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REVIEW ARTICLE

Applications of thermal infrared remote sensing in agriculture

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Abstract

Agriculture is a fundamental sector globally, particularly in developing countries, as it provides food, feed and non-food products essential for economic and societal stability. Advancements in remote sensing technologies have greatly enhanced agricultural productivity and management. Thermal infrared remote sensing (TIRS) is a transformative tool in agriculture, enabling precisemonitoring of crop and soil conditions by capturing and analysing the emitted radiation in the thermal infrared spectrum (3–14 μm). This technology offers critical insights into crop and soil health. Unlike optical sensing, thermal remote sensing supports crop water stressassessment, soil moisture detection, irrigation scheduling, evapotranspiration monitoring, drought stress analysis, disease detection, soil property mapping, crop maturity assessment, yield estimation, tile drainage mapping and residue cover analysis. Integrating TIRS with multispectral and hyperspectral imaging enhances agricultural decision-making, optimises resource allocation and improves crop health. Future research should prioritize AI-driven real-time data processing by integrating machine learning, UAV-based imaging and IoT-enabled monitoring systems. These advancements can enhance precision agriculture, optimize resource use and improve crop stress detection. As technological innovations continue to evolve, thermal remote sensing is poised to play a pivotal role in sustainable agricultural management, offering valuable insights to improve efficiency and resilience in farming practices.

Keywords: agriculture; crop health monitoring; thermal remote sensing; thermal sensors

Introduction

Agriculture is essential critical sector globally, particularly in developing countries. It provides food, animal feed and various non-food products that support the growing global population and numerous industries. In recent decades, the integration of advanced technologies such as satellite remote sensing, geographic information systems (GIS), unmanned aerial vehicles (UAVs), global positioning systems (GPS), precision agriculture (PA), big data analytics, internet of things (IoT) and artificial intelligence (AI) in the agricultural sectors has significantly enhanced the productivity (1). These technologies help optimize agriculture operations and resource management, minimize yield losses and improve crop health assessment and decision-making. Among these, remote sensing (RS) technologies (both active and passive) play an essential role across various platforms. Handheld devices, aircraft and satellites are widely used RS platforms for collecting the data at different spatial, temporal and spectral resolutions enhancing, monitoring and analysis for various applications (2).

Remote sensing refers to the acquisition of information about objects, areas or phenomena without physical contact, typically through the analysis of imagery. RS image analysis is typically accomplished by detecting electromagnetic radiation (EMR) reflected, emitted or backscattered by the target (3). Thermal remote sensing (TRS) is a branch of remote sensing that captures, analyses and interprets data in the thermal infrared (TIR) range. Unlike optical remote sensing, which detects reflected radiations, TRS measures emitted radiation from the target's surface (4). In vegetation analysis, the thermal infrared range typically spans 3–14 μm, further subdivided into mid-wave infrared (MWIR) at 3-5 μm and long-wave infrared (LWIR) at 8-14 μm (Fig. 1). In the 5-8 μm range, atmospheric gases such as water vapor, carbon dioxide (CO_2) and ozone (O_3) completely absorb emitted energy, preventing effective remote sensing (6). TRS captures emitted radiation from an object's surface, converting it into temperature data without direct contact (7, 8).

The behaviour of EMR is governed by several physical laws, including Planck's radiation law, Wien's displacement law, Stefan-Boltzmann law and Kirchhoff's law (3). TRS takes advantage of the principle that all objects above absolute zero (0 K or -273.15 °C) emit radiation within the electromagnetic spectrum's infrared range, producing a thermal image. Compared to a cooler thing, a warmer object releases more thermal energy. Consequently, an image's object becomes apparent more clearly (9). TRS is widely applied across agriculture, forestry, environmental monitoring, urban planning and disaster management (10). In agriculture,

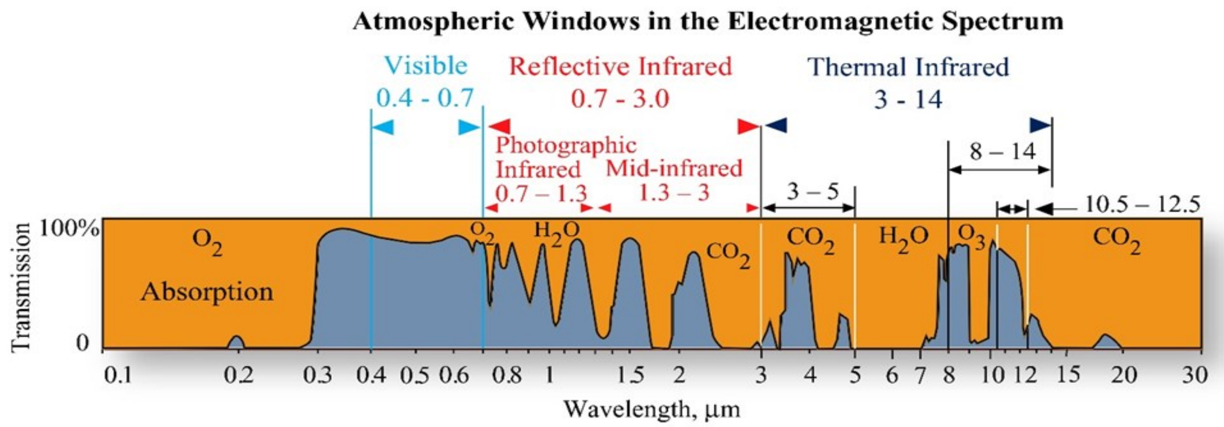

Fig. 1. Electromagnetic radiation spectrum (5).

TRS is involved in crop and soil monitoring, including crop water stress assessment, soil moisture detection, irrigation planning, evapotranspiration analysis, drought stress evaluation, disease and pest damage detection, soil texture mapping, crop maturity, yield assessment, residue cover analysis and tillage mapping (7).

