X. Yuan), yangs@ahau.edu.cn (S. Yang), glc@ahau.edu.cn (L. Gu), ph@stu.ahau.edu.cn (H. Peng), ranawaqaraslam@whu.edu.cn (R.W. Aslam), mdenamulhuq@fsk.ups.edu.my (Md.E. Huq), akibjaved@whu.edu.cn (A. Javed), gbathrellos@upatras.gr (G.D. Bathrellos).

<https://doi.org/10.1016/j.atech.2026.102141>

Received 10 November 2025; Received in revised form 11 April 2026; Accepted 19 April 2026

Available online 20 April 2026

2772-3755/© 2026 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

over time [11].

Recent advances in unmanned aerial vehicle (UAV) technology have significantly improved the capability for high-resolution and flexible monitoring of crop conditions at the field scale [14,15]. UAV-based remote sensing enables detailed spatial analysis of vegetation dynamics, providing valuable insights into crop health and variability within agricultural systems. However, many existing approaches rely on single-date imagery or require ground-truth data for calibration and validation, which may not be feasible in large-scale or resource-limited agricultural environments [16–19]. In addition, static vegetation index-based assessments often fail to capture the temporal dynamics of crop stress, limiting their effectiveness for early detection and timely management interventions.

To address these limitations, we propose the Dynamic Temporal Stress Method (DTSM), a UAV-based framework for multi-temporal, vegetation stress detection that does not require ground truth data or accuracy metrics. DTSM leverages the temporal dimension of UAV-derived NDVI data to map and quantify stress propagation patterns in rice agroecosystems. The methodology integrates binary stress classification via NDVI thresholding, inter-date change detection, stress persistence indexing, and spatial statistical tools such as Getis-Ord G_i^* hotspot analysis [20], to identify emerging stress clusters. A simple cellular automata-inspired rule-based model is incorporated to simulate potential stress spread across neighboring zones.

Unlike prior studies that rely heavily on supervised classification or

regression approaches [21,22], DTSM emphasizes internal consistency and temporal logic to ensure reliability of insights, even in data-scarce environments. Furthermore, by integrating additional indices such as the Normalized Difference Red Edge (NDRE) and Modified Soil-Adjusted Vegetation Index 2 (MSAVI2), DTSM enhances sensitivity to chlorophyll content and minimizes soil background effects, providing a physiologically grounded, spatially explicit view of crop stress.

This study introduces the Dynamic Temporal Stress Method (DTSM), a scalable, interpretable, and field-ready framework for spatiotemporal analysis of crop stress in rice agroecosystems using high-resolution UAV imagery. Addressing a critical methodological gap in current UAV-based remote sensing literature, DTSM enables early vegetation stress detection, persistence mapping, and spatial clustering analysis without relying on in-field calibration or ground truth data. This research makes three primary contributions:

- (1) **Integrated multi-index framework:** A UAV-based approach combining NDVI, NDRE, GNDVI, and MSAVI2 enhances the precision and reliability of crop stress detection across temporal stages.
- (2) **Advanced spatiotemporal stress mapping:** The introduction of stress persistence and hotspot analytics (Getis-Ord G_i^* and zonal analysis) enables precise identification of persistent and emerging stress zones for targeted management.

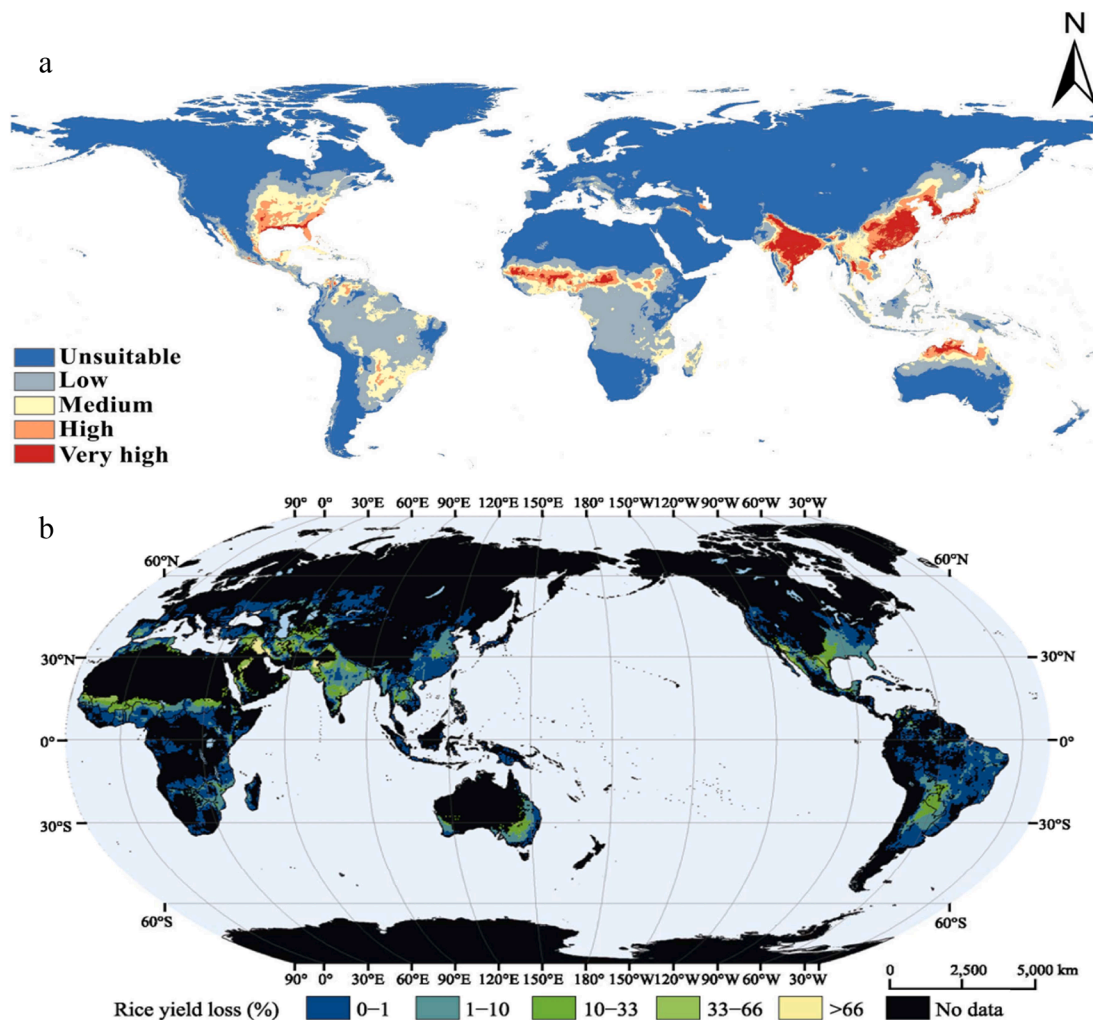


Fig. 1. Global spatial distribution of rice stress: (a) Global rice stress map caused by biotic stressor (*Xanthomonas oryzae*); (b) Global rice stress map caused by an abiotic stressor (high temperature). Source: [12,13].

- (3) **Scalable, data-independent design:** The framework operates effectively without ground-truth data, demonstrating scalability for large-scale agricultural monitoring and supporting sustainable precision agriculture practices.

2. Materials and methods

2.1. Study area and experimental details

Anqing City, located in Anhui Province of China, was used as a case study and relevant data were collected for this study from Jiuchen Farm. The site is geographically positioned at approximately 30°03'25.91"N latitude and 116°32'52.71"E longitude, representing a typical rice cultivation landscape within the lower Yangtze River basin. Intensive agricultural practices characterize this region and offer an ideal setting for evaluating vegetation health and stress dynamics using UAV-based remote sensing techniques. Multispectral UAV flights were conducted on July 17, August 1, and August 12, capturing key phenological stages of rice crop development. Spatial extent and precise location of the study area are presented in Fig. 2, providing geographic context to the analyses performed in this study and enabling integrated knowledge of the regional agricultural context.

2.2. Data acquisition

Multispectral imagery was acquired using the DJI Mavic 3 Multispectral (Mavic 3 M) UAV platform. Flights were conducted at an altitude of 20–25 m with 80 % forward and 70 % side overlap to ensure sufficient spatial coverage. The sensor captures Green, Red, Red Edge, and Near-Infrared (NIR) bands, along with RGB imagery. These data

were used to generate orthomosaic images for vegetation index analysis. Detailed sensor characteristics and the agronomic relevance of each spectral band are summarized in Table 1.

The overview of the rice paddies in the experimental field selected for this study is illustrated in Fig. 3. The multispectral TIFF image typically encompasses four single spectral bands allocated to plant vegetation analysis and biophysical measurements.

High-resolution UAV imagery of the rice field was acquired using the DJI Mavic 3 Multispectral (Mavic 3 M) system across three key phenological stages. Each flight yielded around 500 to 700 individual images in the tile format, collected under clear conditions with replicate flight parameters for uniform spatial coverage. The platform records data from the primary spectral bands Green, Red, Red Edge, and Near-Infrared (NIR) in four-band multispectral TIFF format, while separate RGB imagery is recorded in standard JPEG or TIFF format. These mosaics formed the basis for NDVI and spatiotemporal stress analysis described

Table 1

Characteristic and Bands information of DJI-multispectral UAV Sensor.

