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INTEGRATION OF THERMAL INFRARED IMAGING AND EXERGY ANALYSIS FOR EARLY NUTRIENT STRESS DETECTION IN CUCUMBER (CUCUMIS SATIVUS): A REVIEW

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Abstract: Cucumber (Cucumis sativus L.) is highly sensitive to nitrogen (N), phosphorus (P), and potassium (K) deficiencies, which impair plant physiology several days before any visible symptom appears, leaving growers unable to intervene before yield losses are incurred. This review aims to critically synthesize existing evidence on the integration of UAV-based thermal infrared (TIR) imaging and plant exergy analysis as a combined framework for pre-symptomatic nutrient stress detection in cucumber, and to identify the research gaps that must be resolved before such a framework can be validated for field deployment. A structured narrative review of peer-reviewed literature published between January 2014 and March 2026 was conducted across Web of Science, Scopus, and Google Scholar. From an initial pool of 124 candidate articles, 68 met predefined inclusion criteria based on relevance to four thematic pillars: UAV-based TIR imaging, plant exergy theory, cucumber macronutrient physiology, and machine learning (ML) classification. The result showed that nutrient-stressed cucumber canopies runs 1-3°C warmer than healthy plants, and this thermal signature appears 1 - 3 days before yellowing is visible to the naked eye. The Exergy Destruction Principle (EDP) adds analytical depth that thermal indices alone cannot offer, converting a temperature reading into a physically meaningful measure of wasted solar energy per unit canopy area. The primary unresolved challenge is discriminating nutrient stress from water stress, as both pathologies produce overlapping thermal signatures through shared stomatal closure mechanisms. A controlled factorial greenhouse trial in cucumber with concurrent thermal imaging, gas exchange measurement, and leaf tissue analysis is identified as the most urgent research priority.

Keywords: thermal infrared imaging, exergy analysis, nutrient stress, precision agriculture, cucumber (Cucumis sativus), UAV remote sensing, stomatal conductance

1.0 Introduction

Cucumber (Cucumis sativus L.) is one of the few vegetable crops that has managed to become commercially indispensable on almost every continent 8.7 million hectares under cultivation, a rapid growth cycle, and a price premium that rewards attentive nutrient management [1, 2].

What makes this commercial success fragile is the crop's sensitivity to nitrogen, phosphorus, and potassium imbalances, which together govern fundamental biochemical processes including chlorophyll synthesis, energy transfer, and stomatal regulation [3, 4] as shown in figure 1.

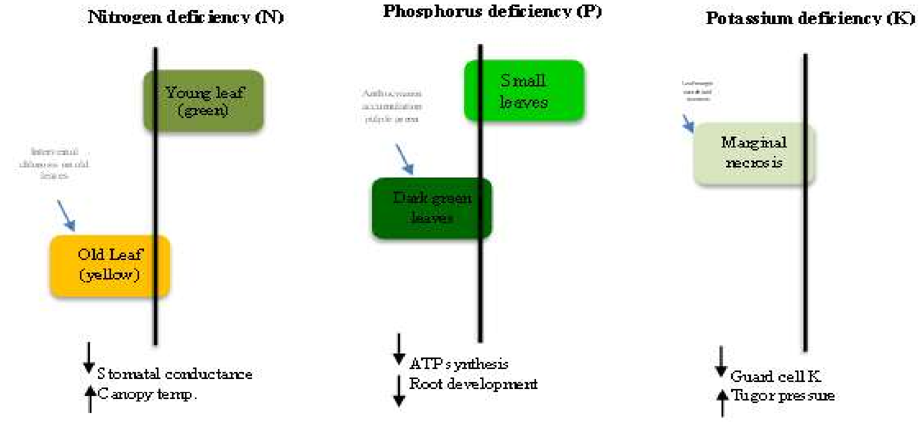

Fig. 1: Visual macronutrient deficiency symptoms in Cucumis sativus L. (a) Nitrogen (N) deficiency showing interveinal chlorosis on older leaves caused by chlorophyll degradation and ATP-dependent stomatal impairment. (b) Phosphorus (P) deficiency characterized by dark-green anthocyanin-rich small leaves and stunted growth. (c) Potassium (K) deficiency showing marginal leaf necrosis due to collapse of guard-cell K+ gradients. Visible symptoms emerge 5-10 days after physiological onset. [68, 3, 31]

The damage from poor nutrient management reaches further than the farm gate: globally, crops utilise only 40-60% of applied nitrogen, with the remainder lost through leaching, volatilisation, and denitrification, contributing substantially to groundwater contamination and greenhouse gas emissions [5, 6]. Conventional nutrient management in cucumber relies on a combination of visual symptom assessment, periodic leaf tissue analysis, and calendar-based fertilisation schedules. Nitrogen deficiency presents as interveinal chlorosis on older leaves; potassium insufficiency causes marginal necrosis; and phosphorus shortage produces characteristic dark-green colouration and growth retardation [3, 7]. These visible symptoms are diagnostic failures, not diagnostic tools. By the time a grower can observe chlorosis or leaf scorch, physiological damage has typically accumulated over five to ten days, during which stomatal conductance, photosynthetic rate, and water use efficiency have all declined significantly [8, 9]. Corrective fertilisation applied at this point cannot fully reverse the physiological disruption, and yield losses may already be locked in. The diagnostic gap between the onset of cellular stress and the emergence of observable symptoms therefore represents the central agronomic problem motivating non-destructive early detection research. Spatially explicit, non-destructive sensing is where the diagnostic gap can realistically be closed that can characterise crop status at the field scale, enabling targeted interventions rather than uniform blanket applications [10, 11]. Thermal infrared (TIR) imaging stands out from the sensing toolkit for a physiologically direct reason: the physiological consequences of nutrient stress, specifically reduced stomatal conductance and impaired transpiration, directly alter the leaf and canopy energy balance in ways that manifest as measurable surface temperature increases [12, 13]. When a nutritionally compromised plant reduces stomatal aperture, the latent heat flux through transpiration declines, energy is redirected to sensible heat, and the canopy surface warms. UAV-mounted thermal cameras can detect these temperature anomalies at sub-metre spatial resolution across entire fields in a single flight campaign [14, 15]. Exergy analysis, rooted in the second law of thermodynamics, adds a dimension that thermal sensing alone cannot provide: Exergy quantifies the maximum useful work extractable from an energy flow as a system moves toward thermodynamic equilibrium with its environment [16, 17]. For a plant canopy intercepting solar radiation, exergy analysis translates the empirically observed temperature increase associated with nutrient stress into a physically interpretable metric: the rate of useful solar energy wasted per unit canopy area [18]. This Exergy Destruction Principle (EDP) offers important advantages over purely empirical correlations. Unlike empirical thermal indices, the EDP index carries physical units, scales across crops without recalibration, and slots naturally into energy efficiency assessments with agronomic energy efficiency assessments [19, 20]. Strikingly, no published review has yet brought these two approaches together for cucumber nutrient management of UAV-based TIR sensing with plant exergy analysis for nutrient stress diagnostics in cucumber. This review addresses that gap by critically looking at the current state of knowledge across four thematic pillars: principles and applications of UAV based thermal infrared imaging in crop stress sensing, thermodynamic foundations and practical applications of plant exergy analysis, cucumber physiological responses to macronutrient deficiency and limitations of existing diagnostic tools and integration pathways, challenges, and future research priorities for a thermal-exergy diagnostic framework. The review specifically targets the early detection window of one to three days before visual symptom emergence, which represents the critical period for intervention if yield penalties are to be avoided. This review has two objectives: (i) to critically synthesize published evidence on the component methods UAV-based TIR sensing, plant exergy analysis, and cucumber macronutrient physiology drawing on the peer-reviewed record to establish what is demonstrated and what remains uncertain and (ii) to propose, on the basis of that evidence, an integrated thermal-exergy processing framework for cucumber and to appraise the assumptions, gaps, and future work required before it can be operationalized.