The thermal characteristics of plants are significantly influenced by their complex and heterogeneous internal structures, including specific water content per unit area. This structural complexity enable detailed investigations of individual plants using TRS, thanks to infrared thermography's high resolution, accuracy and versatility (4). Temperature is a crucial factor that significantly affects key plant physiological processes such as transpiration, leaf water potential and photosynthesis (11). TRS has emerged as a valuable method for assessing surface temperature. In recent years, advancements in sensor technology and declining costs have expanded the application of thermal sensors. These sensors provide sensitive and timely surface temperature information, which is essential for monitoring plant growth and detecting stress (7, 12, 13).

Thermal information is commonly utilized to assess water stress in plants caused by various factors. Canopy temperature measurements using thermal infrared radiometers (IRT) strongly correlate with leaf water potential, confirming that TRS is an effective method for assessing plant water stress (14). TRS holds significant potential for detecting and monitoring several agricultural factors such as yield prediction, plant phenotyping and the assessment and monitoring of both biotic and abiotic stresses (13). This review explores major thermal sensors, their agricultural applications, existing challenges and future perspectives, offering a comprehensive overview of TRS technologies in agriculture.

Fundamentals of thermal remote sensing

In TRS, the radiation emitted by objects surface is quantified to estimate their temperature. These estimated temperatures provide the radiant temperature of an object, which is influenced by both kinetic temperature and emissivity (8). TRS is based on the detection of radiation emitted within the TIR range of the electromagnetic (EM) spectrum. This emitted energy is interpreted and converted into surface temperature data. The infrared (IR) range of the EM spectrum ranging from 0.7 to 100 μm and is divided into two broad segments: reflected IR (0.7-3.0 μm) and TIR (3.0-100 μm). All natural and man-made features on Earth's surface like plants, soil, water bodies and humans emit TIR radiation, mainly between the 3.0 –14 μm region (5). Within this band, there are two major atmospheric windows between 3–5 μm and 8–14 μm through which IR radiation penetrates from the surface of the Earth to space with least absorption (Fig. 1). However, IR radiation of 5-8 μm is mainly absorbed by atmospheric gases such as water vapor, CO_2 and O_3 (13).

According to Planck's law, each energy component (Q) is directly proportional to its frequency (v) with Planck's constant (h) is used to adjust this relationship, as shown in Eqn. 1 (3).

$$Q = hv \qquad \text{(Eqn. 1)}$$

Given that the frequency of a wave (v) is proportional to the speed of light (c) and is inversely proportional to its wavelength (λ), Eqn. 1 is reformulated as follows Eqn. 2 (3):

$$Q = \frac{hc}{\lambda} \qquad \text{(Eqn. 2)}$$

The relation between a black body's radiations and the wavelength of maximum emission with a black body's temperature, is explained by Wien's displacement law and the Stefan-Boltzmann law (15). Wien's displacement law was used to determine a blackbody's dominant wavelength at a specific temperature. The actual temperature (T) of a black body, expressed in Kelvin, is correlated with the wavelength at which it radiates the most energy, referred to as the peak spectral exitance or dominant wavelength (λ_{max}), as described by Eqn. 3 (5). With increasing temperature, the peak of radiation from a black body moves towards the shorter wavelengths (16).

$$\lambda max = \frac{K}{T} \qquad \text{(Eqn. 3)}$$

K is a constant equal to 2898 μm. This equation calculates the wavelength at which maximum radiant spectral exitance is attained. The result of this equation is crucial for determining the appropriate measurement range of the sensor to capture the radiation emitted by a given object (5). The total spectral radiant exitance (E) from a blackbody in watts per square meter is directly proportional to the fourth power of its temperature (T) (3). This relationship is described by the Stefan -Boltzmann law (Eqn. 4) (3).

$$E = \sigma T^4 \qquad \text{(Eqn. 4)}$$

where E represents spectral radiant exitance, σ is Stefan-Boltzmann constant (5.6697×10^{-8} Wm^{-2} K^{-4}) and T is absolute temperature in Kelvin. The equation clearly states that, the total EMR emitted by a black body is a function of its absolute temperature. Kirchhoff's law is based on conditions of thermal equilibrium. It states that, the spectral emissivity of an object equals its spectral absorptance at a given wavelength (Eqn. 5) (3).

$$\varepsilon = \alpha \qquad \text{(Eqn. 5)}$$

Where α represents absorbance and ε emittance. This is derived frequently; materials that are good heat absorbers also emit heat well and vice versa and those that reflect heat well typically emit it poorly. The energy conservation concept is expressed (Eqn. 6).

$$\varepsilon + \tau + \rho = 1 \qquad \text{(Eqn.6)}$$

where τ is transmission and ρ is reflection. Since most of the materials are not transparent to TIR radiation, the above equation becomes (Eqn. 7).

$$\varepsilon + \rho = 1 \qquad \text{(Eqn. 7)}$$

All objects in the real world at temperatures above absolute zero (0 K; -273.16 °C; -459.69 °F) show random motion. Energy of this random motion of the particles is referred as kinetic heat or kinetic temperature T_{kin} (5). The object also emits energy depending on its temperature and this radiated energy is utilized to calculate its temperature radiant T_{rad}. While T_{kin} and T_{rad} are highly positively correlated, T_{rad} is generally less than T_{kin} because of the object's emissivity (ε) (13). Due to this reason, the temperature read by the sensor T_{rad} is always lesser than the actual temperature as described by Kirchhoff's law (16) (Eqn. 8).

$$T_{rad} = \varepsilon^{1/4} T_{kin} \qquad \text{(Eqn. 8)}$$

Emissivity is the ratio of the radiation emitted by a surface to that emitted by a black body at the same temperature (17). Since the radiance of any real object at the same temperature is always less than that of a black body (which has an emissivity of 1), emissivity value range between 0 and 1 (5). According to Planck's law, an object emits and absorbs radiation less effectively than a black body at a given temperature. In practice, materials with low emissivity tend to show significantly lower sensed temperatures compared to nearby objects at the same temperature, leading to less accurate assessments of T_{kin}. Emissivity is influenced by many factors, such as color, surface texture, chemical composition, moisture content, field of view, viewing angle and spectral wavelength (5). Measuring emissivity in materials can be challenging, although it remains relatively stable across the EM spectrum in the 8 to 14 μm range. Vegetation is usually of high emissivity, approximately between 0.96 and 0.99, soil is of relatively low emissivity at around 0.89 and water is of almost 0.99 emissivity (3, 13). Table 1 presents typical emissivity values for various surface materials over the range of 8-14 μm wavelength range.