Band #	Band Name	Central Wavelength (nm)	Description
1	Green	560	Sensitive to leaf pigment and vegetation vigor
2	Red	650	Strong chlorophyll absorption region
3	Red Edge	730	Sensitive to chlorophyll variation and early stress detection
4	NIR	860	Reflectance related to canopy structure and biomass condition
5	RGB	Visible (separate RGB image)	True-color imagery for visual interpretation

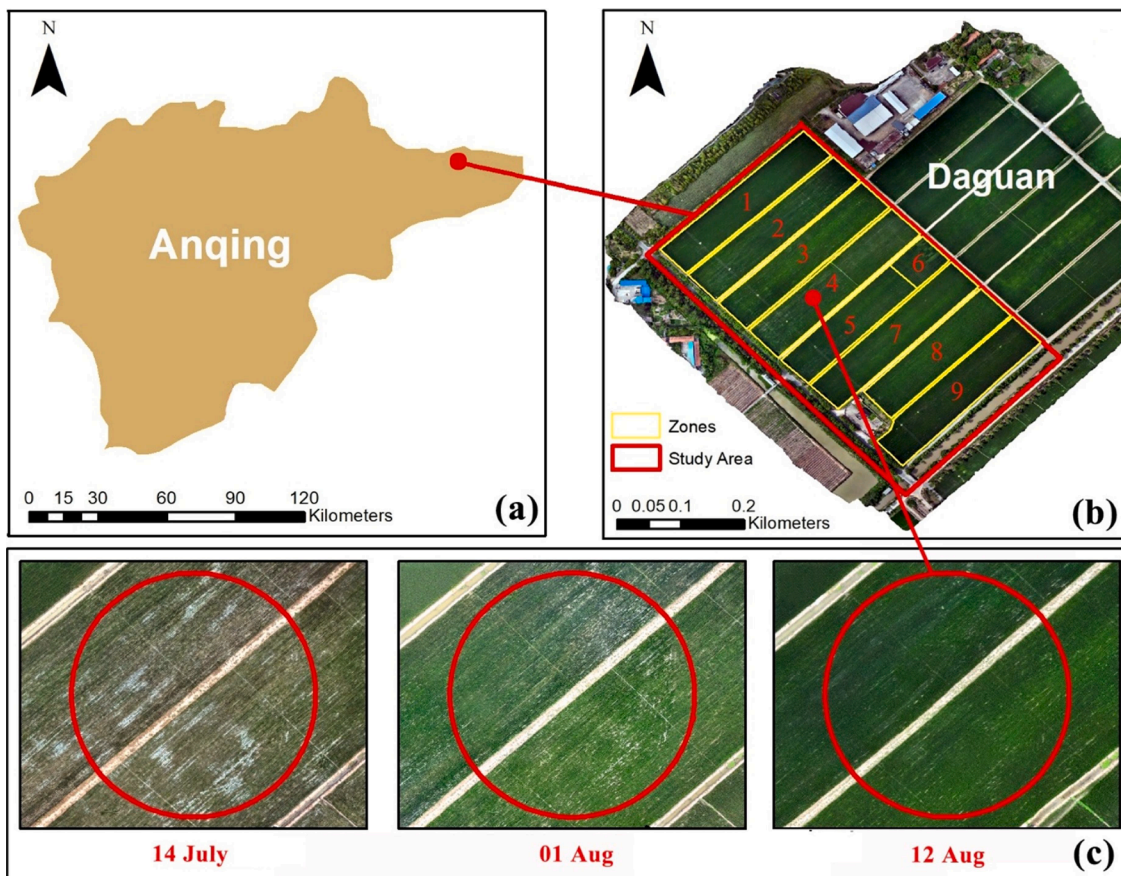


Fig. 2. Study area location and UAV observations. (a) Location of Anqing within Anhui Province, China; (b) study area in Daguan with zone delineation; (c) magnified UAV imagery of Jiuchen Farm showing crop conditions across three observation dates.

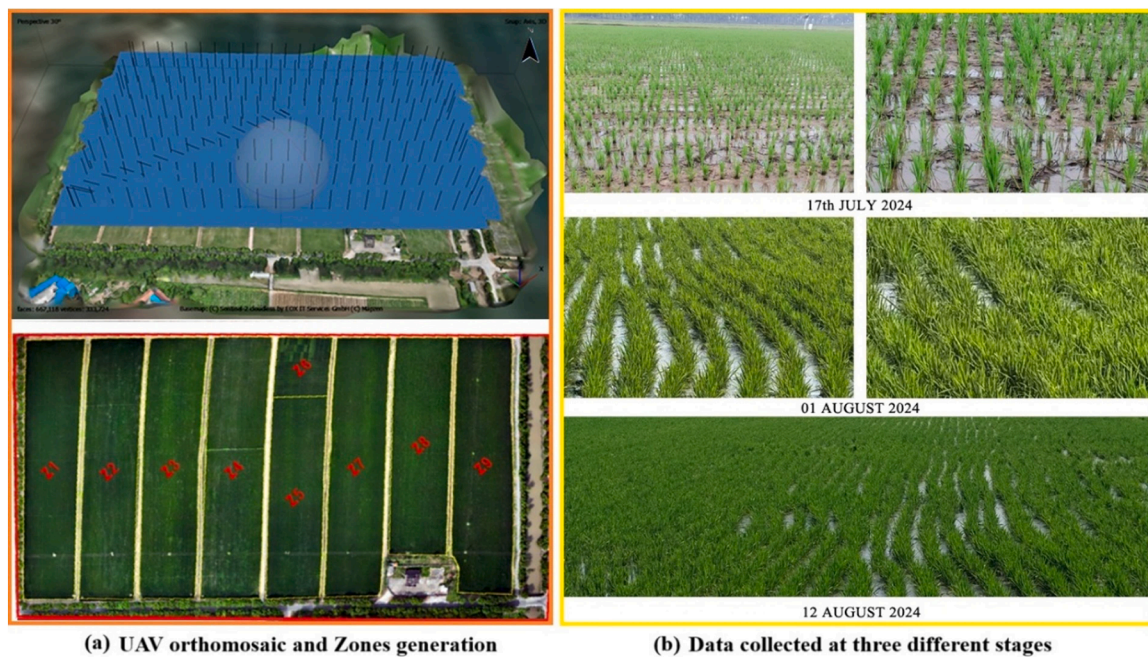


Fig. 3. (a) Orthomosaic generation and Zone-wise distribution of the experimental site (b) UAV data collected at three stages.

in the subsequent methodology section.

2.3. Data pre-processing

UAV imagery was processed using Agisoft Metashape Professional (version 2.1.0) to generate georeferenced multispectral orthomosaics for each acquisition date. Each flight produced approximately 500–700 raw image tiles, comprising Green, Red, Red Edge, and Near-Infrared (NIR) bands, along with RGB imagery.

The processing workflow included photo alignment to estimate camera positions and generate a sparse point cloud, followed by dense point cloud reconstruction and mesh generation to represent scene geometry. These outputs were subsequently used to derive Digital Surface Models (DSM) and orthomosaics through standard photogrammetric orthorectification procedures [23–25].

2.4. Pipeline of DTSM

The Dynamic Temporal Stress Method (DTSM) is a framework for vegetation stress monitoring using multi-temporal UAV imagery. It utilizes vegetation indices derived from UAV data to detect and analyze stress patterns across different phenological stages. The method is based on temporal variation and spatial consistency of vegetation indices. The method utilizes multi-temporal vegetation indices to analyze stress patterns across different phenological stages.

The DTSM workflow consists of vegetation index computation, binary stress classification, temporal differencing, and spatial analysis. Vegetation indices (NDVI, NDRE, GNDVI, and MSAVI2) were derived from UAV imagery and converted into binary stress maps using predefined thresholds. Temporal changes were assessed by comparing stress maps across acquisition dates, while spatial patterns were analyzed using zonal statistics and hotspot analysis.

Multiple vegetation indices were incorporated to capture different physiological aspects of crop condition. Spatial analysis was performed using zonal statistics and Getis-Ord G_i^* hotspot analysis to identify patterns of stress distribution and clustering across the study area. Vegetation index-based change detection was integrated with spatial statistical analysis to evaluate stress patterns across temporal and spatial dimensions.

The DTSM workflow, illustrated in Fig. 4, follows a systematic sequence of UAV-based spatiotemporal analysis steps to detect and monitor crop stress. Following pre-processing, the mosaicked UAV imagery is used to derive key vegetation indices (NDVI, NDRE, GNDVI, MSAVI2) that serve as proxies for rice crop health across critical growth stages. These indices are standardized and thresholded based on physiologically meaningful cutoffs to generate binary stress maps, distinguishing stressed from healthy vegetation at the pixel level. Temporal stacking of these binary layers enables the detection of stress progression and recovery through change maps and the computation of an SPX. To quantitatively assess spatial patterns of stress dynamics, zonal statistics were applied across a predefined 3×3 grid. Getis-Ord G_i^* hotspot analysis [26], was used to identify statistically significant clusters of persistent and emerging stress.

Vegetation indices were computed using raster-based operations, and thresholding was applied to generate binary stress maps. Temporal differencing was used to identify changes in stress conditions across dates. Zonal statistics (Table 2) and tabulate area functions were employed to quantify stress distribution within predefined zones.

This comprehensive methodology allows for a fine assessment of vegetation health and identifying critical stress areas, contributing to informed environmental management and policy decisions.

2.5. Mathematical expressions for stress detection

The DTSM framework relies on a structured series of mathematical operations (Eqs. (1) to (7)) that transform raw multispectral UAV data into interpretable spatiotemporal vegetation stress indicators. This section outlines the core equations formulated to compute vegetation indices, classify stress, detect changes over time, and analyse spatial clustering.

2.5.1. Vegetation index normalization

Eq. (1) normalizes vegetation index (VI) values, including NDVI, NDRE, GNDVI, and MSAVI2, to a standard scale to enable comparison across indices and temporal acquisitions. This normalization step is essential for generating consistent stress classifications over time. To ensure comparability across time and indices, all VI are normalized to a [0,1] scale based on their observed minimum and maximum values.