2.0 Methodology

2.1 Literature search strategy

This review followed a structured narrative review approach to identify peer-reviewed literature relevant to the integration of thermal infrared imaging and exergy analysis for nutrient stress detection in cucumber. Searches were conducted across three major academic databases Web of Science, Scopus, and Google Scholar using combinations of the following keywords: "thermal infrared imaging," "UAV crop sensing," "exergy analysis plants," "cucumber nutrient stress," "stomatal conductance remote sensing," "crop water stress index," "precision agriculture machine learning," and "macronutrient deficiency detection." The search was restricted to publications from January 2014 to March 2026 to ensure contemporary relevance while capturing foundational studies from the past decade. Several foundational studies published before January 2014 are cited in this review. These were not identified through the primary database search but were included as foundational theoretical references where their contributions remain the primary or sole published source for a specific concept. Specifically: Idso et al. (1981) for the original CWSI formulation cited in Section 2.2.2, Petela (2008) [16] for the radiation exergy model, Leinonen and Jones (2004) [13] for combined thermal-visible sensing and some other once. These works were identified through backward citation tracing from included primary studies, a standard supplementary method in structured narrative reviews. Articles were included if they: (i) reported original experimental results or systematic reviews relevant to at least one of the four thematic pillars (TIR sensing, plant exergy, cucumber physiology, or ML classification); (ii) were published in peer reviewed journals or conference proceedings; and (iii) were available in English. Articles were excluded if they: (i) addressed thermal sensing exclusively in non-agricultural industrial contexts; (ii) focused on crop species with no physiological relevance to Cucurbitaceae; or (iii) lacked sufficient methodological detail for critical appraisal. Grey literature defined here as technical reports, manufacturer datasheets, government crop guides, and agricultural extension publications not subject to formal peer review was included selectively where crop-specific agronomic data were absent from the peer-reviewed record. An initial pool of 124 candidate articles was identified, of which 68 met the inclusion criteria and were retained for full-text review and synthesis. The review content is organized into four thematic sections aligned with the four diagnostic pillars identified above, followed by an integrative section proposing and critically evaluating the combined thermal-exergy framework.

2.2 Thermal infrared imaging in crop stress detection

2.2.1 Physical principles of thermal infrared sensing

Thermal infrared imaging operates by detecting mid to longwave infrared radiation (8-14 μm) emitted by objects proportional to their surface temperature, as described by the Stefan-Boltzmann law [21] (Fig. 2). Plant leaves exhibit notably high surface emissivity, typically falling within the range 0.96-0.99, enabling accurate canopy temperature retrieval from calibrated radiometric sensors [22, 23]. This high emissivity is advantageous for agricultural sensing because it reduces the uncertainty associated with emissivity corrections that are necessary when imaging materials with lower or more variable emissivity values such

as bare soil or senescent plant tissue. The canopy energy balance governs the thermal behavior of plant surfaces as shown in Fig. 2.
The net radiation (Rn) intercepted by the canopy is partitioned among sensible heat flux (H), latent heat flux through transpiration (LE), and soil heat flux (G):

$$Rn = H + LE + G \tag{1}$$

Where; H is the sensible heat flux, LE is the transpiration and G is the soil heat flux. Any physiological constraint that reduces stomatal aperture, whether induced by nutrient deficiency, water deficit, or pathogen attack, suppresses LE and redirects energy to H, producing a measurable rise in canopy temperature [13, 24]. For nutrient-stressed plants, this suppression of transpirational cooling occurs through distinct biochemical pathways depending on which macronutrient is limiting. Nitrogen deficiency impairs ATP synthesis and the operation of the ATP dependent K pumps in guard cells, directly reducing stomatal conductance [25]. Potassium deficiency

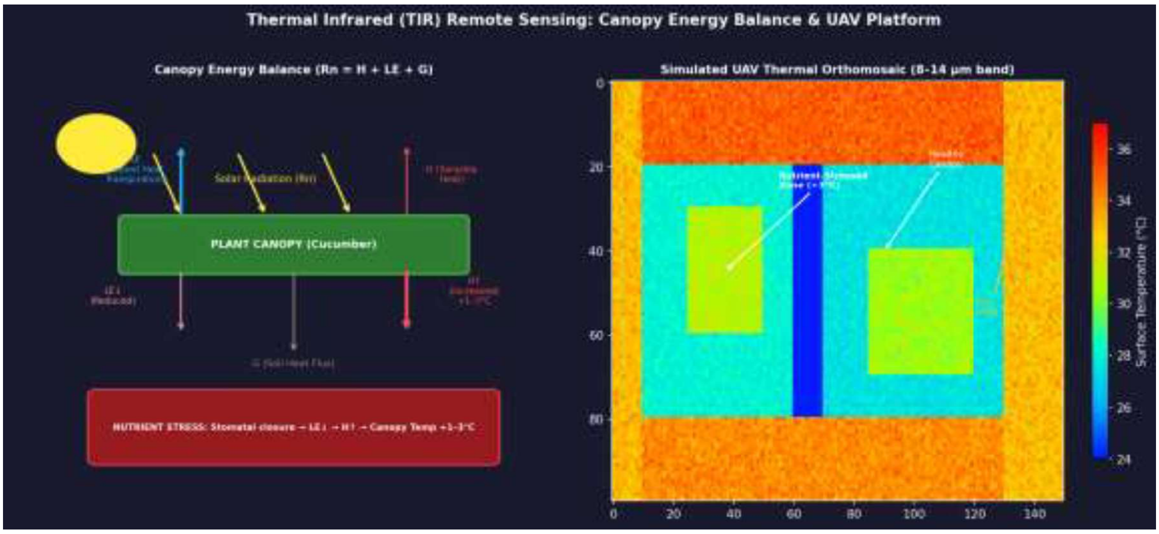

Fig. 2: Thermal infrared (TIR) remote sensing principles applied to crop canopy monitoring. (a) Canopy energy balance diagram showing partitioning of net radiation (Rn) into latent heat (LE), sensible heat (H), and soil heat flux (G). Nutrient stress-induced stomatal closure suppresses LE and elevates H, increasing canopy temperature by 1-3°C. (b) Simulated UAV thermal orthomosaic (false-colour, 8-14 µm band) showing nutrient-stressed zones (warm/red) versus healthy canopy (cool/blue) with soil background. [32]

compromises turgor-driven stomatal mechanics through altered K fluxes [4]. Phosphorus shortage impairs the phosphorylation reactions underpinning guard cell signalling, with measurable effects on stomatal conductance documented in Cucurbit species [8]. Pineda et al. [26] provided a comprehensive review of thermal imaging applications in plant stress detection and phenotyping, emphasising that while the physical basis of canopy temperature as a stress indicator is well established, the translation of raw temperature measurements into reliable stress maps requires careful attention to environmental confounders and calibration protocols. Their analysis of over 80 published studies found that thermal imaging reliably detected abiotic and biotic stresses 2-5 days earlier than visible symptom assessments in a majority of experimental contexts, though the lead time varied substantially with stress type, crop species, and ambient conditions. What Pineda et al.'s aggregated results conceal, however, is substantial heterogeneity in experimental design [26]. Many of the studies they evaluated used controlled chamber or greenhouse conditions where environmental variables were tightly managed, conditions that rarely replicate the variability of open field cucumber production. The reported 2–5-day detection lead times should therefore be interpreted as upper-bound estimates for well-controlled settings. In open-field environments, where wind speed variability, soil moisture heterogeneity, and diurnal temperature fluctuations interact to confound canopy temperature readings, lead times may be reduced. This limitation is often understated in reviews that aggregate chamber and field studies without stratifying results by environmental context. Wen et al. [27] similarly reviewed the use of thermal imaging as a digital eye for high throughput plant phenotyping, concluding that standardised acquisition and analysis protocols remain the most critical unresolved challenge for wider adoption. This broad pattern holds when narrowed to cucumber and related Cucurbit species, as examined next.

2.2.2. Thermal stress indices and quantitative metrics

Raw canopy temperature alone provides limited diagnostic information under variable environmental conditions because air temperature, vapour pressure deficit (VPD), and wind speed independently influence the leaf energy balance. Normalised thermal indices partially resolve this limitation by incorporating concurrent meteorological observations. The Crop Water Stress Index (CWSI), originally proposed by Idso et al. (1981) and subsequently refined by Jones et al. [28], normalises canopy temperature relative to fully transpiring and non-transpiring reference surfaces:

$$CWSI = (Tc - Twet) / (T_{dry} - T_{wet}) \quad (2)$$

where: Tc is the measured canopy temperature (ºC or K), Twet is the temperature of a fully transpiring reference surface representing no-stress conditions, and Tdry is the temperature of a non-transpiring reference surface representing maximum stress conditions. Reference temperatures may be determined from physical reference panels deployed in the field [29] or from biophysical energy balance models; the choice of reference method must be consistent within a study as the two approaches yield non-interchangeable CWSI baselines [28, 29].