Thermal infrared remote sensing platforms and sensors

RS sensors identify, measure and evaluate target objects on, above or below the Earth's surface by analyzing reflected, emitted or scattered EMR signals over long distances.

Table 1. Emissivity of various surface materials over the range of 8-14 μm (13)

Material	Average emissivity (ε)
Clear water	0.98–0.99
Healthy green vegetation	0.96–0.99
Wet soil	0.95–0.98
Dry mineral soil	0.92–0.94
Dry vegetation	0.88–0.94
Wood	0.93–0.94
Wet snow	0.98–0.99
Dry snow	0.85–0.90

Thermal sensors have become essential in agriculture and forestry for monitoring environmental and crop conditions (18). RS systems in PA are classified based on their sensor platforms and types. Platforms include satellites, aerial systems (aircraft and UAVs) and ground-based sensors. Multispectral TIR satellite systems such as advanced spaceborne thermal emission and reflection radiometer (ASTER) effectively distinguish various surface types. The development of hyperspectral TIR sensors has greatly improved the capability for the identification and mapping of a broader range of materials and surface characteristics, providing higher accuracy and attribute information than multispectral thermal sensors. High spatial resolution hyperspectral TIR data is primarily obtained through airborne imaging systems such as spatially-enhanced broadband array spectrograph system (SEBASS), airborne hyperspectral imager (AHI), AisaOWL, Hyper-Cam and hyperspectral thermal emission spectrometer (HyTES) (19).

Satellite-based sensing has been widely used since the 1970s, while UAVs have gained popularity recently. Ground-based sensors such as hand-held, field-mounted and tractor-mounted are called proximal RS systems, as they operate close to plants and soil, unlike satellite and aerial sensors (20). RS sensors vary based on spatial, spectral, radiometric and temporal resolution (21). Spatial resolution refers to the pixel size covering the ground area. Temporal resolution indicates the time a satellite takes to complete an orbit and revisit the same location, while the spectral resolution represents the number of bands recorded in a specified electromagnetic spectrum range (20). TIR sensors are used to quantify energy radiated from a target (e.g., crops) to estimate the temperature of the target, which further estimates crop water stress, evapotranspiration (ET) and irrigation demand (7). For vegetation analysis, mostly TIR sensor radiation emissions in the mid-range (3-8 μm) and more frequently in the long-range (8-14 μm) regions are utilised (2). Various sensors facilitate agricultural data collection directly or indirectly, supporting for crop yield prediction, irrigation planning, water stress assessment, soil moisture analysis, pest monitoring and early warning systems (20, 22, 23). Lists of thermal infrared platforms and sensors are shown in Table 2.

Application of thermal remote sensing in agriculture

TRS is a powerful technique used in agriculture to gather valuable information about surface temperatures. By detecting infrared radiation emitted by objects (4), thermal sensors provide insights into temperature variations across landscapes, aiding in crop health assessment, water management, disease and pest detection, yield estimation and soil moisture monitoring (Fig. 2). This technology enables farmers to make informed decisions regarding irrigation,

Table 2. Thermal infrared platforms and sensors

Name of the platform	Name of the sensor	Wavelength (µm)	No. of bands	Spatial resolution
		Satellite operational		
NOAA-19/B/C	AVHRR3	10.3–12.5 µm	2	1100 m
JPSS-1, JPSS-2	VIIRS	8.55–12.01 µm	4	750 m
GOES-16/17/18	ABI	7.24–13.6 µm	7	2000 m
TERRA	ASTER	8.12-11.65 µm	5	90 m
Landsat 9	TIRS-2	10.5–12 µm	2	100 m
Landsat-8	TIRS	10.6-12.51µm	2	100 m
Landsat-7	ETM+	10.4-12.5 µm	1	60 m
Sentinal-3A/3B	SLSTR	10.85-12 µm	2	1000 m
Terra, Aqua	MODIS	8.4-14.38 µm	8	1000 m
ECOSTRESS	PHyTIR	8–12.5 µm	1	60 m
Himawari-8/9	AHI	7.3–13.28 µm	7	2000 m
PhiSat-1	HyperScout-2	8–14 um	4	390 m
ALOS-2	CIRC	8–12 µm	1	210 m
GCOM-C	SGLI	10.8–12 µm	1	1000 m
HJ-2A/2B	IRMSS-2 (HJ-2)	10.5–12.5 µm	1	300 m
Kanopus-V-IR N2	MSU-IK-SR	8.4–9.4 µm	1	200 m
		Satellite planned		
Sentinel LSTM-A/B	LSTR	8.42–12.47 µm	5	50 m
Landsat series	LandIS	8.3–12 µm	5	60 m
Meteor-MP N1/2/3	Advanced MSU-MR	10.5–12.5 µm	2	1000 m
Resurs-PM N1/2/3/4	BIK-SD 1	8.1–12.5 µm	5	20 m
		Airborne		
ITRES TASI-600	ITRES	8–11.5 µm	32	0.85 m at 1000 m
Aisa Owl	SPECIM	7.6–12.3 µm	96	1.1–1.5 m at 1000 m
Vulcanair P-68 Observer 2	ImageIR 9400	3.6–4.9 µm	1	1 m at 1270 m
Cessna aircraf	SC655	7.5–14 µm	1	0.6 m at 350 m