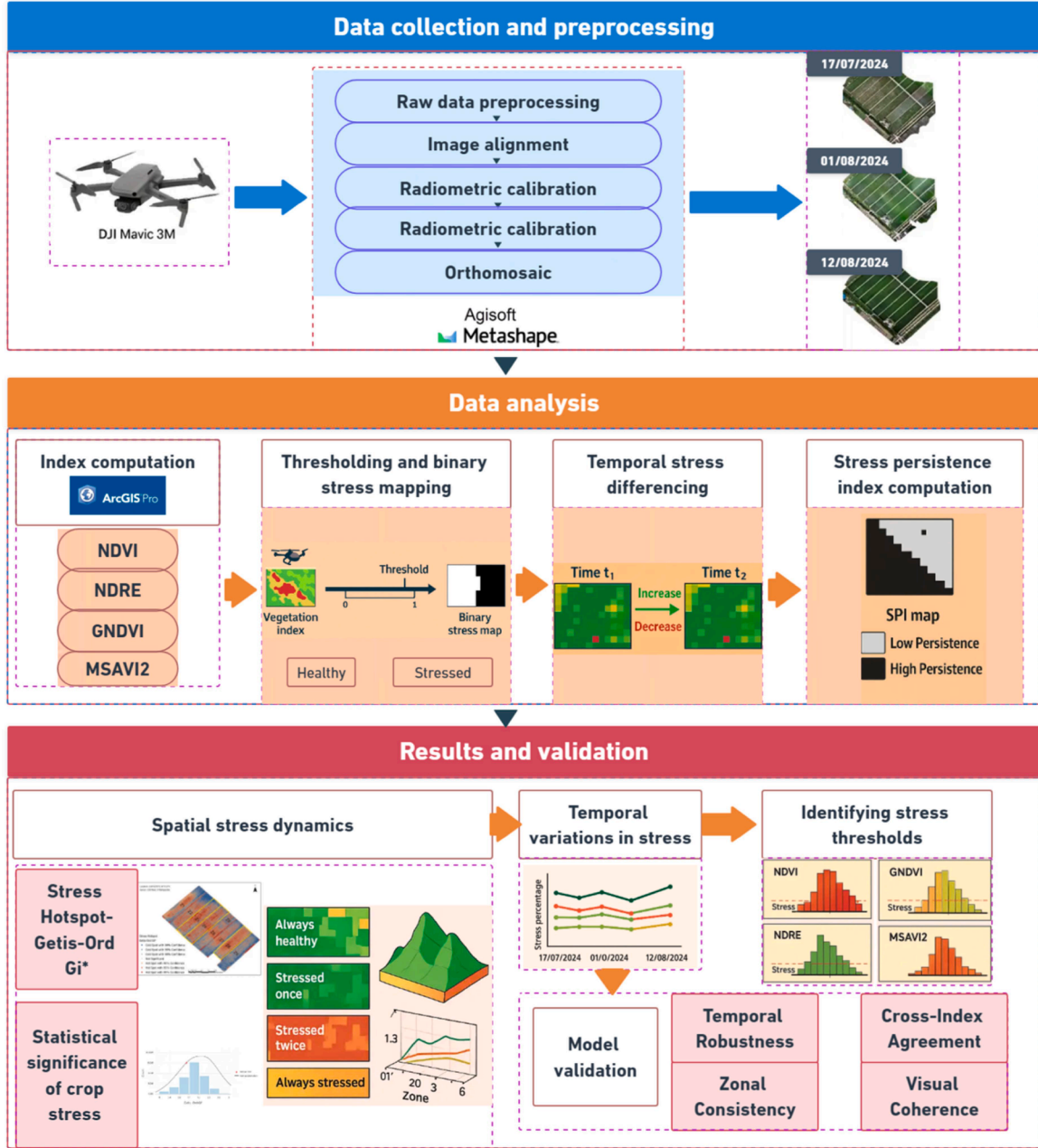


Fig. 4. Conceptual diagram for rice stress propagation.

$$VI_n(x, y, t) = \frac{VI(x, y, t) - V_{I_{\min}}}{V_{I_{\max}} - V_{I_{\min}}} \quad (1)$$

This step standardizes the dynamic range across all VIs, reducing bias from acquisition variability.

2.5.2. Binary stress mapping

Eq. (2) translates the normalized indices into binary stress maps, where a pixel is classified as stressed or healthy based on predefined thresholds. These binary layers form the backbone of subsequent temporal and spatial analyses. Each normalized VI raster is converted to a binary stress map using a predefined threshold T_i , where pixels below the threshold are classified as stressed. Threshold values for stress classification were determined based on the statistical distribution of vegetation indices and supported by commonly reported ranges in the literature. Histogram analysis was used to identify separation points between stressed and non-stressed vegetation, ensuring consistency

across temporal observations.

$$S_i(x, y, t) = \begin{cases} 1, & \text{if } VI_{\text{norm}}(x, y, t) < T_i \\ 0, & \text{otherwise} \end{cases} \quad (2)$$

2.5.3. Temporal stress differencing

Eq. (3) detects temporal stress changes by subtracting stress layers across time steps, revealing new stress emergence, recovery, or stability. This change map enables monitoring how stress evolves between phenological stages. To track changes in stress conditions over time, a pixel-wise difference is computed between binary stress maps from successive dates. Due to the availability of three UAV acquisition dates, temporal differencing was performed between successive observations, resulting in two temporal comparisons. These dates correspond to key phenological stages, enabling the analysis of stress progression within the growing season. The limited temporal resolution represents a constraint of the current dataset and is acknowledged as a limitation of

Table 2

Raster-based tools and analytical functions used in the DTSM workflow.

No.	Tool	Function	Output	Recent Studies
1	Raster Calculator	Calculate vegetation indices from multispectral bands	VI raster	[27]
2	Raster Calculator (Conditional)	Create binary stress masks (VI < threshold = 1, otherwise 0)	Binary stress map	[28]
3	Raster Calculator (Minus/Subtract)	Perform temporal differencing: $\Delta\text{Stress} = \text{Stress}_{t2} - \text{Stress}_{t1}$	Change detection map	[29]
4	Raster Calculator (Sum)	Calculate stress persistence: $\text{SPX} = \sum$ binary stress maps	SPX raster (0 to n)	[30]
5	Tabulate Area / Zonal Statistics	Quantify stress within each zone or grid cell	Zone-level stress statistics	[31]
6	Optimized Hot Spot Analysis (Gi*)	Identify statistically significant stress clusters	Hotspot map / clustering statistics	[32]

the study.

$$\Delta S(x, y) = S(x, y, t_2) - S(x, y, t_1) \quad (3)$$

This allows the detection of new stress emergence (positive values), recovery (negative values), and persistent conditions (zero). These values (+1, -1, 0) were used in temporal stress mapping.

2.5.4. Stress persistence index (SPX)

To quantify chronic stress, binary layers across time are summed. The Stress Persistence Index (SPX) quantifies the frequency of stress occurrence at each pixel across multiple observation dates. It is based on the principle that repeated stress signals over time indicate persistent or chronic stress conditions. This cumulative approach provides a simple yet effective measure for identifying areas with sustained stress exposure.

$$\text{SPX}(x, y) = \sum_{t=1}^{\{n\}} S(x, y, t) \quad (4)$$

2.6. Zonal stress quantification

Eq. (5) uses zonal statistics to calculate the percentage of stressed area within each management zone or grid, providing spatially explicit summaries of stress distribution. We calculate the percentage of stressed pixels within each zone to aggregate stress at a relevant management scale (e.g., plots or grid cells).

$$\% \text{Stress}(Z) = \frac{\sum (x, y) \in \text{ZS}(x, y)}{\{|Z|\}} \quad (5)$$

2.7. Spatial autocorrelation – Getis-Ord G_i^*

Eq. (6) introduces spatial clustering through the Getis-Ord G_i^* statistic, which identifies statistically significant hotspots of stress that may not be evident through thresholding alone. To identify spatial clustering of stress, Getis-Ord G_i^* is used to evaluate whether zones with high stress are statistically clustered. For the Getis-Ord G_i^* hotspot analysis, spatial relationships were defined based on the predefined zonal structure of the study area. Each zone within the 3×3 grid was treated as a spatial unit, and neighboring relationships were determined using a contiguity-based approach, where adjacent zones were considered neighbors. This configuration reflects the field-scale spatial organization and ensures consistency in local spatial autocorrelation analysis. Future work may incorporate approaches such as Incremental Spatial Autocorrelation (ISA) [33] to optimize spatial scale selection.

$$G_i^* = \frac{\sum_j w_{ij} x_j - \bar{X} \sum_j w_{ij}}{\sqrt{n \sum_j w_{ij} - (\sum_j w_{ij})^2 / (n-1)}} \quad (6)$$

Where Eqs. (1)–(6): $VI(x, y, t)$ represents the vegetation index value at pixel (x, y) and time t , $VI_{\min}$ and $VI_{\max}$ denote the minimum and maximum values used for normalization, and $VI_{\text{norm}}(x, y, t)$ is the normalized vegetation index. T_i represents the threshold for vegetation index i , and $S(x, y, t) \in \{0, 1\}$ denotes the binary stress mask (1 = stressed, 0 = healthy).

$\Delta S(x, y)$ represents temporal stress change, $\text{SPX}(x, y)$ denotes the Stress Persistence Index, and Z represents the spatial unit (zone or grid cell) used for zonal analysis. In the Getis-Ord G_i^* statistic, w_{ij} represents spatial weights, x_j denotes the attribute value at location j , $\bar{X}$ is the mean, S is the standard deviation, and n is the number of spatial units.

2.8. Dynamic temporal stress method (DTSM) equation

Finally, building upon the preceding equations, the formulation of DTSM integrates all components, individual stress indices, change maps, and spatial clustering to generate a comprehensive stress propagation method. The integrated DTSM equation combines multi-index binary layers, temporal differencing, and spatial clustering into a unified stress propagation method:

$$\text{DTSM}(x, y) = f \left(\sum_{t=1}^m S_i(x, y, t), \Delta S(x, y), G_i^*(x, y) \right) \quad (7)$$

Where, $S_i(x, y, t) \in \{0, 1\}$ represents the binary stress mask for vegetation index i at pixel (x, y) and time t , $\Delta S(x, y)$ denotes the temporal stress change at pixel (x, y) , and $G_i^*(x, y)$ represents the Getis-Ord G_i^* statistic indicating spatial clustering of stress. The function $f(\cdot)$ denotes the integration of multi-index stress information, temporal change, and spatial clustering within the DTSM framework.

The integration of temporal differencing and spatial statistical analysis was used to identify and evaluate spatial and temporal patterns of vegetation stress across the study area.

2.8.1. Model validation and reliability assessment

Without in-field ground truth, DTSM validation was performed using spatiotemporal consistency, cross-index agreement, and zonal coherence.