A CWSI of zero denotes no stress; a value of one indicates maximum stress. The index was initially developed for water stress but has been successfully extended to nutrient stress detection on the basis that both stresses converge mechanistically on stomatal closure [24, 29]. Jones et al. [28] conducted foundational field experiments across multiple crop species demonstrating that TIR-derived CWSI values correlated strongly with gas exchange measurements of stomatal conductance under both water and nutrient stress, though they cautioned that the two stress types could not be reliably discriminated from CWSI alone without ancillary information. Costa et al. [29] extended this analysis through a comprehensive review of thermography in plant-environment interactions, identifying CWSI as the most widely validated index for field-scale stress assessment and highlighting the importance of standardised reference surface construction for cross-site comparability. Their systematic comparison of reference surface methodologies found that artificial wet and dry references provided more consistent CWSI baselines than the biophysically modelled equivalents used in some studies, a result that should feed directly into the reference surface protocols used in cucumber precision systems. Additional derived metrics of practical relevance include the Canopy Temperature Depression (CTD), defined as the difference between air temperature and canopy temperature, and hotspot area fraction, which quantifies the proportion of the canopy exceeding a defined thermal threshold. Prashar and Jones [30] reviewed the application of infrared thermography in field agriculture, documenting that CTD provided robust stress discrimination in cereals but was less reliable in crops with complex canopy architectures. Mertens et al. [12] demonstrated that proximal thermal imaging combined with hyperspectral sensors in an indoor automated phenotyping platform could quantify drought-induced transpiration decline with greater precision than individual sensor modalities alone, evidence that underpins the multi-sensor integration strategy at the core of this review's framework. In cucumber specifically, whose large, thin laminar leaves exhibit rapid turgor responses, CTD and CWSI have strong theoretical utility as nutrient stress proxies, though experimental validation under factorial nutrient treatments remains limited.

2.2.3. UAV Thermal imaging platforms and calibration protocols

State of the art UAV thermal platforms incorporate uncooled microbolometer sensors achieving thermal noise equivalent temperature differences (NETD) below 0.05°C at spatial resolutions of up to 640 × 512 pixels (Fig. 3) [14, 32]. Commercial sensors widely used in precision agriculture research include the FLIR Vue Pro R 640 and the DJI Zenmuse XT2, which can be mounted on multi-rotor or fixed-wing platforms. Typical operating altitudes of 30-60 m above the crop canopy yield ground sampling distances of 3-15 cm per pixel, sufficient to resolve individual plant canopies in row crops and to detect spatially heterogeneous stress patterns [14, 15].

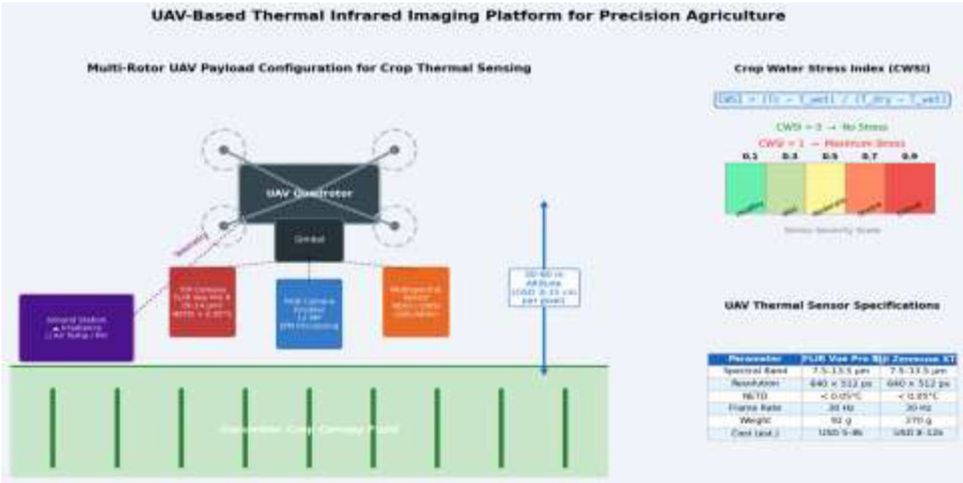

Fig. 3: UAV-based thermal imaging platform configuration for precision cucumber monitoring. Main panel: Multi-rotor UAV quadrotor carrying a thermal infrared camera (FLIR Vue Pro R, 8-14 µm), RGB camera for SfM photogrammetry, and multispectral sensor for NDVI computation, operating at 30-60 m above the crop canopy. Upper right: Crop Water Stress Index (CWSI) scale from no-stress (0) to maximum-stress (1). Lower right: Comparative specifications for the two most widely deployed UAV thermal sensors in precision agriculture research. [32, 33]

Of all the steps between UAV flight and a reliable stress map, calibration is where most quantitative errors originate. Kelly et al. [33] conducted a systematic evaluation of the challenges and best practices for deriving accurate temperature data from uncalibrated UAV thermal cameras, identifying four principal sources of error: (a) sensor self-heating artefacts that evolve during flight and must be corrected using onboard blackbody references or empirical drift models; (b) atmospheric attenuation and emission requiring correction based on measured air temperature and relative humidity; (c) vignetting and lens distortion in wide-angle thermal optics that produce systematic temperature biases toward image edges; and (d) reflected solar radiation from hot soil or metallic structures that can elevate apparent canopy temperatures by 0.5-2.0°C in clear-sky midday conditions. Sagan et al. [14] compared three thermal cameras (ICI 8640 P, FLIR Vue Pro R 640, and thermoMap) across vegetation targets and found that systematic radiometric differences of up to 3°C existed between sensors even after manufacturer calibration, underscoring the need for independent ground truthing with contact thermometers or blackbody targets deployed in the field of view during UAV flights (table 1). Paciolla et al. [34] demonstrated that photogrammetric processing of UAV thermal imagery using structure-from-motion (SfM) algorithms in MATLAB produced georeferenced thermal orthomosaics with sub-decimetre positional accuracy, enabling spatially explicit stress mapping across entire field plots. Critically, they found that vegetation masking using co-registered NDVI from a multispectral camera significantly reduced the confounding effect of warm soil pixels on canopy temperature statistics, improving the sensitivity of thermal stress indices in sparse canopy conditions. This masking step is particularly important in early growth stages of cucumber when canopy cover is incomplete and soil-to-canopy pixel ratios are high. Chakhvashvili et al. [35] reviewed sensor synergies for UAV-based crop stress detection across precision agriculture applications, concluding that combined thermal-multispectral platforms consistently outperformed single-sensor approaches for stress type discrimination, the strongest platform-level argument in the literature for the multi-modal design this review proposes.

Table 1: Comparison of non-destructive methods for early nutrient stress detection in horticultural crops

Method	Lead time before symptoms	Spatial Scale	Limitation	
Visual Scouting	0 (post-symptomatic)	Point	Subjective; detects only after damage accumulates	[3]
Leaf Tissue Analysis	None (retrospective)	Point (destructive)	5-7 day laboratory turnaround; spatially limited	[5]
SPAD Chlorophyll Meter	2-4 days (N only)	Leaf-scale	Detects N only; low spatial coverage	[36]
Hyperspectral Imaging	2-5 days	Field (UAV)	High sensor cost; large data volumes	[37]
Thermal Infrared (TIR)	1-3 days	Field (UAV)	Environmental sensitivity; multi-stress ambiguity	[38]
TIR + Exergy (proposed)	1-3 days (physically interpretable)	Field (pixel-scale)	Requires crop-specific calibration; field validation needed	[39]

2.3. Exergy analysis in plant systems

2.3.1. Thermodynamic Foundations

Exergy, sometimes referred to as available energy or exergetic content, is defined as the maximum useful work that a system can perform as it interacts reversibly with a specified reference environment and reaches complete thermodynamic equilibrium [16, 40]. Unlike energy, which is conserved according to the first law of thermodynamics, exergy is destroyed whenever an irreversible process occurs, providing a direct measure of thermodynamic inefficiency. In biological systems, where complex networks of biochemical reactions operate under conditions far from equilibrium, exergy analysis quantifies the thermodynamic penalty imposed by each irreversible process at the cellular, organ, or whole-plant level [17, 19]. For solar radiation driving plant photosynthesis, the exergy content of incident solar flux is determined by Petela's radiation exergy model, as extended by Kabelac's finite-area formulation [16, 68]

$$x_{solar} = \Phi_{solar} \left[1 - (4/3)(T_{canopy}/T_{sun}) + (1/3)(T_{canopy}/T_{sun})^4\right] \quad (3)$$

where Φ_{solar} is the incident irradiance (W m^{-2}), T_{canopy} is the absolute canopy temperature (K), and T_{sun} = 5762 K represents the effective radiative temperature of the solar disc.

In the differential stress detection application, T_{canopy} deviates measurably from T_0 under stress conditions; this deviation is the basis for the differential exergy destruction metric in Equation 5, where the stressed and healthy canopy temperatures substitute for T_0 in comparative calculations [39]. This expression encodes an important physical insight: a cooler canopy intercepts a larger fraction of incident solar radiation as thermodynamically useful exergy. For two canopy pixels receiving identical irradiance, the pixel with a surface temperature 2°C higher will capture measurably less solar exergy, the difference manifesting as additional entropy production and waste heat emission. This relationship directly connects the thermal signal observable by a UAV sensor to a thermodynamically grounded measure of plant performance.