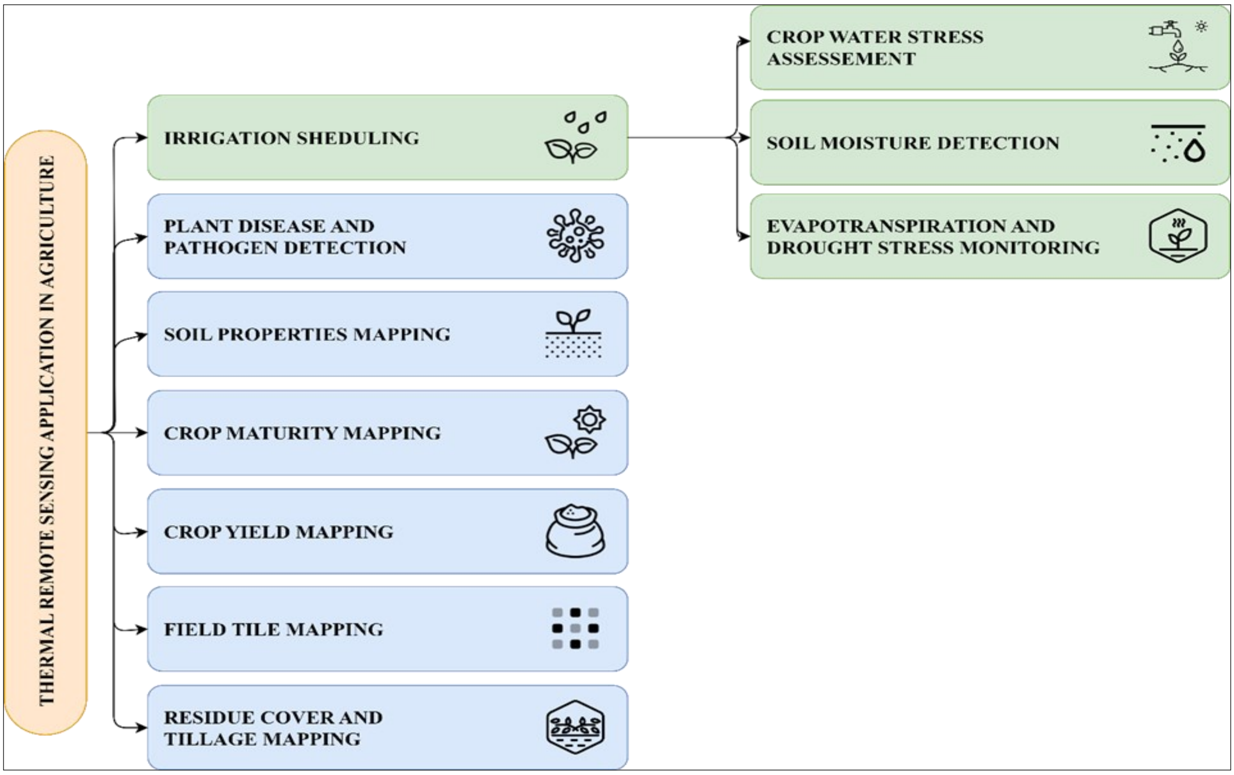

Fig. 2. Thermal remote sensing applications in agriculture.

fertilization, pest control and other management practices, ultimately optimizing crop yields and resource efficiency (7). Furthermore, TRS aids in the early detection of stress and environmental factors such as drought, heat stress and salinity affecting crops, enhancing resilience and sustainable agricultural practices. Its non-destructive, large-area coverage makes TRS essential in precision agriculture and environmental monitoring, accelerating innovation and advances in the agricultural sector (13).

Irrigation scheduling

Adequate irrigation is crucial in agriculture, as in-season rainfall is often insufficient to meet crop water requirements. Consequently, improper irrigation timing and inadequate water application are significant challenges that constrain production in many farming areas (24). As plants undergo changes in water potential, their stomata were closed and, increased the water stress (25). Optimizing irrigation timing, location and quantity is essential for minimizing yield losses, enhancing responsiveness to management practices and maximizing water-use efficiency-agricultural productivity.

The necessity for irrigation depends on four key factors: soil water availability, crop requirements and precipitation (7). Thermal imaging provides a valuable tool for water management in agricultural crops, as it allows rapid assessment of canopy surface temperature, which is linked to transpiration and reflects (26, 27). UAV-based thermal imaging offers an effective approach to improving irrigation efficiency in pecan cultivation by accurately determining water requirements and optimizing (28). Irrigation scheduling based on canopy temperature relies on thermal stress indices such as stress day index, degrees above non-stressed plants (DANS), crop water stress index (CWSI) (29). Thermal imaging and the CWSI method facilitate monitoring spatial and temporal crop water stress, enabling variable irrigation scheduling across different field zones (30). Thermal infrared sensors measure canopy temperature, aiding in CWSI calculation and plant water status assessment for irrigation scheduling in crops like cotton, corn, sunflower and grapevine (31). In addition to canopy temperature assessment, irrigation scheduling also involves soil moisture detection, crop water stress assessment, evapotranspiration and drought stress monitoring.

Crop water stress assessment

Identifying plant water stress is crucial for global food and water security. Water stress causes dehydration, disrupting plant cell ability to maintain optimal water balance (25). As a major abiotic factor, crop water stress reduces growth, lowers yield and affects food quality, posing a serious challenge to agricultural production (32). Key physiological indicators of crop water stress assessment include leaf water potential, stem water potential and stomatal conductance (33, 34). Traditional assessment methods such as soil moisture estimation, meteorological variables and physiological measurements such as water potential and stomatal conductivity provide direct insights. However, they are time-consuming, labour intensive and unsuitable for large-scale monitoring (35).