- Temporal Robustness: Stress progression patterns observed from August 1 to August 12 align with known physiological stress phases in rice crops. This trend was consistent across all four VIs.
- Cross-Index Agreement: NDRE consistently reported higher stress percentages (up to 41.4 %) than NDVI (36.8 %), supporting NDRE's sensitivity to chlorophyll loss. GNDVI and MSAVI2 mirrored the temporal trends, reinforcing robustness.
- Zonal Consistency: Zones 3, 4, and 8 were consistently flagged as high-stress areas across indices and dates. G_i^* analysis confirmed these as statistically significant clusters ($p < 0.05$).
- Visual Coherence: Smooth transitions in hotspot and change maps indicate the physiological relevance of detected stress patterns, reducing the likelihood of noise-driven classification.

These validation outcomes support DTSM's reliability for UAV-based crop stress monitoring, even without direct field calibration.

3. Results

This section presents the results derived from the DTSM framework, including multi-temporal vegetation stress detection, spatial clustering, and propagation analysis. Each result is further detailed in the following subsections, highlighting specific components of the DTSM analysis for

enhanced clarity and interpretation.

3.1. Identifying vegetation stress thresholds using spectral index distributions

Fig. 5 shows the distribution patterns for four of the most significant vegetation indices, NDVI, NDRE, GNDVI, and MSAVI2 to be utilized for vegetation health estimation in the experiment areas. Each histogram delineates the pixel-level range for a respective index, with red dashed lines indicating stress threshold values. These thresholds were determined within a value range of 0.1 to 1.0. A concentration of pixel values around 0.35 to 0.40 was observed for all indices, indicating consistent stress detection boundaries.

Fig. 5 illustrates the pixel-level distribution of vegetation indices across the study area. These distributions represent the variability of spectral responses at the pixel scale and provide the basis for threshold selection. The observed clustering of pixel values around threshold ranges supports the separation of stressed and non-stressed vegetation across different indices.

NDVI exhibited values above the 0.4 threshold, highlighting canopy health and photosynthetic activity. NDRE, more sensitive to chlorophyll content, demonstrated a broader distribution with more frequent values below 0.35, suggesting variability in early stress symptoms. GNDVI values indicated overall healthy biomass but highlighted pockets of potential decline near the stress threshold.

MSAVI2 effectively suppressed soil background noise, aiding detection in areas with sparse canopy. The 0.4 threshold again proved critical for separating healthy and stressed zones. These distributions together informed threshold selection, allowing systematic classification of stress across phenological stages.

NDVI and NDRE provided distinct cutoff points for stress classification, while GNDVI and MSAVI2 captured subtler variations in canopy structure and density. This analysis formed the quantitative foundation for subsequent binary stress mapping and temporal modelling.

3.2. Spatial and temporal stress variations across phenological stages

Following Section 4.1, VIs were calculated at three critical phenological stages of rice development: July 17, August 1, and August 12, 2024. Temporal sequence facilitated the detection of altered stress regimes and the determination of periods with heightened physiological disturbances. Fig. 6 (b, g, n) show that NDVI values declined steadily in the northern and central regions of the experimental field, with the most significant decline on August 1. This period likely overlapped with inducers of environmental or physiological stress, i.e., water or heat stress.

NDRE values (Fig. 6c, h, p) were also more responsive to chlorophyll content and heterogeneity of the canopy, responding to stress indicators before NDVI. The extent of stress based on the NDRE peak at 41.4 % on August 1 further testifies to its sensitivity in identifying early nutrient stress and disease onset.

GNDVI maps (Fig. 6d, j, q) captured increased stress heterogeneity in south plots, which may be attributed to nitrogen imbalances. Because of the strong correlation of GNDVI with chlorophyll content in green vegetation, these spatial trends underscore its diagnostic capability for identifying minute changes in leaf health. MSAVI2 outcomes (Fig. 6e, k, r) further enhanced the detection of early-stage stress by filtering the soil background interferences, particularly effective on July 17 with low vegetative cover.

In all the indices, August 1 consistently marked the peak of vegetation stress, followed by the recovery on August 12, potentially due to adaptive crop responses or improved environmental conditions. This is endorsed by the summary statistics reported in Table 3. NDRE again proved effective at discriminating extensive stressed areas, and MSAVI2 at effective early-stage monitoring.

Fig. 7 illustrates this temporal trajectory, confirming that stress peaked on August 1 most significantly in the NDRE index—and decreased modestly by August 12. The results affirm the complementary roles of each VI: NDRE excels in early stress detection; MSAVI2 compensates for low canopy density; and NDVI and GNDVI provide broader

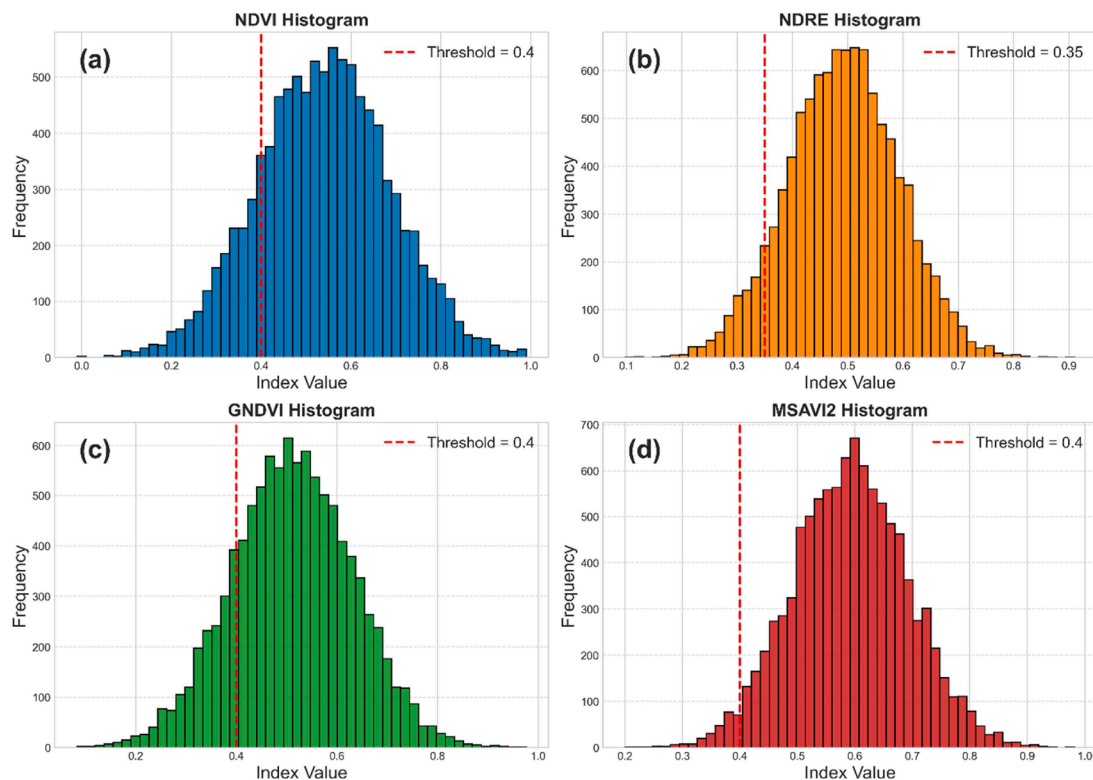


Fig. 5. Pixel-level distribution of vegetation indices (NDVI, NDRE, GNDVI, and MSAVI2) across the study area, with threshold values indicated by dashed lines for stress classification.