Exergy destruction (xdestr) quantifies the loss of thermodynamically useful energy associated with irreversible processes within the plant system as shown in equation (4):

$$x_{destr} = x_{solar} - x_{utilized} \quad (4)$$

where $x_{utilized}$ represents the exergy captured in biomass synthesis, chemical concentration gradients, and metabolic products.

Under nutrient stress, biochemical inefficiencies reduce xutilized, forcing a proportional increase in xdestr, manifested as elevated thermal emission detectable by TIR sensors. This causal chain, from nutrient limitation through metabolic inefficiency to measurable thermal signal, provides the physical basis for the integrated framework proposed in this review.

2.3.2. Review of plant exergy studies

Plant exergy analysis is a comparatively young field. While industrial applications of exergy have a long-established literature, its adaptation to living systems where boundary conditions shift continuously and irreversibility is inherent to biochemical function has only gained traction over the past ten to fifteen years, and major methodological questions remain unsettled. Silva et al. [41] conducted a comprehensive theoretical analysis of the exergy efficiency of plant photosynthesis, deriving efficiency expressions for the full photosynthetic pathway from solar photon absorption to glucose synthesis. Their analysis established that the maximum theoretical exergy efficiency of oxygenic photosynthesis is approximately 11%, far below the theoretical maximum set by the Carnot limit, and that the primary sources of exergy destruction are the photochemical excitation steps and the entropy generation associated with carbon fixation. This foundational analysis clarifies what portion of the exergy budget is amenable to agronomic intervention: while the theoretical photochemical losses are irreducible, the additional exergy destruction imposed by nutrient stress on top of the baseline is the diagnostically relevant signal. Righetto and Mady [42] applied exergy analysis to an entire sugarcane crop from planting through harvest, demonstrating that exergy efficiency metrics could meaningfully distinguish growth phases and detect periods of suboptimal management. Their study is particularly relevant because it demonstrates the practical feasibility of computing exergy fluxes at the field scale using routinely available agronomic and meteorological data, rather than requiring high-precision laboratory instrumentation. Alzaben and Fraser [39] extended this approach by applying energy and exergy analyses specifically to a crop plant system under contrasting fertilisation regimes. Their results showed that well-fertilised plants maintained significantly lower surface temperatures and higher exergy efficiencies than nutrient-stressed counterparts, with midday differences in canopy exergy efficiency of 8-12 percentage points between fertilised and unfertilised treatments. Critically, these differences in exergy metrics preceded visual stress symptoms by two to three days in their experimental protocol, providing direct empirical support for the early detection potential of exergy-based indices. Dincer and Rosen [40] provided a systematic review of exergy analysis applications in biological and environmental systems, noting that while the theoretical basis for biological exergy analysis is sound, standardisation of reference environment definitions and emissivity corrections for different plant surfaces remains incomplete. Their review identified the crop canopy as an underexplored domain for exergy-based stress detection, explicitly citing the lack of studies linking pixel-scale thermal remote sensing data to exergy destruction rates as a critical research gap. That gap is precisely what the framework proposed here attempts to fill.. More recently, Patel et al. [43] reviewed thermodynamic efficiency metrics in agricultural production systems, concluding that exergy-based indicators provide a theoretically consistent framework for evaluating crop performance under variable resource availability, though the gap between elegant theory and messy field reality remains wide, largely because the required measurements are still too complex for routine deployment.

2.3.3. Connecting exergy theory to thermal remote sensing

The conceptual bridge between exergy theory and UAV thermal sensing lies in the equivalence between pixel-scale canopy temperature and the exergy input term in Equation 3. Because UAV thermal cameras provide spatially continuous maps of canopy temperature at centimetre resolution, they in principle provide the Tcanopy values needed to compute the spatial distribution of solar exergy input across the entire field. By subtracting the exergy associated with a healthy reference canopy temperature from the exergy at each stressed pixel, the differential exergy destruction attributable to stress can be mapped at field scale [39] as displayed in equation (5)

$$X_{dest,stress} = X_{solar}(T_{stressed}) - X_{solar}(T_{healthy}) \qquad (5)$$

Where; Xdest,stress is the exergy destruction, Xsolar(Tstressed) is the solar exergy on temperature. This differential approach has the practical advantage of cancelling out systematic biases common to both the stressed and reference pixels, such as atmospheric attenuation and sensor drift, while preserving the stress-specific signal. It also allows the framework to be self-referencing within a single flight campaign, because healthy reference plots within the same field can be identified from co-registered spectral indices such as NDVI. The requirement for well-fertilised reference plots is a practical limitation but is already standard practice in precision agriculture research designs. The resulting exergy destruction map can be interpreted as a spatially continuous indicator of nutrient use inefficiency, with units of W m^{-2} of wasted solar work, which can be directly compared against thresholds derived from controlled calibration experiments.

3.0. Cucumber nutrient stress (physiology and diagnostics)

3.1. Macronutrient deficiency responses in cucumber

Cucumber's physiological response to macronutrient shortage follows a sequence that differs meaningfully depending on whether N, P, or K is limiting and the distinctions matter more than is often acknowledged, though the specific cascade and timeline differ meaningfully among N, P, and K deficiencies (Fig. 4) [3, 44]. Getting this wrong at the protocol design stage means building a framework that detects general impairment but misidentifies which nutrient is limiting that can discriminate among deficiency types rather than simply detecting general physiological impairment. Nitrogen deficiency in cucumber initially manifests as interveinal chlorosis on older leaves as chlorophyll is degraded and N is mobilised from senescent tissue toward meristematic sinks (Fig. 4).

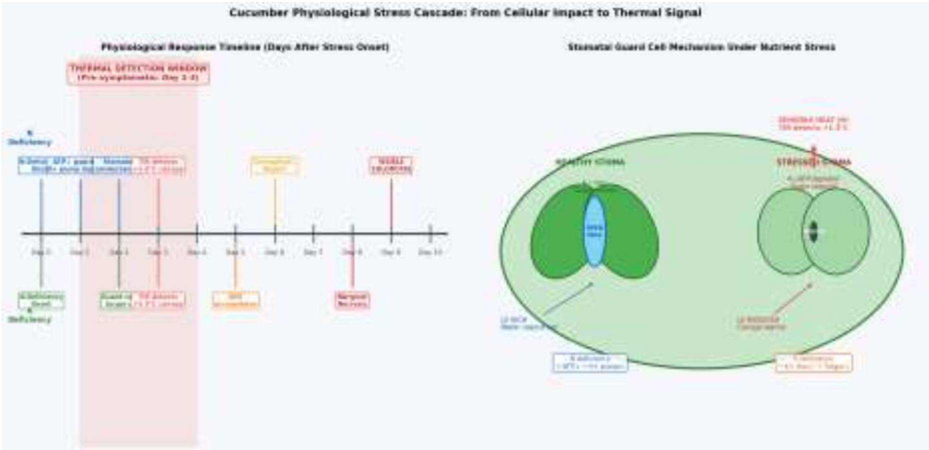

Fig. 4: Cucumber stomatal physiology under macronutrient stress. (a) Physiological stress cascade timeline showing the pre-symptomatic sequence from N and K deficiency onset to measurable thermal signal (Days 1-3) and eventual visible symptom emergence (Days 6-10), highlighting the critical early detection window. (b) Schematic cross-section of cucumber leaf stomatal guard cells contrasting healthy (open pore, high latent heat flux LE, normal K+ turgor) versus nutrient-stressed (closed pore, reduced LE, elevated sensible heat H) states. The TIR-detectable temperature anomaly of +1-3°C precedes visible chlorosis by several days. [46,47,48].

Because N is a primary constituent of chlorophyll molecules, ribulose-1,5-bisphosphate carboxylase/oxygenase (RuBisCO), and the electron transport chain complexes, its depletion directly impairs photosynthetic electron transport capacity [5, 44]. Reduced electron transport generates excess excitation energy that must be dissipated non-photochemically, increasing heat emission at the leaf surface and reducing exergy efficiency [25]. Stomatal closure under N deficiency appears to be mediated primarily by reduced ATP availability for guard cell K+ pumps rather than by direct hydraulic signals, which means the onset of stomatal closure can precede visible chlorophyll loss by several days. Potassium deficiency produces a different physiological signature. K+ is essential for turgor-driven stomatal opening and closing mechanics, for phloem loading and unloading, and for enzyme activation in both photosynthesis and photorespiration [4, 45]. Foliar symptoms of K deficiency in cucumber appear as marginal leaf scorch and necrosis as K+ is withdrawn from peripheral cells. However, the earlier metabolic effects include impaired stomatal conductance, reduced photosynthate export from leaves, and increased accumulation of reactive oxygen species (ROS) due to compromised antioxidant enzyme activity. Islam et al. [3] demonstrated in cucumber seedlings that K and N deficiencies could be distinguished through combined visual spectrum and computational analysis using convolutional neural networks, achieving classification accuracies above 90%, but noted that the two deficiencies generated overlapping thermal signatures in early stages. This ambiguity is a major challenge for the proposed thermal-exergy framework. Phosphorus deficiency in cucumber produces a characteristic dark-green colouration due to anthocyanin accumulation, delays maturity, and significantly retards root and shoot development. At the cellular level, P deficiency impairs ATP synthesis, reducing the energy available for all active transport processes, including stomatal control

[8, 46]. Moualeu-Ngangue et al. [47] demonstrated through 3D reconstruction of cucumber plants under nutrient stress that morphological and physiological changes, including reduced internode elongation and altered leaf dimension ratios, were detectable by day 3 of stress application, well before any visual discoloration appeared [54]. Their study quantified the lead time advantage of structural and thermal sensing over visual assessment and established that pre symptomatic detection windows of at least 3-5 days are achievable in controlled cucumber environments.