Plants respond to water stress by closing stomata to reduce transpiration, leading to increased leaf and canopy temperatures compared to well-hydrated plants (36). Crop canopy temperature is a widely recognized water stress indicator (37). Timely monitoring and detection of plant responses to water stress are crucial for effective agricultural management. RS provides high spatial, spectral and temporal resolution data, supporting precision agriculture (38). TIR techniques effectively detect crop water stress by analyzing the mean leaf temperature and foliage regions. TIR imaging systems include cooled and uncooled cameras, cooled cameras offer high sensitivity at small spatial scales and detect minute temperature changes from highly sensitive data. In contrast, uncooled infrared cameras are cost-effective and widely used for canopy temperature in crop water stress assessment and are used in ground-based and UAV systems due to their light weight (39). UAVs are increasingly used over ground-based platforms for thermal imagery acquisition in large-scale commercial agriculture. The continued advancement of UAV-based technology enhances crop stress detection and optimizes irrigation scheduling (33).

Thermal infrared systems analyze imagery data to assess crop water levels and monitor water stress (39). CWSI is widely used to evaluate plant water stress based on TRS data (34). The CWSI was initially introduced to monitor the crops using canopy temperature, subsequently, refinements based on the energy balance approach and a method utilizing wet and dry reference surfaces were developed for field screening applications (40-42). The commonly used formula to calculate the CWSI is following (25, 33):

$$CWSI = \frac{T_{canopy} - T_{wet}}{T_{dry} - T_{wet}} \quad \text{(Eqn. 9)}$$

Where, T_{canopy} is the measured canopy temperature, T_{wet} is the minimum canopy temperature, assuming fully open stomata and maximum transpiration. T_{dry} is the upper boundary, where a non-transpiring leaf has fully closed stomata and minimal potential transpiration. The CWSI has been applied to evaluate water stress in various field crops, including potatoes (32), grapevines (43), olives (44), wheat (45) and cotton (46).

Soil moisture detection

Soil moisture regulates water availability to plants and mediates water exchange between the atmosphere and the Earth's surface and subsurface (47). The uppermost 0-5 cm of soil controls energy and material exchanges. Surface soil moisture impacts hydrology and meteorology, influencing environmental and climatic processes (48). It is essential to determine optimum management strategies for planting, fertilization and irrigation (49). Soil moisture acts as a medium for nutrient supply, supports microbial growth and helps regulate soil temperature (50). RS technology is essential for large-scale near-surface soil moisture monitoring, surpassing conventional methods like thermo-gravimetric and calcium-carbide techniques. TIR sensing utilizes wavelengths of 3,500–14,000 nm to assess soil moisture. ET is frequently employed to measure land-surface temperature (LST) for accurate soil moisture prediction (51). The common thermal-based soil moisture detection methods include thermal inertia (TI), triangle method (TM) and the soil moisture index. TI technique developed using TIRS data in the TIR region represents the resistance to temperature change induced by external energy (52). TI governs temperature fluctuation amplitude and depends on surface layer characteristics, soil thermal conductivity and soil heat capacity. Higher TI results in lower temperature fluctuation. Quantitative TI-soil moisture relationships can be derived from soil temperature variation between TI and soil moisture or diurnal surface temperature amplitude (53-56).

Triangle method (TM) interprets the distribution of image pixels by relating surface radiant temperature to fractional vegetation cover. As vegetation cover increases, surface radiant temperature decreases, forming a triangle pattern, with a vertex representing limited temperature variation in dense vegetation (7, 57). The perpendicular soil moisture index (PSMI) is evaluated pixel-by-pixel using red, near infrared and thermal bands from Landsat imagery without requiring atmospheric calibration (7, 24, 58). Historically, TRS for soil moisture estimation has been constrained by acquisition costs. However, advancements in UAV-based platforms have made high-resolution thermal imagery more economical, significantly enhancing the ability to assess the spatial variability of soil conditions (51). RS data can be integrated with other geospatial data sets to provide greater insights into the drivers of soil properties. This integrated approach also tracks environmental dynamics, such as deforestation and urban growth (59).

Evapotranspiration and drought stress monitoring

Precise crop water requirement calculations are essential for optimizing irrigation scheduling in agriculture (60). ET estimation is critical in precision agriculture, influencing irrigation strategies. Remote sensing-based ET monitoring is widely used in agriculture, hydrology, climatology and meteorology, with applications ranging from irrigation optimization to predicting floods and droughts (61). ET is a combined process of evaporation, such as water transitioning from liquid to gas from plants, soil and water bodies and transpiration, where plants release water through leaves after root absorption (62). Factors affecting evapotranspiration are shown in Table 3. ET estimation using conventional methods like the Bowen ratio and Eddy correlation is reliable for homogeneous regions, but their accuracy declines when extrapolated to larger landscape or regional scales (63). RS is widely recognized as a cost-effective and reliable approach for regional and mesoscale ET mapping. It utilizes surface radiances and surface energy balance components for precise ET assessments, making it an essential tool for large-scale ET monitoring (62, 63). Satellite-based LST measurements from TIR imagery have been proven for assessing ET and plant stress (64).

NASA's GRACE follow-on and ECOSTRESS missions enhance the accuracy of terrestrial ET estimation. ECOSTRESS, equipped with a TIR multispectral scanner, captures high-resolution diurnal temperature variations, providing insights into plant water stress responses and sub-daily ET fluctuations (65). Over the past decades, several TIR-based ET models have been developed. Single-source surface energy balance includes surface energy balance system (SEBS), simplified surface energy balance operational application (SSEBop), simplified surface energy balance (SSEB), surface energy balance algorithm for land (SEBAL) and atmosphere-land exchange inverse (ALEXI). In addition, two-source surface energy balance (TSEB), disaggregated atmosphere-land exchange inverse (DisALEXI) models are widely used for ET estimation (61-63). The physically based two-source energy balance (TSEB) model effectively predicts surface energy fluxes, particularly in ET estimation. Initially, it was applied to high-resolution wide-angle Infrared dual-mode line/area array scanner (WiDAS) and advanced spaceborne thermal emission and reflection radiometer (ASTER) satellite data to assess ET over agricultural landscapes (63). Thermal indices such as CWSI, canopy temperature ratio (Tcratio), degrees above non-stressed (DANS) and degrees above canopy threshold (DACT) are effective for deriving stress crop coefficients, requiring minimal data and demonstrating a strong response to water stress, as indicated by their low root mean square error (RMSE) in ET estimation (24, 66). Agricultural drought occurs when soil moisture fails to meet crop water demand due to factors like abnormal rainfall and temperature rise, leading to reduced soil moisture (67). Most commonly used thermal remote sensing-based indices, including apparent thermal inertia (ATI), temperature condition index (TCI) and normalized difference temperature index (NDTI), serve as indirect indicators for vegetation health assessment, drought detection, moisture evaluation and thermal variation monitoring (7, 68-70).