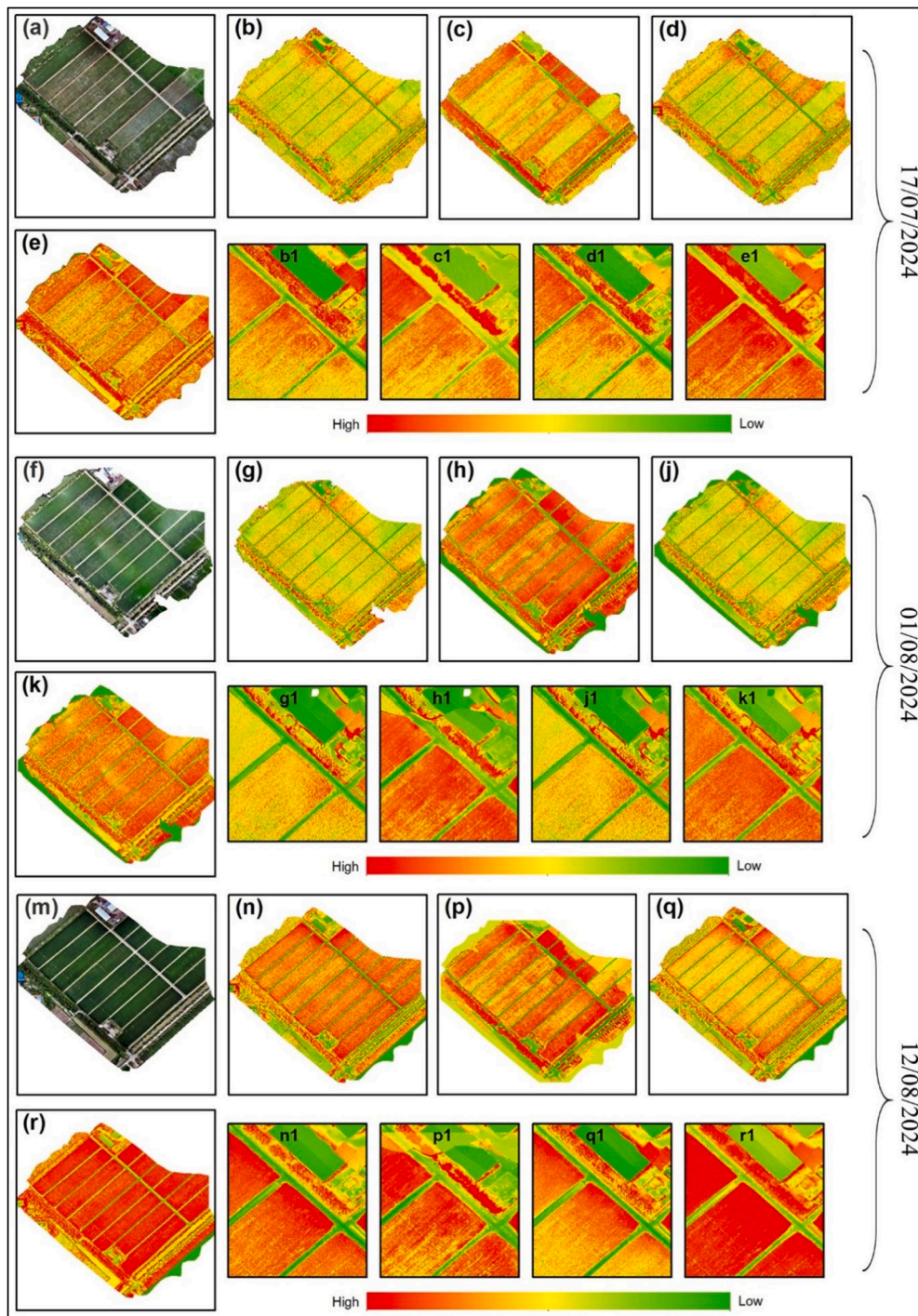


Fig. 6. Spatiotemporal vegetation stress maps across three dates (July 17, August 1, August 12). Columns show RGB orthomosaics (a, f, m), and stress maps from NDVI (b, g, n), NDRE (c, h, o), GNDVI (d, i, p), and MSAVI2 (e, j, q). Insets (b1–e1, g1–j1, n1–q1) provide zoomed views of key stress zones for each index and date.

trends in biomass and vigour. These findings strengthen the case for multi-index integration in operational crop stress assessment.

3.3. Spatial shifts in vegetation stress and early detection patterns

Binary stress mapping was conducted to quantify spatial patterns of crop stress using two vegetation indices. NDRE was selected for its high sensitivity to stress-related physiological changes, while NDVI offered a broader overview of overall vegetation health. These indices support spatiotemporal stress monitoring through binary mapping, given their sensitivity to canopy vigour and chlorophyll content. Thresholding

NDVI and NDRE using established cutoff values (< 0.4 and < 0.3 , respectively) enabled binary classification of vegetative health. The resulting maps in Fig. 8 (a–c) show that the stress pattern notably differs from July to August. NDVI-based pixel values highlighted emerging stress along field margins and low-lying areas, while NDRE-based stress masks identified chlorotic conditions even when NDVI remained relatively high. The binary transformation of continuous indices enables temporal comparison, change analysis, and propagation modelling. NDRE enhanced sensitivity to physiological stress highlights its value in pre-symptomatic detection as a key feature of the DTSM framework.

Building upon the binary stress mapping, change detection analysis

Table 3

Summary statistics of vegetation indices and stress classification across three UAV acquisition dates.

Date	Vegetation Index	Mean Value	Std. Dev.	Threshold for Stress	% Area Under Stress
17/07/2024	NDVI	0.58	0.14	< 0.40	12.5 %
	NDRE	0.38	0.10	< 0.35	17.3 %
	GNDVI	0.52	0.13	< 0.45	15.1 %
	MSAVI2	0.43	0.11	< 0.40	18.6 %
01/08/2024	NDVI	0.48	0.16	< 0.40	32.7 %
	NDRE	0.31	0.12	< 0.35	41.4 %
	GNDVI	0.46	0.14	< 0.45	34.5 %
	MSAVI2	0.39	0.13	< 0.40	38.2 %
12/08/2024	NDVI	0.52	0.15	< 0.40	21.6 %
	NDRE	0.36	0.11	< 0.35	26.9 %
	GNDVI	0.49	0.13	< 0.45	24.3 %
	MSAVI2	0.41	0.12	< 0.40	27.8 %

was conducted to assess the temporal dynamics of stress propagation. As shown in Fig. 8, difference maps generated from successive binary stress layers revealed substantial spatial turnover. Between July 17 and August 1, approximately 23 % of the study area transitioned into stressed conditions, while 12 % exhibited signs of recovery. A subsequent stress wave emerged between August 1 and 12, intensifying new stress in previously unaffected regions. These temporal insights, derived from NDVI and NDRE-based binary masks, underscore the dynamic nature of crop stress and highlight the utility of sequential monitoring.

3.4. Stress persistence index

To identify chronic stress zones, a 9-zone shapefile was integrated into the analysis, enabling stratified spatial assessment of stress persistence and propagation dynamics. A Stress Persistence Index (SPX) was computed by summing the binary stress maps across all three dates (Eq. (4)), as presented in Fig. 9. The SPX was classified into three categories: high (SPX = 3), medium (SPX = 2), and low (SPX = 1), reflecting the frequency of stress occurrence across the monitoring period. These pixel-level SPX values were then aggregated to zone-level classes based on the density of high-stress pixels within each zone. While some zones

may contain low and high SPX values, zones with a higher concentration of persistently stressed pixels were designated as high-stress areas. Notably, 15.7 % of the study area exhibited continuous stress (SPX = 3), with zones Z3, Z4, and Z8 identified as chronic stress hotspots. These areas consistently recorded NDVI values below 0.4, indicating prolonged physiological degradation and the need for targeted management strategies.

3.5. Spatial clustering patterns and identification of stress hotspots

Building upon the SPX-based analysis, spatial clustering was conducted using the Getis-Ord G_i^* statistic to identify statistically significant stress concentrations across the study area. This geostatistical approach differentiates between random and spatially dependent stress patterns. Fig. 10 illustrates the resulting hotspot and cold spot zones. High-confidence hotspots were predominantly concentrated in the western and central plots, with strong alignment to previously identified persistent stress zones (Z3, Z6, and Z8). These clusters validate the SPX-based findings by confirming localised spatial aggregation of stress beyond temporal fluctuations.

Conversely, cold spots—areas with significantly lower stress intensity were detected in elevated or better-drained zones, notably Z1 and Z9. These zones consistently recorded minimal stress across all observation periods, reflecting favourable field conditions such as better water drainage or nutrient availability.

Zone-wise stress percentages, calculated using the Tabulate Area tool, justified these spatial categories. Zones Z3, Z4, and Z8 exceeded the 35 % stress mark on all observation dates, whereas Z1 and Z9 remained below 15 %. This spatial clustering study adds another dimension to the DTSM framework in quantifying the statistical likelihood of stress concentration at a local level. By including both temporal and spatial indicators, this technique allows one to find areas of priority interventions for agronomic interventions and field management.

In summary, the clustering patterns complement SPX and binary maps by capturing statistically significant stress concentrations, offering a spatially differentiated window for precision agriculture.

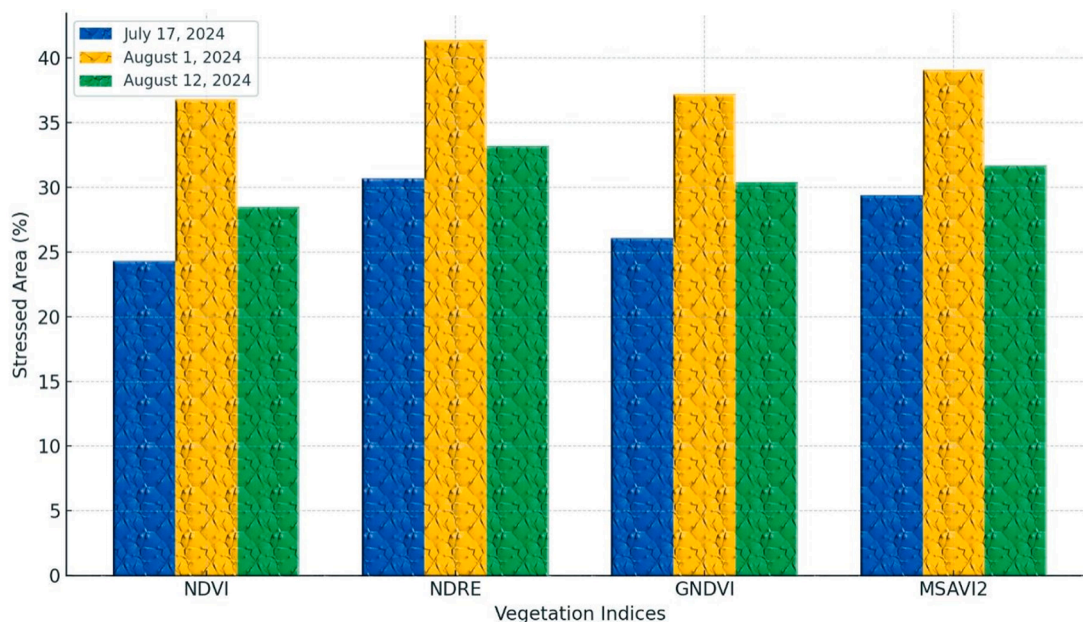


Fig. 7. Temporal variation in rice crop stress percentages estimated using four vegetation indices (NDVI, NDRE, GNDVI, and MSAVI2) across three monitoring dates.