3.2. Limitations of existing diagnostic approaches

Every tool currently used to diagnose cucumber nutrient status has a disqualifying flaw for early detection as shown in Fig. 5 [3, 36, 47]. Visual scouting by trained agronomists remains the most widely used diagnostic method in commercial cucumber production, but it is inherently post-symptomatic, subjective, and unable to produce spatially continuous field maps. Disease symptoms, environmental stresses, and nutrient deficiencies frequently produce overlapping visual phenotypes, leading to misdiagnosis and delayed or incorrect intervention (Fig. 5) [36]. Leaf tissue analysis provides quantitative and chemically specific nutrient concentration data but is destructive, requires laboratory processing with typical turnaround times of 5-7 days, and produces only point measurements that inadequately represent spatial variability within commercial fields. Handheld SPAD meters provide rapid non-destructive estimates of leaf chlorophyll content correlated with nitrogen concentration, but cannot detect phosphorus or potassium deficiencies, are restricted to individual leaf measurements, and cannot generate field-scale maps as shown in figure 5) [5].

Govindasamy et al. [5] reviewed nitrogen use efficiency across crop species and explicitly identified the absence of real-time, spatially resolved N status monitoring as the primary bottleneck to improving NUE in horticultural systems including cucumber. Hyperspectral imaging offers biochemical specificity through red edge shifts associated with chlorophyll decline, enabling detection 2-5 days before visual symptoms in controlled conditions [37]. Adao et al. [37] reviewed UAV-based hyperspectral imaging across agricultural applications and concluded that while the technology is scientifically validated, its adoption in commercial horticulture is constrained by high sensor costs (USD 30,000-80,000 for research-grade units), complex radiometric calibration requirements, and the computational burden of processing hypercubes containing hundreds of spectral bands. Thermal infrared imaging offers 1–3-day

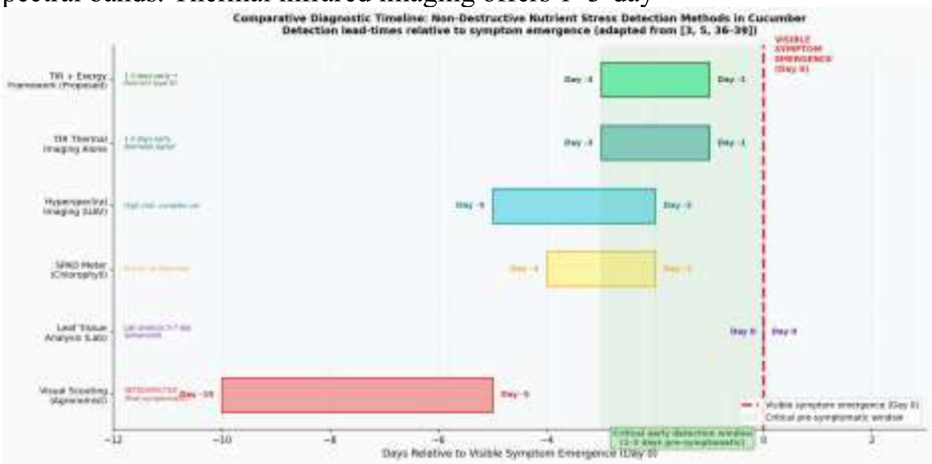

Fig. 5: Comparative diagnostic timeline for non-destructive nutrient stress detection methods in cucumber. Methods are ranked by detection lead time relative to visible symptom emergence (Day 0). Visual scouting and leaf tissue analysis are retrospective or concurrent with symptom emergence. SPAD meters, hyperspectral imaging, and TIR thermal imaging alone offer pre-symptomatic detection windows of 2-5 days. The proposed TIR + Exergy Framework achieves equivalent thermal detection (1-3 days) while additionally enabling nutrient type classification (N, P, or K), addressing the critical water-nutrient stress discrimination challenge. [5, 37, 38, 39]

early detection at significantly lower sensor cost (USD 3,000-15,000 for UAV-grade thermal cameras), but its critical limitation is the inability to independently discriminate nutrient stress from water stress based on thermal data alone, since both pathologies converge on stomatal closure and canopy warming [38]. This diagnostic ambiguity has been reviewed independently by Prashar and Jones [61], who examined infrared thermography across multiple water and nutrient stress contexts and concluded that spectral co-registration is a necessary complement to thermal data for reliable discrimination, and by Lopez et al. [62], who reviewed systemic plant physiological responses to vapour pressure deficit and demonstrated that ambient VPD independently drives canopy temperature fluctuations that can mask nutrient stress signals in warm growing environments. Precision agriculture reviews have consistently soft-pedalled this ambiguity, which is a problem for any grower expecting the tool to work in a real field. Stutsel et al. [38] identified the ambiguity but did not propose a validated discrimination protocol, and most subsequent thermal sensing studies have either worked with irrigated crops where water stress is excluded by design or have acknowledged the problem without quantifying its effect on classification accuracy. From a practical standpoint, commercial cucumber growers cannot guarantee that water and nutrient stress will never co-occur particularly in open-field systems dependent on rainfall. Any framework that claims operational utility for nutrient stress detection in cucumber must therefore demonstrate its discrimination performance under conditions of co-occurring stresses, not just individual stresses applied in isolation under controlled conditions. This is a gap in the current evidence base that the proposed thermal exergy framework explicitly acknowledges but which future experimental work must address directly. Solving the ambiguity not just acknowledging it is why this review proposes integrating TIR sensing with exergy analysis and soil moisture data.

3.3. Potential of thermal-exergy integration for cucumber

Cucumber's physiological characteristics make it a particularly favourable candidate for thermal-exergy monitoring compared with many other horticultural crops. The species' characteristically large, thin laminar leaves with high stomatal density (reported as 100-250 stomata per mm² on the abaxial surface) exhibit rapid and measurable transpirational responses to guard cell perturbation, producing large thermal signals per unit of stomatal conductance change [47, 48]. The species' horizontal leaf architecture minimises sun-view angle effects that complicate thermal sensing in erectophile canopies. Dense planting configurations in commercial cucumber production, particularly in greenhouse systems, reduce soil background interference in thermal imagery. Several studies have demonstrated the feasibility of early thermal detection in cucumber. Stutsel et al. [38] provided the most directly relevant evidence, detecting plant stress through UAV mounted thermal and optical sensors in advance of yellowing symptoms, observing canopy temperature differences of 1-3°C in stressed versus healthy plots. Islam et al. [3] demonstrated in cucumber seedlings that nutrient stress altered thermal signatures measurably before visual symptom emergence under controlled growth chamber conditions. The 1-3°C canopy warming within 1-3 days before visible chlorosis aligns closely with theoretical predictions from the Exergy Destruction Principle: as photosynthetic exergy utilisation decreases by the amount attributable to metabolic impairment, waste heat flux to the canopy surface must increase proportionally. The thermal exergy approach offers two complementary diagnostic advantages over TIR sensing alone. First, exergy destruction rates provide a physically interpretable quantitative metric, expressed in $W\ m^{-2}$ of wasted solar energy, that is dimensionally consistent and theoretically comparable across crops, growing conditions, and measurement platforms. Second, the spatial patterns of exergy destruction may carry additional information about the biochemical mechanism of stress. Nitrogen stress primarily reduces photosynthetic electron transport capacity and is expressed throughout the canopy, while potassium deficiency primarily impairs guard cell function and may produce more pronounced thermal signatures at leaf margins where K^+ gradients collapse first. Whether these mechanistic differences produce reliably distinguishable exergy destruction spatial patterns in field conditions remains a major empirical question requiring dedicated experimentation. It should be noted that the evidence cited in this section from Stutsel et al. [38] and Islam et al. [3] was obtained under UAV optical sensing and controlled seedling conditions respectively, not through a combined TIR-exergy workflow. The assertion that the integrated framework would perform with equivalent or superior sensitivity is therefore a hypothesis warranting experimental testing, not a conclusion drawn from direct evidence.