Table 3. Factors affecting evapotranspiration (24)

Weather parameters	Crop factors	Environmental conditions
Humidity	Crop height	Ground cover
Air temperature	Difference in resistance to transpiration	Plant density
Net radiation	Crop roughness	Soil water content
Wind speed	Crop rooting characteristics	

Detection of plant disease and pest infestation

Plant diseases cause significant economic losses in agriculture worldwide. Early pathogen detection and continuous plant health monitoring are crucial for disease management (71). Some foliar diseases, such as rusts and leaf spots, induce local tissue alterations, while root pathogens (e.g., *Rhizoctonia solani* or *Pythium* spp.) and systemic infections (e.g., *Fusarium* spp.) impact transpiration rates and water circulation throughout the plant (72). Infrared thermography (IRT) is an effective technique for measuring plant temperature, assessing water status and evaluating transpiration differences, which serve as early indicators of pathogen-induced stress (73). Diseased plant areas exhibit higher thermal radiation than healthy ones due to tissue degradation, as observed in necrotic diseases like *Cercospora* leaf spot. Due to infection, the necrotic or severely dehydrated tissue would have a significantly different spectral response than healthy tissue (74). However, TRS is limited to detecting water-related plant diseases, such as root infections or stem water transport disruptions (75). Fungal infections can induce plant stress, disrupting essential physiological functions such as photosynthesis, respiration and transpiration. These factors can cause temperature variations in the leaf surface. Thermal imaging can detect temperature changes in infected areas compared to healthy ones. Consequently, thermal imaging was utilized to potentially detect powdery mildew disease agents in okra at an early stage (76, 77). Infrared thermal imaging has been shown to allow for early detection of wheat stripe rust, providing a fast, non-invasive and reliable method of detecting the disease. Consequently, the technique is of significant importance for the timely diagnosis and continuous monitoring of plant health problems (78).

Local temperature fluctuations due to pathogenic infections or plant defence mechanisms were observed in tobacco plant virus interactions (79). Thermal imagery effectively detected early-stage fungal infections (*Plasmopara viticola*) in grapevine. Additionally, thermal image analysis distinguished biotic stress (root rot) from abiotic stress (drought) in cotton (80). Thermal imaging effectively detects plant diseases by identifying temperature differences in infected regions. Machine learning techniques enhance disease severity differentiation, as pre-infected areas exhibit higher temperatures than healthy ones, serving as a fingerprint for early pathogen detection in oilseed rape leaves (81). Beyond direct disease detection, thermal imaging can assess environmental factors such as leaf wetness and duration of wet conditions, aiding in crop disease risk estimation models (7). Thermal sensing is essential in disease prediction models due to its high sensitivity to temporal and spatial plant temperature variations, improving disease identification precision (82). Different plant diseases detected by using TRS are shown in Table 4.

Table 4. Plant disease detected by using thermal infrared remote sensing

Crop	Disease	References
Wheat	Leaf rust	(78)
Sugar beet	*Cercospora* leaf spot	(79)
Rose	Downy mildew and grey mold	(83)
Apple	Apple scab	(84)
Grape	Downy mildew	(85)
Cucumber	Downy mildew	(86)
Sweet potato	Sweet potato virus	(87)
Peanut	Early leaf spot and late leaf spot	(74)

Thermal imaging offers an alternative approach for the detection of insect infestations, as respiration from the insect releases heat that is warmer than that of the surrounding grain. As a result, insects such as the rusty grain beetle can be identified by mapping the surface temperature of the grain (88, 89). An infrared thermal imaging system was developed to detect infestation by *Cryptolestes ferrugineus* inside wheat kernels. This system was used to detect infestations by six developmental stages (four larval instars, pupae and adults) of *C. ferrugineus* under the seed coat on the germ of the wheat kernels. The highest surface temperatures of the grains were much greater ($\alpha = 0.05$) in those infested with young larvae than in grains having pupae inside. Surface temperature patterns of infested kernels at different developmental stages of *C. ferrugineus* show a strong correlation with the respiration rate of each stage. While the system effectively detects if the grain is infested or not, it is less effective in identifying which developmental stage is present (90). Thermal images were taken with an infrared camera for un-infested mung beans and for beans infested with the egg, larval and pupal instars of the cowpea seed beetle, including fully infested (hollowed-out) mung beans. Classification models, namely linear discriminant analysis (LDA) and quadratic discriminant analysis (QDA), were designed based on features extracted from thermal images by image processing techniques. QDA classification model accurately detected more than 80 % of mung beans infested with the early stages of *C. maculatus* infestation (91).

Soil properties mapping

Soil property mapping, including soil texture and pH, is fundamental to understanding agri-environmental processes. It enables enhanced soil fertility, efficient fertilizer use and water resource management (92). Precise knowledge of spatial variability in soil properties supports innovative farming systems, optimizing management and preventing soil degradation. Among these, soil texture is critical in water retention, movement and chemical transport, influencing crop productivity and nutrient balance in the root zone (93). Soil texture also regulates thermal capacity, permeability and water retention, impacting climate, environmental, hydrological, smart agricultural modelling and soil pollution control (94). However, existing soil texture maps often lack the resolution needed for effective cropland management and precise modelling (93). Soil texture significantly influences soil water content, which in turn affects LST. Sandy soil, with low water-holding capacity, loses moisture rapidly during dry periods, leading to higher LST. In contrast, clay soil with greater water retention depletes moisture gradually, maintaining lower LST (7). Linear regression models were developed using daily LST data from the MODIS satellite, incorporating sand (>0.05 mm), clay (<0.001 mm) and physical clay (<0.01 mm) content measurements. These models generated spatial distribution maps of soil texture across the Yangtze-Huai River Plain in East China (95).