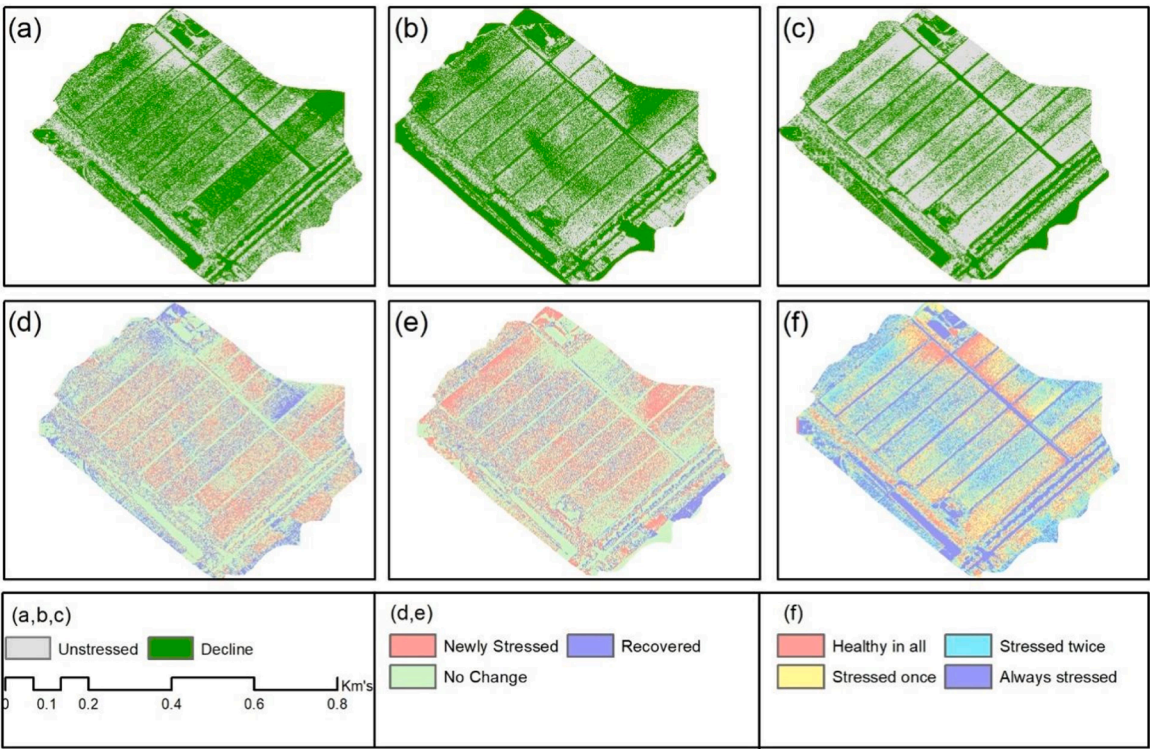


Fig. 8. Binary and cumulative stress dynamics derived. (a-c) present threshold-based binary stress masks across three dates; (d, e) show SPX differencing to highlight newly stressed, recovered, and stable areas; (f) summarizes temporal stress frequency into four classes: always healthy, stressed once, stressed twice, and constantly stressed.



Fig. 9. Chronic stress zones based on the highest density and mean value.

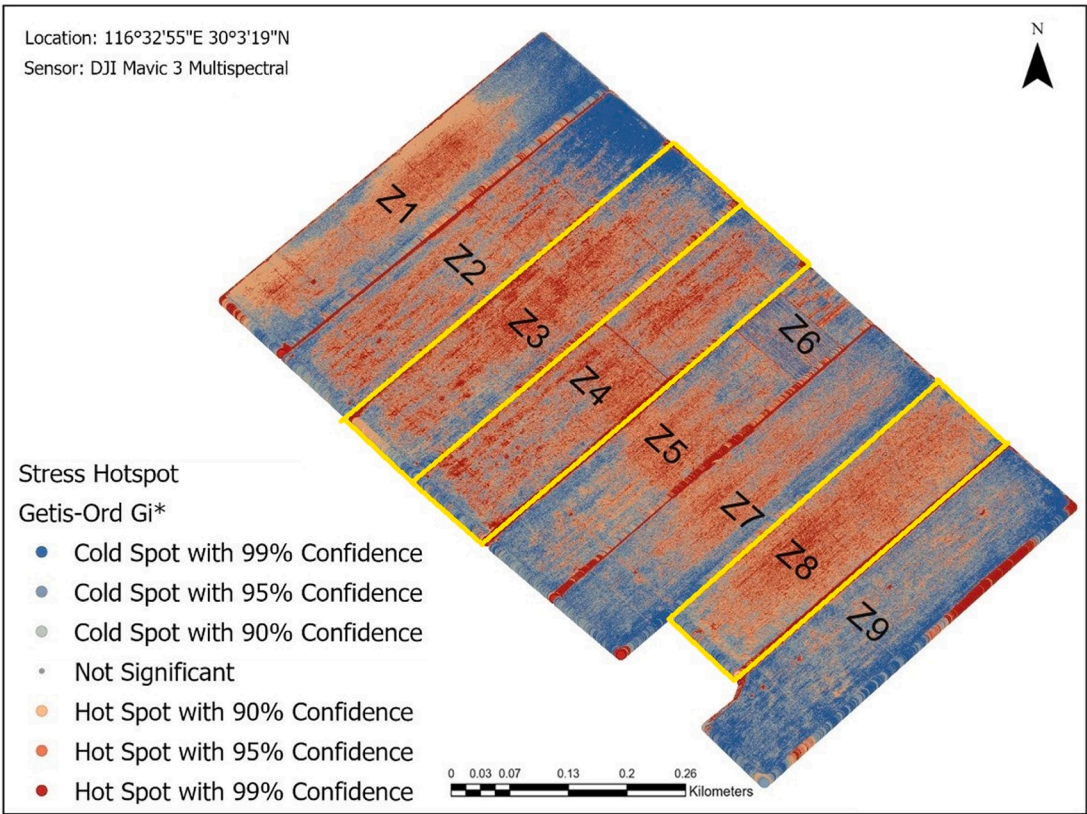


Fig. 10. Hot spot clustering of stress using Getis-Ord Gi*; Simulated stress spread based on spatial neighbourhood modelling.

3.6. Composite propagation trends and 3D visualisation of stress dynamics

To combine the temporal spread and spatial persistence of crop stress, a composite propagation map was produced by fusing binary

change detection output and the Stress Persistence Index (SPX). This fusion revealed a directional propagation pattern initiating in the southwestern parts and progressing northeast across the study region. This spatial trajectory aligns with observed field constraints, including localised water stagnation and sub-optimality drainage performance,

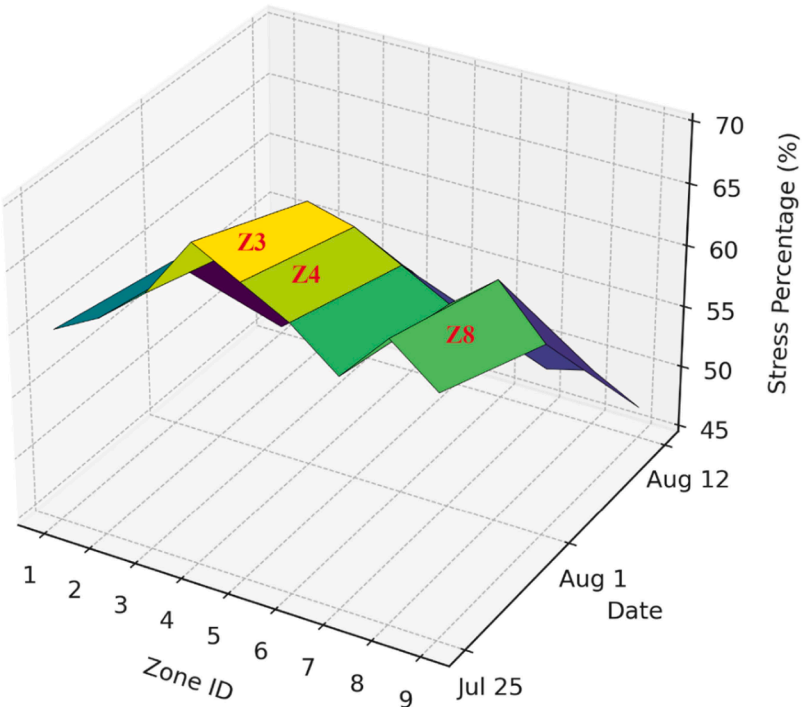


Fig. 11. 3D surface plot illustrating zone-wise stress propagation over three monitoring dates.

thus validating the DTSM-derived outputs.

To enhance spatial interpretability, a 3D surface plot (Fig. 11) was produced to represent the proportion of stressed area in the nine established zones on three UAV observation dates. The plot naturally reflects the temporal dynamics of the stress intensity: a high value on August 1—particularly in Zones 3 and 8—followed by a partial reduction by August 12. This trend verifies the presence of residual physiological stress in central zones, likely due to structural or agronomic deficiencies.

Peripheral regions (Z1, Z2, and Z9), in contrast, generally experienced lower stress throughout the period, suggesting greater field resilience or better conditions for growth. Surface visualisation not only situates temporal variability in context, but also shows spatial exposure hierarchies.

To further verify these findings, Getis-Ord G_i^* z-score histograms (Fig. 12) were used to evaluate the statistical significance of clusterings. Pixels were observed to cluster at intermediate z-score values (~ 1.5), and significant tails on both ends ($z > 2.3$ and $z < 0.4$) set the presence of statistically significant hotspots and cold spots. These cluster patterns identify the effects of non-random spatial influences, like heterogeneity in soil type, irrigation extent, or exposure to disease.

In summary, the composite propagation mapping and 3D visual outputs confirm the capability of the DTSM model to identify, track, and analyze stress dynamics in space and time. By bridging numerical analysis with geospatial visualization, these tools enable communication with stakeholders such as agronomists and farm managers, decision-making being spatially informed to avoid crop stress.

4. Discussions

4.1. Spatiotemporal stress patterns and multi-index performance

The Dynamic Temporal Stress Model (DTSM) revealed clear spatial and temporal heterogeneity in crop stress severity across the experimental field. Zones 3, 4, and 8 consistently exhibited high stress levels above 65 %, indicating persistent stress concentration in specific parts of the study area. This recurring spatial pattern suggests that DTSM can effectively identify chronically affected zones, particularly in situations where ground calibration data are limited or unavailable. As a rule-based, vegetation index-driven framework, DTSM provides a practical approach for monitoring field-scale stress dynamics in precision agriculture.

Previous studies have highlighted the usefulness of multi-temporal vegetation index analysis for early stress detection and zone delineation. For example, the Spatio-Temporal Cube (ST-Cube) model applied to Sentinel-2 EVI series successfully identified stable rice stress zones and characterized their persistence using intra- and inter-annual indices

[34]. In a similar context, DTSM integrates NDVI, NDRE, GNDVI, and MSAVI2 within a temporally explicit framework to evaluate stress progression and persistence across phenological stages. This multi-temporal structure improves interpretability by distinguishing transient stress fluctuations from recurring or chronic stress patterns.