4.0 Integrated thermal exergy framework

4.1. Conceptual processing workflow

The five-stage workflow described in this section is a proposed framework, not a validated system. Its constituent components (UAV thermal acquisition, exergy computation, ML classification) are each evidenced individually in the literature reviewed above; however, their integration into a single operational pipeline for cucumber has not yet been experimentally demonstrated. Claims made in this section should be read as design proposals supported by analogical evidence, not as proven performance. The proposed integrated framework operates as a modular five stage (Fig. 6) pipeline designed to translate raw UAV thermal observations into geo-referenced field maps of probable nutrient deficiency.

The workflow builds on established components from UAV remote sensing, plant thermodynamics, and agricultural machine learning, combining them in a sequence that preserves physical interpretability at each step. In Stage 1, UAV data acquisition, periodic flight campaigns are conducted during the vegetative growth phase of cucumber, with recommended frequency of every three to five days during the period of peak nutrient demand.

The UAV payload combines a calibrated thermal infrared camera with RGB and multispectral sensors for concurrent acquisition. Portable ground stations record solar irradiance, air temperature, relative humidity, and wind speed at five-minute intervals throughout the flight. Raw thermal imagery is processed using SfM photogrammetry to generate georeferenced thermal orthomosaics with sub-decimetre resolution, followed by radiometric correction using ground-deployed blackbody targets [33, 34]. In Stage 2, vegetation segmentation and thermal index computation, crop canopy pixels are isolated from background soil and shadow using NDVI thresholds derived from co-registered multispectral imagery or convolutional neural network (CNN) based semantic segmentation. Per-pixel thermal indices, including CWSI (Equation 2), canopy temperature deviation from reference (ΔT), and hotspot area fraction, are computed for each orthomosaic. Reference 'healthy' pixel temperatures are defined from well-fertilised control plots within the same field. In Stage 3, exergy computation, the pixel-scale solar exergy input (xsolar) is calculated using Equation 3 with measured irradiance and extracted canopy temperature for each pixel. The differential exergy destruction rate per unit area is computed following Equation 5. The resulting pixel-scale exergy destruction map provides a spatially continuous indicator of nutrient use inefficiency. This physically interpretable map complements the empirical CWSI by providing a metric grounded in thermodynamic first principles. In Stage 4, machine learning classification, a combined feature set incorporating thermal indices (CWSI, ΔT, thermal variance) and exergy metrics (xdestr, pixel exergy efficiency ratio) is assembled for each mosaic pixel. Random forest classifiers, gradient boosting models, or convolutional neural networks are trained on ground-truth data from controlled plots with factorial N, P, and K treatment combinations spanning a range of deficiency severities [49, 50]. The classifier is tasked not only with stress detection (stressed verses healthy) but also stress identification (which nutrient is most likely limiting), addressing the multiclass discrimination challenge that is beyond the capability of thermal sensing alone. In Stage 5, decision support output, the system produces georeferenced field maps indicating zones of probable N, P, or K deficiency with associated confidence scores. These maps can be exported to variable-rate fertiliser applicators, viewed through tablet-based decision interfaces, or integrated with dynamic crop growth models. Multi-temporal data from repeat flight campaigns permit tracking of stress onset, spatial progression, and recovery following corrective intervention, enabling retrospective assessment of management effectiveness.

4.2. Machine learning integration for stress classification

Making sense of the data volumes that UAV thermal campaigns generate requires machine learning there is no realistic alternative at field scale. [49, 50, 51]. In the context of the proposed framework, ML is required at two levels: semantic segmentation of crop versus non-crop pixels, and multi-class nutrient stress classification. Shahi et al. [49] reviewed ML methods for precision agriculture with UAV imagery, evaluating random forests, support vector machines, gradient boosting, and deep convolutional networks across crop sensing applications. They found that ensemble methods (random forest, gradient boosting) consistently outperformed individual classifiers for multi-stress discrimination tasks and required substantially less training data than deep convolutional approaches to achieve comparable accuracy. For the proposed framework, which will initially depend on small ground-truth datasets, this is the most reassuring finding in the ML literature in its initial implementation before sufficient labelled field data accumulate. Tran et al. [50] reviewed AI-powered UAV technologies for precision agriculture across multiple crop types, identifying transfer learning as the most promising approach for applying models trained on well-studied crops to data-sparse horticultural contexts. Because thermal-spectral datasets from controlled nutrient stress experiments in wheat, maize, and tomato are considerably more abundant than those for cucumber, transfer learning could enable effective classification before a cucumber-specific dataset of sufficient size is assembled. Yang et al. [51] reviewed modelling methods and influencing factors

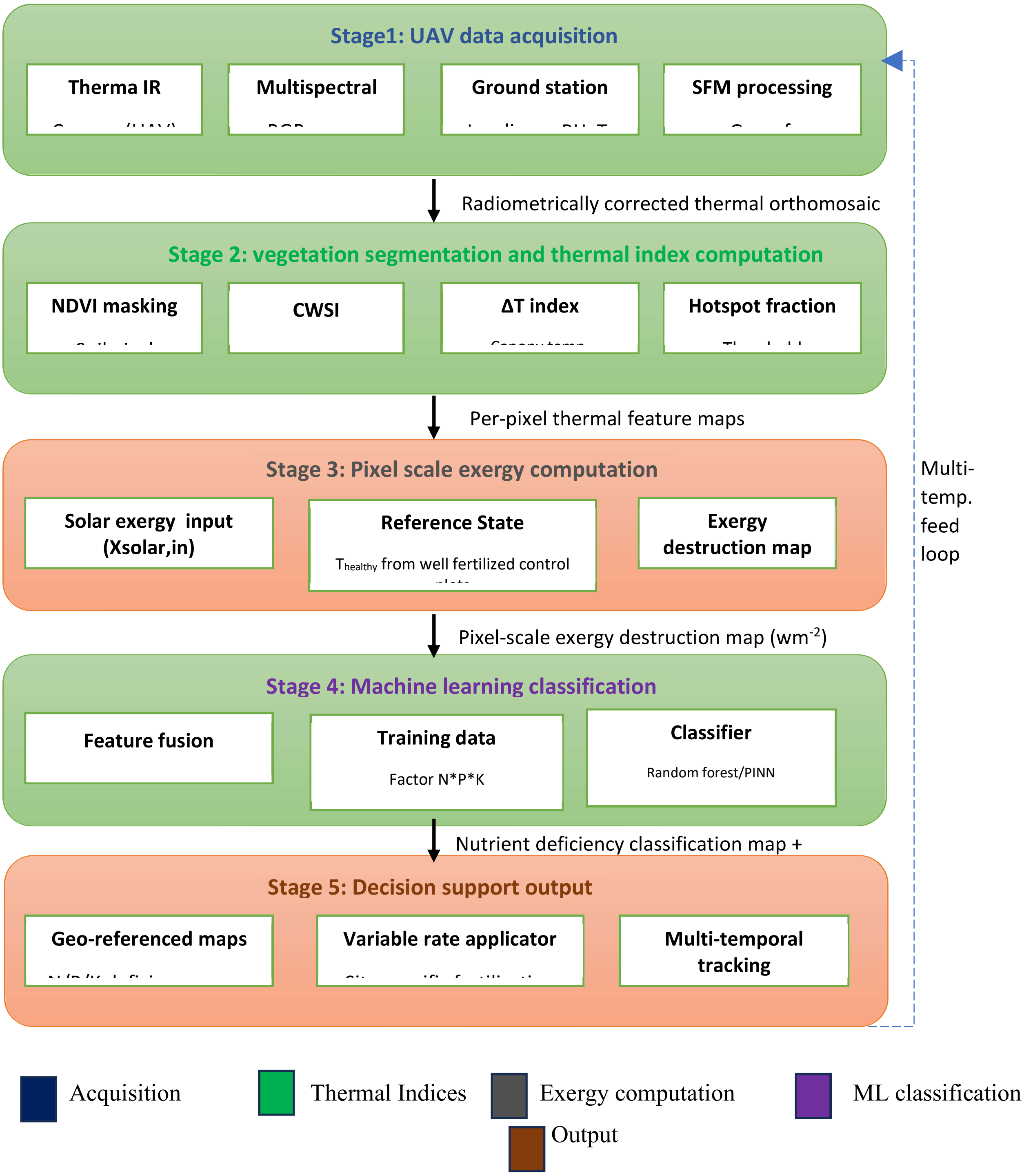

Fig. 6: Proposed integrated thermal-exergy processing workflow for early nutrient stress detection in cucumber. Stages are connected sequentially with a temporal feedback loop enabling multi-campaign stress tracking [39]

in UAV remote sensing for crop water and nutrient status, concluding that feature fusion combining thermal and spectral variables consistently produced better model performance than either modality alone across all reviewed crop species, with an average improvement in R^2 of 0.12-0.18 over the best single-sensor result. Physics-informed neural networks (PINNs) represent a particularly promising algorithmic direction for the proposed framework. These architectures embed thermodynamic governing equations, including the canopy energy balance (Equation 1) and the Petela-Kabelac exergy model (Equation 3), as hard constraints within the network structure, forcing predictions to respect physical laws while remaining data-adaptive [52]. A PINN trained on combined thermal and exergy inputs would be simultaneously data-driven and physically self-consistent, potentially improving generalisation to unseen environmental conditions and reducing the quantity of labelled training data required. This approach directly addresses the criticism that purely empirical ML models for crop stress classification can behave unpredictably when deployed in environments outside their training distribution. The use of transfer learning from other crops is explicitly treated here as a provisional strategy pending accumulation of a cucumber-specific labelled dataset, not as evidence that cross-species performance equivalence is assumed.