Crop maturity mapping

Monitoring crop maturity is essential for harvest planning, particularly under adverse weather conditions (7). Early maturity assessment helps evaluate crop adaptability to stress conditions, such as drought (96). Traditionally, maturity assessments such as crop dissection and visual inspection are used, but these subjective, time-consuming methods limit observation capacity and measurement repeatability (4, 96). RS has demonstrated the ability to forecast crop maturity in various crops (97). Time-series vegetation index analysis is a conventional remote-sensing method for maturity assessment (98). A crop model data assimilation scheme successfully predicted 2018 winter wheat maturity in Henan province with high accuracy (RMSE = 2.42 d) (99). As row crops mature, the respiration rate is less than in the early growth stage. Typically, reduced transpiration leads to increased canopy temperature. In fruit trees, fruit presence influences transpiration and respiration. Fruitless trees have greater canopy temperatures than fruiting trees. Thus, thermal imaging tracks crop temperature variations to determine maturity stages in row crops and estimate fruit yields in tree crops (7).

Crop yield mapping

Yield prediction is essential for crop production and PA, impacting food security, economic stability and resource management (100). Accurate pre-harvest yield estimation helps farmers mitigate production risks and optimize logistics, resource allocation and market strategies. However, conventional methods are often expensive, subjective and time-consuming (101). Time-series data models are widely used for yield estimation, though variations between predicted and actual yields exist. Thermal imaging, relying on object heat radiation, offers an alternative yield prediction approach (24). LST combined with NDVI can further enhance crop yield predictions at regional and global scales (102). Canopy thermal data has been used to evaluate plant transpiration and monitor crop yield and growth. Integrating thermal, spectral and structural characteristics strengthens yield predictions under varying weather conditions (103). LST measurements have the potential to be a valuable indicator of such stress and thus can be related to changes in the harvest index. RS methods can determine crop water status through indices based on the difference between air and surface temperatures. Such indices are good water stress indicators, which is highly correlated with yield prediction (104).

Several satellite-based models have been developed, a MODIS-based corn yield estimation model was developed to assess the spatial distribution of corn grain yield across the entire the USA over a period of more than a decade, using 8-day time series datasets from the MODIS satellite (105). While vegetation indices from MODIS were applied to forecast barley, canola, field pea and wheat yields across the Canadian Prairies (106). Thermal infrared imaging was investigated for winter wheat yield estimation, assessing drip, sprinkler and flood irrigation systems. The infrared crop water stress index (ICWSI) was derived from thermal imagery, validated for precision and used to predict soil moisture, biomass and wheat yield. Among the models tested, the cubic model was superior for thermal-based yield predictions (107). Crop maturity is generally determined by dissection and visual inspection. While automated techniques are available, conventional methods remain widespread. They are subjective and labour-intensive, which results in inconsistent outcomes and restricted observations (4). Thermography is used to detect mechanical injury, bruising and apple ripeness found thermal imaging to estimate fruit and vegetable maturity. It can even distinguish between different varieties at the same ripeness level (108). Thermal imaging is therefore valuable for evaluating produce quality and maturity since it records transpiration patterns and environmental interactions to determine optimal harvest time and inform postharvest equipment design (4).

Field tile mapping

Tile drainage is highly advantageous for agriculture because it increases soil moisture balance, encourages aeration, reduces surface runoff and erosion and increases water infiltration (109). Subsurface drainage systems are implemented in farmlands to drain excess water and transform poorly drained soil into productive farmland (110). Tile drainage systems provide economic and ecological advantages and simultaneously, large amounts of nutrients (nitrogen and phosphorus) in tile drainage water potentially contribute to low-quality water (7, 111, 112). Effective monitoring of tile drainage helps farmers and planners prevent environmental damage, detect broken tiles and improve crop yield and farm income (7). Thermal images provide additional opportunities in field tile mapping by measuring temperature variations in a field. Remote sensing-derived image differencing techniques and GIS-derived decision tree classification (DTC) were subjected to subsurface tile-drained areas, indicating that image differencing with remote sensing is more accurate when compared to the DTC (24).

Thermal sensors have been shown to more effectively map tile drainage in corn fields compared to visible and near-infrared sensors (113). Thermal sensors measure emitted radiation, reflecting surface temperature and can detect subtle differences in heat retention often missed by visible or near-infrared sensors. For example, drained soils cool and heat faster due to lower water content, while undrained soils retain heat longer. These thermal contrasts provide better insights into soil moisture, irrigation efficiency and early crop stress (7). A small-scale experimental device was developed to simulate tile drainage, employing temperature sensors to delineate tile lines, showing promise for drainage detection (114). Recent research focuses on UAV-based thermal and optical sensors for tile drainage mapping, evaluating the impact of temperature variation, rainfall, crop cover and growth stages on mapping accuracy. UAVs equipped with visible, thermal and multispectral cameras have been used to map subsurface tile lines, but success depends on linear features from farming activities, camera type, soil moisture and vegetation variability (115). RS studies indicate limited field tile mapping success, as crop residue and soil often exhibit similar spectral values.