The use of multiple vegetation indices further strengthens the framework because each index responds differently to plant physiological and structural characteristics. In agreement with [35], NDRE in the present study showed higher sensitivity to early physiological disturbances than NDVI, particularly in Zones 3 and 4. This supports the value of red-edge-based indices for pre-symptomatic stress detection and timely agronomic intervention. In addition, GNDVI and MSAVI2 contributed complementary information related to chlorophyll dynamics and reduced soil background influence. Similar sensor-based systems, including UAV-IoT platforms, have also demonstrated strong potential for early detection, disease-risk zonation, and physiological monitoring [36,37].

4.2. Thresholding, temporal differencing, and stress persistence

An important methodological aspect of DTSM is the use of fixed, index-specific thresholds across all acquisition dates. This thresholding strategy was based on the statistical distribution of vegetation index values and was used to preserve comparability across temporal observations. Maintaining consistent thresholds is especially important for temporal differencing and persistence analysis, because recalculating thresholds independently for each date may introduce artificial variation unrelated to actual vegetation dynamics. In this sense, the thresholds used in DTSM should be interpreted as an operational stress-screening rule rather than a definitive diagnosis of stress cause.

Temporal differencing in DTSM was designed to track stress emergence and recovery between successive UAV observations. Although only three UAV acquisition dates were available in this study, the selected dates corresponded to key phenological stages of rice development, allowing two meaningful temporal comparisons within the growing season. The resulting change maps provided a practical representation of short-term stress evolution rather than a long-term temporal trajectory.

The Stress Persistence Index (SPX) offered a cumulative measure of repeated stress occurrence over time. The rationale behind SPX is that repeated detection of stress at the same location is more likely to indicate persistent or chronic stress conditions than an isolated single-date anomaly. This cumulative perspective improves the identification of zones requiring sustained management attention. In this regard, DTSM extends beyond single-date vegetation stress mapping by integrating stress occurrence, temporal change, and spatial persistence within one analytical framework.

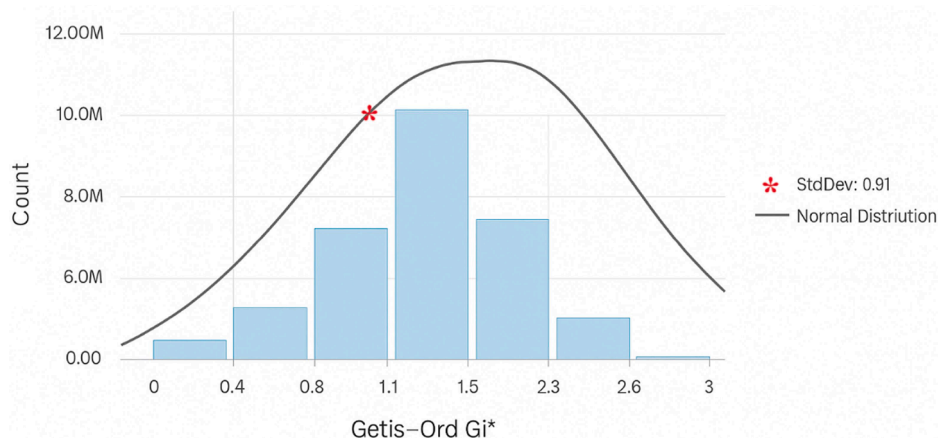


Fig. 12. Histogram of Getis-Ord G_i^* z-scores showing the distribution and statistical significance of crop stress clustering across the study area.

The stress propagation component of DTSM, based on binary stress mapping and spatial analytical logic, is conceptually comparable to outbreak-tracking approaches used in UAV-based monitoring of rice diseases and pest spread, where spatial contagion behavior has been identified using drone observations [38]. Although the present framework does not claim causal prediction of future stress, the integration of temporal change detection and spatial clustering provides useful evidence for identifying areas with elevated risk of continued stress development.

4.3. Practical implications for precision agriculture

The delineation of chronically stressed zones, particularly Zones 3, 4, and 8, has direct practical relevance for field management. These zones can be prioritized for irrigation inspection, fertilizer adjustment, and pest or disease scouting, consistent with UAV-based decision-support applications in precision agriculture [39]. This is also in line with previous applications of UAV phenotyping in drought-tolerant rice genotype selection and crop monitoring [40,41]. By providing zone-specific stress information, DTSM contributes to more targeted and resource-efficient intervention planning.

Compared with phenotype-dependent approaches such as QTL mapping or GWAS-based drought tolerance studies [42], DTSM is entirely remote sensing-driven and therefore more suitable for data-limited or operational agricultural settings. Its modular design also aligns with current developments in vegetation stress modelling, including machine learning-based approaches such as CNN and RNN frameworks [40,43]. However, unlike many black-box models, DTSM provides spatially explicit and interpretable outputs, which may be advantageous for practical decision-making by agronomists and land managers.

4.4. Limitations and future directions

Several limitations should be acknowledged. First, the validation strategy in this study relied on internal consistency among vegetation indices, temporal patterns, and spatial clustering, rather than independent field-based ground truth. While this provides useful evidence of methodological coherence, it does not replace direct external validation. Second, UAV-derived stress maps indicate spectral stress responses but do not uniquely identify the underlying cause of stress without complementary agronomic observations. Third, the limited number of acquisition dates constrains the temporal depth of analysis, and denser time-series observations would strengthen future applications. Fourth, threshold selection and stress interpretation may vary across cultivars, seasons, and management conditions, so recalibration may be necessary when transferring the framework to other agricultural settings.

Future studies should incorporate field measurements, independent validation datasets, and extended temporal coverage to further evaluate and refine the DTSM framework. Additional integration with thermal or SAR data may also strengthen stress characterization and improve the discrimination of stress drivers under diverse environmental conditions.

5. Conclusions

The present study developed the Dynamic Temporal Stress Model (DTSM), a vegetation index-based framework for UAV-driven crop stress monitoring using multispectral imagery. By integrating NDVI, NDRE, GNDVI, and MSAVI2 across key phenological stages, DTSM enabled binary stress mapping, temporal differencing, stress persistence assessment, and spatial hotspot analysis for rice fields. The results revealed clear spatial and temporal heterogeneity in crop stress, with Zones 3, 4, and 8 consistently identified as priority stress areas across the monitoring period.

Among the tested indices, NDRE showed greater sensitivity to early-stage stress, while MSAVI2 improved stress detection in areas with

sparse canopy cover by reducing soil background effects. Temporal differencing captured stress emergence and recovery between observation dates, while the Stress Persistence Index (SPX) identified areas exposed to repeated stress over time. In addition, Getis-Ord G_i^* analysis confirmed statistically significant clustering of stress in the same high-priority zones, strengthening the spatial interpretation of the results.

Methodologically, DTSM provides an interpretable and transferable framework for precision agriculture, particularly in data-limited settings where extensive field calibration may not be feasible. The use of commonly available vegetation indices, together with standard GIS-based processing, improves its practical applicability for agronomists and land managers. By translating pixel-level stress information into zone-level management priorities, DTSM supports targeted field inspection and more efficient intervention planning.

From an applied perspective, the framework can support climate-resilient and resource-efficient agricultural management by helping identify high-risk areas for irrigation checks, nutrient management, and pest or disease scouting. The integration of temporal and spatial analysis also improves communication of stress dynamics to decision-makers through clear and interpretable outputs.

Several limitations should be acknowledged. The framework identifies stress-related spectral responses but does not uniquely determine the underlying cause of stress without complementary agronomic observations. In addition, the limited number of UAV acquisition dates constrains the temporal depth of the analysis, and the current evaluation relies on internal consistency among vegetation indices and spatiotemporal patterns rather than independent field-based validation. Future studies should extend DTSM through multi-season and multi-site applications, incorporate field measurements for stronger validation, and evaluate complementary sensing modalities such as thermal or SAR data to improve stress characterization. Overall, DTSM provides a spatially explicit and temporally informed framework for UAV-based crop stress monitoring and zone-based management in rice production systems.

Funding support

Funding provided by Sultan Idris University.

Ethical statement for manuscript submission

In submitting this manuscript to *Smart Agricultural Technology*, I affirm the following ethical considerations:

- Research Integrity:** This work is original, accurate, and has not been published elsewhere. It has been conducted without fabrication or falsification.
- Data Transparency:** Methodologies and data are detailed to enable replication. All supporting data are available upon request.
- Conflict of Interest:** I declare no conflicts of interest that may influence this research.
- Respect for Intellectual Property:** All references are properly cited, and permissions for copyrighted material have been obtained.
- Collaborative Research:** This research aims to benefit a diverse range of stakeholders in the agricultural sector.
- Publication Ethics:** I understand and agree to adhere to the journal's ethical publishing practices and guidelines throughout the review and publication process.

By submitting this manuscript, I commit to upholding these ethical standards and acknowledge that failure to comply may result in retraction of the manuscript or other actions as deemed appropriate by the journal.