4.3. Challenges and research priorities

Four problems stand between the proposed framework and a deployment-ready tool and they are not equally tractable. Table 3 summarizes the major challenges and proposed mitigation. The most significant diagnostic challenge is discriminating nutrient stress from water stress, which produces mechanistically overlapping thermal signatures [28, 38]. Both stresses reduce stomatal conductance and generate CWSI increases and exergy destruction anomalies. Mitigation strategies evidenced in the literature include: timing UAV surveys immediately after irrigation events when soil water availability is uniform (reducing the probability that observed canopy warming is water-mediated); incorporating concurrent soil moisture data from capacitance sensor networks as a discriminating covariate in ML models; measuring leaf water potential in reference plots as a normalisation factor; and training classifiers on datasets containing explicitly labelled examples of both stress types to learn their distinguishing thermal-spectral-exergy feature combinations [35, 38]. Mertens et al. [12] demonstrated that combined thermal-hyperspectral sensing reduced stress-type misclassification rates by 34% compared with thermal sensing alone in controlled conditions, suggesting that spectral co-registration significantly improves discrimination power. Crop-specific calibration of the exergy model requires establishing accurate baseline canopy temperatures for healthy cucumber under a range of vapour pressure deficit conditions, growing stages, and cultivars. Cucumber leaf emissivity, while expected to lie near 0.98, requires experimental confirmation across cultivars and developmental stages, as Pineda et al. [26] documented emissivity variation of up to 0.02 within a single species across leaf ages, which translates to temperature retrieval errors of 0.5-1.0°C. Scale mismatch between pixel-level thermal measurements and plant-level exergy calculations requires assumptions about leaf area index and canopy radiation interception geometry. Integration of SfM 3D canopy models or LiDAR derived canopy height models, as demonstrated by Paciolla et al. [34] and Yang et al. [51], provides the geometric information needed to aggregate pixel exergy contributions to meaningful agronomic spatial units. Finally, and most critically, the proposed framework requires extensive field.

Table 2. Major challenges and proposed mitigation strategies for the integrated thermal-exergy framework

Challenge	Specific Issue	Proposed mitigation strategy
Water verses. nutrient stress discrimination	Both cause stomatal closure and canopy warming; CWSI ambiguous	Post-irrigation flight timing; soil moisture covariate; ML trained on multi-stress datasets [12, 35]
Crop-specific calibration	Baseline canopy temperature varies with VPD, cultivar, and growth stage	Controlled greenhouse calibration trials; factorial growth stage experiments; emissivity validation [26, 33]
Leaf emissivity uncertainty	Variation across leaf ages and cultivars introduces 0.5-1.0°C retrieval error	Experimental emissivity mapping across cucumber cultivars; field emissometer validation [22, 26]
Scale mismatch	Pixel exergy aggregation to plant/field level requires geometric information	SfM 3D canopy models or LiDAR for canopy architecture parameterisation [34, 51]
Environmental noise	Solar angle, wind, and cloud cover confound thermal readings	Clear-sky surveys near solar noon; meteorological normalisation; on-ground microclimate references [33, 38]
Data volume and processing	High-resolution thermal mosaics contain millions of pixels	Edge computing onboard UAV, lightweight ML models; cloud processing pipelines [49, 50]
Field validation deficit	No study has co-measured UAV thermal maps, exergy computations, and leaf nutrient assays at field scale	Factorial N × P × K treatment trials; concurrent gas exchange, tissue analysis, and multi-temporal thermal surveys [38, 39]

validation with concurrent measurements of UAV thermal orthomosaics, computed exergy destruction maps, leaf tissue nutrient concentrations, gas exchange parameters, and yield outcomes across multiple growing seasons and agronomic environments. No study has yet co-measured all of these variables simultaneously in cucumber. Dedicated factorial N × P × K treatment trials under both greenhouse and open-field conditions are needed to quantify achievable detection lead times, validate nutrient type discrimination accuracy, and establish the relationship between exergy destruction anomalies and actual tissue nutrient concentrations

5.0 Comparative review

A direct appreciation of the proposed framework's potential and its current limitations requires situating it within the broader literature on thermal and exergy-based crop stress detection. The following section critically examines evidence from related crops and sensing contexts, extracting lessons directly applicable to cucumber.

5.1. Thermal stress detection across crop species

The evidence base for UAV thermal imaging as an early stress detection tool is most developed in cereals. Chandel et al. [53] applied state-of-the-art AI techniques with high resolution thermal and RGB imagery to identify water stress in winter wheat, achieving classification accuracies of 88-93% using combined thermal-spectral feature sets. The numbers are instructive: thermal features alone yielded 74-79% accuracy, while spectral features alone reached 80-85%, but the fusion of both modalities achieved 88-93%, providing strong quantitative evidence for the added diagnostic value of sensor integration. In rice, Messina and Modica [32] reviewed UAV thermal imagery applications in precision agriculture and found consistent evidence that thermal sensing could detect drought and nutrient stress 3-5 days before visible symptoms across multiple Asian rice cultivars, though they noted that sensitivity degraded substantially in humid environments where vapour pressure deficit was low. For horticultural crops more directly comparable to cucumber, Xie et al. [55] investigated nutrient deficiencies in lettuce using advanced multidimensional image analysis. Their multi-nutrient experiment demonstrated that thermal maps correlated with leaf N content when integrated with spectral reflectance indices, achieving coefficient of determination values of 0.71-0.84 for N prediction. The authors explicitly recommended extending this multi-modal approach to larger-leaved Cucurbit species as the next logical step, noting that cucumber's leaf morphology should provide stronger thermal signals per unit of stomatal conductance change. Abdulridha et al. [56] demonstrated the utility of remote sensing for distinguishing biotic from abiotic stress in avocado in the presence of multiple co-occurring stressors, a multi-class discrimination challenge analogous to the water-nutrient stress discrimination problem in the proposed cucumber framework. Accuracy figures across these studies should not be treated as a common currency the experimental designs are too different., because studies vary substantially in the number of stress classes, the severity of imposed stresses, and whether classification was performed at the leaf, plant, or pixel level. Chandel et al. [53] worked at the field scale with continuous thermal orthomosaics in wheat, while Xie et al. [55] used proximal imaging of individual lettuce plants under controlled hydroponic conditions. Extrapolating classification accuracies from one study context to another or to cucumber in open-field production requires explicit justification that is frequently absent in the literature. Treating those 88-93% figures as performance targets for cucumber would be a methodological mistake without first establishing comparable experimental conditions in cucumber. The use of results from wheat [53]), lettuce [55], and maize [39] as analogical support for a cucumber framework requires explicit justification. This review treats these cross-species results as mechanistic analogues, not as quantitative targets. The justification rests on three shared physiological properties: (i) all species regulate stomatal aperture through guard cell K+ dynamics and ATP-dependent pumps, meaning nutrient stress converges on the same thermal signal regardless of species [25, 44]; (ii) the Petela-Kabelac exergy model (Equation 3) is a thermodynamic identity that applies equally to any plant surface intercepting solar radiation, irrespective of species [16]; and (iii) lettuce and cucumber share broad-leaf laminar canopy architecture with high stomatal density, making the thermal signal per unit conductance change more directly comparable between these species than between cucumber and cereal crops [47, 55]. Where inter-species extrapolation carries meaningful uncertainty particularly regarding calibration constants, detection lead times, and classification accuracy this is acknowledged in Table 2 and the challenges section (Section 4.3). Accuracy figures from non-cucumber studies should not be treated as performance benchmarks for cucumber without first establishing comparable experimental conditions in cucumber [53].