Residue cover and tillage mapping

Crop residues have a significant role in soil and water conservation by creating a protective cover on farmlands that defends soil from wind and water erosion, reduces moisture loss and improves soil quality (7). An accurate crop residue evaluation is essential for effective conservation tillage monitoring. Crop residues influence soil temperature regimes and radiation balance by capturing solar radiation, thereby minimizing thermal fluctuations, reducing evaporation and enhancing root-zone water availability. These temperature variations directly affect plant growth, mineralization rate and nutrient availability (116). Crop residue management remains a key conservation practice in modern tillage methods, contributing to sustainable agriculture (117). TRS captures surface temperature data, aiding crop residue cover studies. Generally, residues are warmer than bare soil, enabling large-scale residue detection (118, 119). Spectral indices from Landsat (OLI) and TIR sensor bands were used to enhance crop residue discrimination, leveraging temperature differences between residue and bare soil (118). An airborne multispectral scanner with thermal bands and a handheld multispectral spectroradiometer were employed to map residue cover and results indicated that thermal bands significantly improved precision by distinguishing residues from bare soil under varied field conditions (120).

Challenges and future directions

TRS in agriculture faces several challenges that affect its precision. Spatial and temporal resolution limitations hinder the fine-scale detection of crop stress and soil moisture, requiring frequent high-resolution acquisition to monitor the dynamic temperature fluctuations. Atmospheric effects, including cloud cover, humidity and thermal distortions, introduce uncertainties in temperature measurements, impacting stress detection and water use assessments. Calibration and emissivity corrections are crucial for maintaining consistency across different thermal sensors and imaging periods, as sensor performance and surface emissivity variations affect temperature readings. Environmental factors such as solar radiation, sensor viewing angle, altitude and image acquisition timing influence thermal data accuracy.

Crop growth stages and species variations introduce further complexities, as different crops exhibit unique thermal signatures based on canopy structure, transpiration rates and water stress levels, requiring customized models for accurate classification. Data processing and analytics remain challenging, with large thermal datasets requiring advanced computational tools, machine learning and automated workflows for efficient interpretation. TRS data interpretation and processing in agriculture are complex because the large datasets exhibit variability. Effective extraction of meaningful insights requires sophisticated computational tools that incorporate machine learning algorithms with the ability to deal with non-linear patterns and environmental noise.

Currently, machine learning algorithms such as random forest (RF), support vector machines (SVM), artificial neural networks (ANN), convolutional neural networks (CNN) and gradient boosting machines (GBM) are widely used to estimate ET, assess plant stress and predict soil moisture from TRS data. Furthermore, a fusion of thermal data with other remote sensing sources necessitates automated workflows and strong models to facilitate timely and accurate decision-making for crop management. Addressing these challenges will enhance agricultural monitoring, enabling improved irrigation strategies, stress detection and precision farming advancements.

Future UAV applications in agriculture should focus on advancing TRS for real-time data processing through AI and machine learning, improving precision agriculture decision-making. Integrating UAV-based thermal imaging with the IoT and TRS will enable accurate crop water stress, soil moisture variability and heat stress detection. Enhanced temperature-based crop discrimination using thermal, multispectral and hyperspectral imaging with deep learning refines the classification algorithms and irrigation management. Hybrid AI-driven stress assessment models, combining machine learning, deep learning and IoT sensors, will aid early disease detection and crop health monitoring, with validation across diverse climates for improved robustness. Yield forecasting models should incorporate thermal remote sensing data, historical yield trends, soil characteristics and climatic factors to enhance prediction accuracy.

Future research should explore automated UAV swarms equipped with thermal sensors for large-scale, real-time agricultural monitoring, detecting stress and irrigation inefficiencies. Interdisciplinary collaboration among agronomists, data scientists and UAV engineers will be crucial in scaling thermal sensing advancements into practical, sustainable solutions. Data scientists will develop machine learning models for precision irrigation and stress detection, while agronomists will use the insights to design optimal farming systems. UAV engineers will focus on developing advanced drone technologies for effective data capture and real -time processing, as well as ensuring scalability in various agricultural environments.

Conclusion

TIRS is a transformative tool in agriculture, enabling crop water stress assessment, soil moisture detection, irrigation scheduling, evapotranspiration monitoring, drought stress analysis, disease detection, soil property mapping, crop maturity assessment, yield estimation, tile drainage mapping and residue coverage analysis. Combining thermal infrared imaging with multispectral and hyperspectral data enhances agricultural decision-making accuracy. However, challenges such as atmospheric sensitivity, cloud cover and humidity continue to impact measurement reliability. Spatial and temporal resolution constraints, calibration requirements and variations in crop species and growth stages complicate data acquisition and interpretation. Overcoming these limitations necessitates sensor advancements, improved calibration techniques and standardized crop models for different crops and environmental conditions.

Sustainable agriculture can be improved by combining TIRS and PA techniques to achieve optimized water use and effective irrigation scheduling. With multispectral and hyperspectral information, farmers can observe crop health, soil moisture and water stress, enhancing yield forecasting and resource management. Future research should focus on AI-driven real-time data processing, leveraging machine learning and IoT for enhanced precision agriculture. UAV-based thermal imaging integrated with high-resolution TIRS can refine stress detection and irrigation management. Hybrid AI strategies combining machine learning, deep learning and IoT sensor networks will support early disease detection and plant health monitoring and validation in diverse climates. Additionally, thermal-assisted yield forecasting models incorporating historical trends, soil characteristics and climate data can improve predictive accuracy.

In conclusion, TRS holds immense potential for transforming agriculture by offering crucial insights into crop and soil conditions. Among its most impactful applications is irrigation management, where TIRS enables precise monitoring of crop water stress and evapotranspiration, allowing for optimized water use and improved yield. Additionally, its role in early disease detection and soil moisture assessment further underscores its practical value in advancing sustainable agricultural practices. Overcoming its limitations through technological advancements and interdisciplinary collaboration will be key to maximizing its impact. As research progresses, this technology is set to play an increasingly vital role in sustainable and efficient agricultural management.

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Authors' contributions

SP collected the literature review, structured the manuscript and prepared the initial draft. MD developed the framework and revised the manuscript. PS, JR and GK contributed to the revision and refinement of the manuscript.

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