CRediT authorship contribution statement

Muhammad Nasar Ahmad: Writing – original draft, Visualization,

Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Xiaohui Yuan:** Writing – review & editing, Funding acquisition. **Shuai Yang:** Data curation. **Lichuan Gu:** Supervision. **Hui Peng:** Validation. **Rana Waqar Aslam:** Validation. **Md. Enamul Huq:** Methodology. **Akib Javed:** Visualization, Conceptualization. **George D. Bathrellos:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

- [1] R.K. Rai, M.S. Karada, R. Mishra, D. Agnihotri, K.K. Patel, S. Thakur, D. Singh, Transformative role of Remote sensing in advancing horticulture: optimizing sustainability, efficiency and resilience, *Int. J. Environ. Clim. Chang.* 13 (2023) 3559–3567.
- [2] X. Yuan, S. Li, J. Chen, H. Yu, T. Yang, C. Wang, S. Huang, H. Chen, X. Ao, Impacts of global climate change on agricultural production: a comprehensive review, *Agronomy* 14 (2024) 1360.
- [3] Z. Yuan, W. Chen, A. Yang, W. Shao, Remote sensing crop classification model integrating 1D convolutional residual blocks and temporal attention, in: Fourth International Conference on Machine Learning and Computer Application (ICMLCA 2023), SPIE, 2024, pp. 519–524.
- [4] B. Duchemin, R. Hadria, S. Erraki, G. Boulet, P. Maisongrande, A. Chehbouni, R. Escadafal, J. Ezzahar, J.C.B. Hoedjes, Monitoring wheat phenology and irrigation in Central Morocco: on the use of relationships between evapotranspiration, crops coefficients, leaf area index and remotely-sensed vegetation indices, *Agric. Water Manag.* 79 (2006) 1–27.
- [5] X. Huang, J. Wang, Z. Li, Mapping paddy rice planting areas through time series analysis of MODIS land surface temperature and vegetation index data, *Int. J. Remote Sens.* 35 (2014) 441–453.
- [6] A.K. Jukanti, D. Karapati, V. Bharali, M. Gudla, S. Thati, S. Yadla, M. Kumar, R. M. Sundaram, From gene to plate: molecular insights into and health implications of rice (*Oryza sativa* L.) grain protein, *Int. J. Mol. Sci.* 26 (2025) 3163.
- [7] I.N. Alou, J.M. Steyn, J.G. Annandale, M. Van der Laan, Growth, phenological, and yield response of upland rice (*Oryza sativa* L. cv. Nerica 4®) to water stress during different growth stages, *Agric. Water Manag.* 198 (2018) 39–52.
- [8] G. Tmušić, S. Manfreda, H. Aasen, M.R. James, G. Gonçalves, E. Ben-Dor, A. Brook, M. Polinova, P. Arranz Justel, Vegetation indices for crop monitoring from remote sensing: a review, *Agronomy* 10 (2020) 1043.
- [9] C.J. Tucker, Red and photographic infrared linear combinations for monitoring vegetation, *Remote Sens. Environ.* 8 (1979) 127–150.
- [10] L. Zhang, H. Zhang, Y. Niu, W. Han, Mapping maize water stress based on UAV multispectral remote sensing, *Remote Sens.* 11 (2019) 605.
- [11] D. Gómez-Candón, A.I. De Castro, F. López-Granados, Multi-temporal analysis of high resolution UAV imagery for precision agriculture: evaluation of vegetation indices for detecting temporal changes, *Precis. Agric.* 17 (2016) 159–175.
- [12] S.M.H. Khalaf, M.S.M. Alqahtani, M.R.M. Ali, I.T.I. Abdelalim, M.S. Hodhod, Modeling climate-related global risk maps of rice bacterial blight caused by *Xanthomonas oryzae* (Ishiyama 1922) using geographical information system (GIS), *Environ. Monit. Assess.* 196 (2024) 1064.
- [13] P. Su, J.A. Wang, A.Y. Zhang, Global high-temperature disaster risk of rice dataset [J], *J. Glob. Chang. Data Discov.* 4 (2022) 545–556.
- [14] Y. Huang, Y. Lan, S.J. Thomson, A. Fang, W.C. Hoffmann, UAV-based remote sensing for precision agriculture: a review, *Comput. Electron. Agric.* 179 (2021) 105824.
- [15] C. Zhang, Q. Hu, X. Zhang, Y. Zhang, J. Wang, Evaluation of UAV-based hyperspectral and thermal sensing for monitoring water stress in winter wheat, *Agric. Water Manag.* 239 (2020) 106266.
- [16] D.J. Mulla, Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps, *Biosyst. Eng.* 114 (2013) 358–371.
- [17] C. Zhang, J.M. Kovacs, The application of small unmanned aerial systems for precision agriculture: a review, *Precis. Agric.* 13 (2012) 693–712.
- [18] K. De Vos, B. Campforts, L. Tits, K. Van Tricht, K. Bonte, G. Govers, L. Jacobs, Potential and limitations of crowdsourcing data for high-resolution rice mapping in Madagascar: the importance of representation, *Int. J. Applied Earth Observ. Geoinfor.* 117 (2023) 103204.
- [19] C. Lin, L. Zhong, X.-P. Song, J. Dong, D.B. Lobell, Early-and in-season crop type mapping without current-year ground truth: generating labels from historical information via a topology-based approach, *Remote Sens. Environ.* 274 (2022) 112994.
- [20] J.K. Ord, A. Getis, Local spatial autocorrelation statistics: distributional issues and an application, *Geogr. Anal.* 27 (1995) 286–306.
- [21] X. Liu, C. Zhang, J. Wu, W. Wu, Estimating leaf area index in maize using UAV-based multispectral vegetation indices and machine learning algorithms, *Agric. For. Meteorol.* 287 (2020) 107938.
- [22] N. Vigneau, M. Ecartot, G. Rabatel, P. Roumet, Estimation of wheat grain protein content from aerial hyperspectral imagery using partial least squares regression and support vector machines, *F. Crop. Res.* 122 (2011) 49–59.
- [23] S. Jarahizadeh, B. Salehi, A comparative analysis of UAV photogrammetric software performance for forest 3D modeling: a case study using AgiSoft photscan, PIX4DMapper, and DJI Terra, *Sensors* 24 (2024) 286.
- [24] K. Kanaley, M.J. Murdock, T. Qiu, E. Liu, S.E. Seyram, D. Starzmann, L.B. Smart, K. M. Gold, Y. Jiang, Maui: modular analytics of UAS imagery for specialty crop research, *Plant Method.* 21 (2025) 1–17.
- [25] C. Zhang, et al., Optimal sensor payload configuration for UAV-based precision agriculture, *Agric. Syst.* 173 (2019) 130–140.
- [26] U.R. Manepalli, G.H. Bham, S. Kandada, Evaluation of hotspots identification using kernel density estimation (K) and Getis-Ord (Gi*) on I-630, in: 3rd International Conference on Road Safety and Simulation, United States, National Academy of Sciences Indianapolis Indiana, 2011, pp. 14–16.
- [27] P. Lemenkova, O. Debeir, Multispectral satellite image analysis for computing vegetation indices by R in the Khartoum Region of Sudan, Northeast Africa, *J. Imag.* 9 (5) (2023) 98.
- [28] H. Yarahmadi, Y. Desille, J. Goold, F. Pietracaprina, Identifying vegetation patterns for a qualitative assessment of land degradation using a cellular automata model and satellite imagery, *Phys. Rev. E* 110 (2) (2024) 024136.
- [29] S.V. Stehman, J.D. Wickham, Pixels, blocks of pixels, and polygons: choosing a spatial unit for thematic accuracy assessment, *Remote Sens. Environ.* 115 (2011) 3044–3055.
- [30] D. Gómez-Candón, A.I. De Castro, F. López-Granados, Multi-temporal analysis of high resolution UAV imagery for precision agriculture: evaluation of vegetation indices for detecting temporal changes, *Precis. Agric.* 17 (2016) 159–175.
- [31] S.A. Nallan, L.J. Armstrong, A.K. Tripathy, P. Teluguntla, Hot spot analysis using NDVI data for impact assessment of watershed development, in: Proceedings, IEEE, 2015.
- [32] A. Lanorte, G. Nolè, G. Cillis, Application of Getis-Ord correlation index (Gi) for burned area detection improvement in Mediterranean ecosystems (Southern Italy and Sardinia) using Sentinel-2 data, *Remote Sens.* 16 (2024) 2943.
- [33] G. Modica, A. Pulvirenti, D. Spina, S. Bracco, M. D'Amico, G. Di Vita, Clustering olive oil mills through a spatial and economic GIS-based approach, *Clean. Environ. Syst.* 14 (2024) 100207.
- [34] S. Wang, M. Liu, Y. Li, L. Wu, B. Zhou, L. Tian, Spatiotemporal cube model based on stress features for identification of heavy metal stress in rice, *IEEE Trans. Geosci. Remote Sens.* 62 (2024) 1–13.
- [35] M.F. BDR, H.S. Renhard, N.Q.Z. Muharram, M. Mukminati, M.F. Anshori, N. Amier, A.I. Sakinah, Tolerance of some rice varieties to drought based on drone-vegetation index, *Agrotech J.* 8 (2023) 33–41.
- [36] D. Gao, Q. Sun, B. Hu, S. Zhang, A framework for agricultural pest and disease monitoring based on internet-of-things and unmanned aerial vehicles, *Sensors* 20 (2020) 1487.
- [37] N. Kitpo, M. Inoue, Early rice disease detection and position mapping system using drone and IoT architecture, in: 2018 12th South East Asian Technical University Consortium (SEATUC), IEEE, 2018, pp. 1–5.
- [38] X.-G. Zhou, D. Zhang, F. Lin, UAV remote sensing: an innovative tool for detection and management of rice diseases. Diagnostics of Plant Diseases, IntechOpen, 2021.
- [39] A. Abbas, Z. Zhang, H. Zheng, M.M. Alami, A.F. Alrefaei, Q. Abbas, S.A.H. Naqvi, M.J. Rao, W.F.A. Mosa, Q. Abbas, Drones in plant disease assessment, efficient monitoring, and detection: a way forward to smart agriculture, *Agronomy* 13 (2023) 1524.
- [40] X. Bai, H. Fang, Y. He, J. Zhang, M. Tao, Q. Wu, G. Yang, Y. Wei, Y. Tang, L. Tang, Dynamic UAV phenotyping for rice disease resistance analysis based on multisource data, *Plant Phenomic.* 5 (2023) 19.
- [41] Z. Jiang, H. Tu, B. Bai, C. Yang, B. Zhao, Z. Guo, Q. Liu, H. Zhao, W. Yang, L. Xiong, Combining UAV-RGB high-throughput field phenotyping and genome-wide association study to reveal genetic variation of rice germplasms in dynamic response to drought stress, *New Phytol.* 232 (2021) 440–455.
- [42] J. Agrawal, M.Y. Arafat, Transforming farming: a review of AI-powered UAV technologies in precision agriculture, *Drones* (2504–446X) (2024) 8.
- [43] J. Li, T. Xie, Y. Chen, Y. Zhang, C. Wang, Z. Jiang, W. Yang, G. Zhou, L. Guo, J. Zhang, High-throughput UAV-based phenotyping provides insights into the dynamic process and genetic basis of rapeseed waterlogging response in the field, *J. Exp. Bot.* 73 (2022) 5264–5278.