5.2. Hyperspectral complementarity and multi-sensor integration

Thermal imaging captures the functional consequence of stress (altered energy partitioning) while hyperspectral imaging detects the biochemical signatures (chlorophyll decline, carotenoid changes, water content alterations). The case for combining thermal and hyperspectral imaging does not rest on theoretical argument alone several studies have put numbers on the accuracy gain.

Table 3 Related studies on thermal and exergy-based nutrient and water stress detection across crops

Crop	Platform/Sensor	Stress Type	Results	
Cucumber	UAV TIR + RGB	N, P, K deficiency (seedlings)	Stress specific symptom patterns detectable; CNN classified deficiency types >90% accuracy	[3]
Cucumber (3D)	Photogrammetry	Nutrient/salinity stress	Morphological and physiological changes detectable by Day 3 before visual symptoms	[47]
Corn (maize)	Field TIR + exergy model	N and multi nutrient	Fertilised plants had 8-12 pp higher exergy efficiency; thermal difference preceded symptoms by 2-3 days	[39]
Wheat	UAV TIR + NDVI	Water + N stress	CWSI correlated with stomatal conductance (R^2=0.63-0.68); fused features outperformed single sensor	[53]
Lettuce	Multidimensional imaging	Multi-nutrient deficiencies	Thermal + spectral maps correlated with leaf N (R^2=0.71-0.84); recommended extension to Cucurbits	[55]
Sugarcane	Field energy/exergy model	Growth stage and management	Exergy efficiency distinguished growth phases; field-scale computation feasible	[42]
Multiple crops	UAV-TIR review	Drought and nutrient	Thermal detected stress 2-5 days before symptoms in majority of studies; calibration critical	[26]
Winter wheat	UAV thermal + RGB AI	Water stress	Combined thermal-spectral AI: 88-93% accuracy; thermal alone: 74-79%	[53]

Barbedo [15] reviewed the use of UAVs and imaging sensors for monitoring plant stresses across agronomic contexts, concluding that multi-sensor payloads combining thermal and hyperspectral sensors represented the most scientifically validated path toward reliable multi-stress discrimination. Singh et al. [58] reviewed image processing based plant disease analysis using TIR spectroscopy and found that the inclusion of thermal band data alongside visible and NIR spectral bands increased disease detection accuracy by 15-20 percentage points across six pathosystems studied.

Sivakumar et al. [59] reviewed applications of thermal infrared remote sensing in agriculture with particular emphasis on identifying the specific crop development stages where TIR sensitivity is highest, concluding that the vegetative phase with rapid canopy development provided the greatest sensitivity to stress induced temperature anomalies in most horticultural crops. This result is directly applicable to cucumber because the vegetative phase of commercial cucumber production, typically spanning 20-40 days post transplanting, represents the period of maximum macronutrient demand and, consequently, the period of greatest risk from undetected deficiencies.

6.0 Future directions in precision horticulture

6.1. Sensor and algorithmic advances

Several converging technological trends are expected to substantially reduce the barriers to adoption of the proposed framework in commercial cucumber production over the next five years. On the sensor side, next generation uncooled microbolometer arrays are already approaching NETD values of 0.03°C at resolutions of 1280 × 1024 pixels at price points accessible to commercial growers, removing what has been the principal technical barrier to widespread adoption [32, 51, 64]. Hybrid hyperspectral thermal infrared platforms currently in development at several university and commercial laboratories promise to capture stress related reflectance signatures and surface temperatures co registered in a single pass, enabling immediate feature fusion without the geometric co registration error that currently limits multi sensor integration [35, 60]. On the algorithmic frontier, physics informed neural networks represent perhaps the most technically promising direction for the proposed framework [52]. By embedding the canopy energy balance equation (Equation 1) and the Petela-Kabelac solar exergy model (Equation 3) as hard constraints within the neural network architecture, PINNs force learned models to remain physically self consistent even in extrapolation, a critical property for deployment across diverse growing environments. Demissie et al. [60] reviewed the integration of AI and remote sensing for crop prediction in Mediterranean agroecosystems and identified physics constrained deep learning as the approach most likely to achieve reliable deployment at commercial scale given the relative scarcity of training data in horticultural sensing contexts.

6.2. Agronomic integration and sustainability impact

For practical adoption by cucumber growers, the end product of the thermal exergy system must be actionable and accessible without requiring expertise in remote sensing or thermodynamics. A geo referenced stress map identifying zones of probable N, P, or K deficiency with associated confidence levels and severity estimates, delivered to a tablet or integrated with farm management software, could directly interface with variable rate fertiliser applicators. Because the thermal exergy approach inherently quantifies both nutrient efficiency and water use efficiency through the energy balance, a dual purpose output supporting both nutrient and irrigation management decision making is technically achievable from a single UAV survey, compounding the economic value relative to single stress diagnostic systems [51, 66]. Li et al. [63] reviewed machine learning models fusing spectral and textural UAV features for nitrogen estimation in winter wheat and concluded that the precision and spatial continuity of UAV-derived nutrient maps are primary prerequisites for variable-rate fertilizer systems to deliver measurable input reductions which is the exact bottleneck standing between the proposed cucumber framework and commercial deployment. Govindasamy et al. [5] further contextualized the agronomic stakes, demonstrating through a multi-species review that nitrogen use efficiency in horticultural crops remains below 45% under conventional management, a figure that precision sensing approaches specifically target for improvement. The economic case has been made in the literature repeatedly: spatially targeted fertilisation, guided by accurate early stress mapping, typically cuts fertiliser use by 10-30% without yield penalty [6, 51]. For commercial greenhouse cucumber, where fertiliser inputs represent a substantial fraction of variable production costs, even a 10% reduction in N, P, and K applications while maintaining marketable yield would deliver a return on UAV survey investment within a single growing cycle. Environmentally, precise nutrient application reduces nitrogen leaching, nitrous oxide emissions, and phosphorus runoff, contributing to the sustainability targets increasingly embedded in agricultural policy frameworks and retailer sustainability certification requirements. Looking further ahead, thermal exergy profiling could serve as a phenotyping tool in cucumber breeding programmes, enabling identification of cultivars that maintain lower canopy temperatures and higher exergy efficiencies under nutrient limited conditions. This would select for improved nutrient use efficiency (NUE) without destructive biochemical assays, at a scale and throughput that conventional phenotyping cannot match. Integration of thermal exergy outputs into dynamic crop growth models such as AquaCrop or DSSAT could further improve yield forecasting accuracy under variable nutrient management regimes, enabling pre-season planning of fertiliser application schedules informed by crop model projections.

7.0. Conclusion

Three findings have accumulated sufficient independent replication across controlled experimental settings to be treated as an established evidential base for this framework.

(i) Thermal imaging detects canopy temperature anomalies of 1-3°C in nutrient-stressed plants 1-3 days before visual symptoms across multiple crops including cucumber, under controlled greenhouse and growth-chamber conditions [3, 26, 38, 47].

(ii) Exergy analysis at the field or crop scale is technically feasible using routinely available meteorological and radiometric data, and exergy efficiency metrics show statistically meaningful separation between fertilized and unfertilized treatments in at least one controlled field study in maize [39].

(iii) Multi-sensor integration (thermal and spectral) consistently improves stress-type classification accuracy by 10-20 percentage points over single-sensor approaches in controlled conditions [12, 35, 53].

However, the integrated thermal-exergy framework proposed in this review remains conceptual with respect to cucumber in open-field production. No study has simultaneously measured UAV thermal orthomosaics, computed pixel-scale exergy destruction maps, and determined leaf tissue nutrient concentrations in cucumber under factorial macronutrient treatments. Water-nutrient stress discrimination has not been validated under co-occurring stress conditions in cucumber. Crop-specific exergy baselines for cucumber have not been established across cultivars, growth stages, or field environments. Evidence from wheat, lettuce, and maize is used as mechanistic analogues, not as direct proof of framework performance in cucumber. The pathway from conceptual framework to validated diagnostic tool requires, above all, a controlled factorial cucumber trial with concurrent thermal imaging, gas exchange, and tissue analysis a foundational experiment that, if conducted rigorously, would resolve the most critical uncertainties in a single study.

Table 4 List of Abbreviations

Abbreviation	Name
ATP	Adenosine triphosphate
CWSI	Crop Water Stress Index
EDP	Exergy Destruction Principle
FLIR	Forward Looking Infrared
LiDAR	Light Detection and Ranging
NDVI	Normalised Difference Vegetation Index
NETD	Noise Equivalent Temperature Difference
NIR	Near Infrared
NUE	Nitrogen Use Efficiency
PINN	Physics-Informed Neural Network
ROS	Reactive Oxygen Species
SPAD	Soil Plant Analysis Development (chlorophyll meter)

TIR	Thermal Infrared
UAV	Unmanned Aerial Vehicle
VPD	Vapour Pressure Deficit

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