

# THERMAL IMAGING FOR CANOPY TEMPERATURE MONITORING AND SMART IRRIGATION IN PRECISION AGRICULTURE: A SYSTEMATIC REVIEW WITH BIBLIOMETRIC ANALYSIS

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## ABSTRACT

Increasing water scarcity and the growing demand for sustainable agricultural production have accelerated the adoption of precision irrigation technologies. Thermal imaging has emerged as a non-destructive and efficient approach for monitoring canopy temperature and assessing crop water status, thereby supporting irrigation scheduling and water-use efficiency. This study systematically reviews and bibliometrically analyses the evolution of thermal imaging for canopy temperature monitoring and smart irrigation in precision agriculture. A comprehensive literature search was conducted using the Scopus database following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. After applying predefined inclusion and exclusion criteria, 115 peer-reviewed publications published between 2005 and 2025 were selected for analysis. Bibliometric mapping was performed using VOSviewer to evaluate publication trends, author collaborations, keyword co-occurrence, bibliographic coupling, and co-citation networks. The findings reveal a clear technological transition from handheld infrared thermometers to unmanned aerial vehicle (UAV)-based thermal imaging integrated with multispectral, hyperspectral, LiDAR, and soil moisture sensing technologies. The Crop Water Stress Index (CWSI) remains the most widely adopted indicator for crop water stress assessment, while machine learning and deep learning techniques have significantly improved the accuracy of irrigation decision support. Bibliometric analysis identified canopy temperature, UAVs, remote sensing, thermal imaging, and precision irrigation as the dominant research themes, with China and Spain emerging as leading contributors to the field. Despite substantial technological progress, challenges remain in sensor calibration, model transferability, protocol standardization, economic feasibility, and integration with automated irrigation systems. Emerging research opportunities include explainable artificial intelligence, standardized thermal imaging protocols, multi-environment validation, and real-time closed-loop irrigation systems to facilitate the large-scale adoption of thermal imaging for sustainable water management in precision agriculture.

**KEYWORDS:** Crop Water Stress Index, Machine learning, Precision irrigation, Remote sensing, Thermal infrared imaging, Unmanned aerial vehicles.

## INTRODUCTION

Agriculture accounts for about 70 per cent of global freshwater withdrawals, but food production needs to rise by 60 per cent by 2050 to meet growing population demand. This growing pressure required better irrigation practices that deliver water only when and where crops need it. One of the most effective methods is to monitor canopy temperature ( $T_c$ ), which is an indicator of plant water status through the relationship between stomatal conductance and evaporative cooling. Water stress in plants leads to stomatal closure, a reduction in transpiration and an increase in leaf surface temperature above ambient air temperature. Thermal infrared (TIR) imaging offers a non-invasive, high spatial resolution measurement of these temperature changes and is thus useful for irrigation management. The most widely used thermal index is the Crop Water Stress Index (CWSI), which normalizes the difference between canopy and air temperature against reference baselines representing fully transpiring and non-transpiring conditions. The association between CWSI and plant water status was initially confirmed in cotton [1] and grapevine [2]. Since then, several alternative indices have been proposed to overcome specific limitations of CWSI such as the need for reference conditions that are not always available in practice. These include the Igawa Index, Stress Degree Day and Water Deficit Index.

The field has undergone substantial transformation since 2015, driven by three major technological advancements. The first one is the widespread usage of unmanned aerial vehicles (UAVs) equipped with low-cost thermal cameras, allowing centimeter-scale canopy temperature mapping. Early UAV studies showed that UAVs can be used for drought phenotyping in poplar trees [3], water stress assessment in olive orchards [4], monitoring variability in vineyards [5] and evaluating the water status of grapevines using affordable thermal systems [6]. These findings were extended to cotton [7], potato [8], kiwifruit [9] and rice [10]. The second development is multi-sensor data fusion, where thermal

imagery is fused with multispectral, hyperspectral or LiDAR data to improve water stress detection and to differentiate water stress from other factors such as nutrient deficiency and disease [11,12]. Recent fusion frameworks have combined satellite and UAV data to generate high-resolution soil moisture products [13,14]. Third, the application of machine learning and deep learning methods has substituted the empirical methods in the study of canopy temperature and stress prediction [15-17]. These approaches have been applied to diverse crops including watermelon [18], wheat [19] and strawberry [20].

Even though there are many technological advancements, there are some research gaps still existing. UAV-borne thermal data is affected by radiometric calibration inconsistencies, atmospheric disturbances and viewing angle effects [21,22]. Calibration protocols have been refined but remain inconsistent across studies [23]. Thermal sensors on satellites provide reliable temporal coverage, but their spatial resolution is too coarse for heterogeneous orchards and vineyards [24]. Proximal and fixed-sensor networks provide ongoing monitoring needed for establishing reference baselines, but they have limited spatial coverage [25]. Moreover, most studies validate their methods with data from one site, season or crop type, meaning that the transferability of developed models remains unclear. Real-time closed-loop irrigation systems actuated automatically by thermal imagery are still rare [26]. There are no standardized protocols for UAV thermal data acquisition, calibration and reporting, and very few studies provide economic analysis comparing the cost of thermal sensing systems against the value of water saved. Previous reviews of thermal remote sensing in agriculture are outdated by the recent convergence of UAV technology, multi-sensor fusion and artificial intelligence. Thus, they do not capture the fast-moving developments over the past five years. This systematic literature review fills this gap by analyzing 115 peer-reviewed articles published between 2005 and 2025. The review is organized around three research questions:

- 1) How have sensor platforms, thermal indices, data fusion strategies and computational methods evolved during this time?
- 2) What are the dominant crop types, spatial scales and validation approaches in the literature?
- 3) What are the major research gaps and future directions for operationalization of thermal imaging in closed-loop smart irrigation systems?

## METHODOLOGY

This bibliometric analysis was conducted to systematically evaluate the scientific literature on thermal imaging for canopy temperature monitoring and smart irrigation in precision agriculture. Although the present study is bibliometric in nature, the literature identification and screening process was guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework to ensure a transparent and reproducible selection of relevant publications. The Scopus database was selected as the primary source of bibliographic data because of its extensive coverage of high-quality, peer-reviewed scientific publications across multidisciplinary research fields. Literature retrieval was performed through the Tamil Nadu Agricultural University (TNAU) Library Gateway, which provides institutional access to the Scopus database. The inclusion and exclusion criteria adopted for the study are presented in Table 5.

Research on thermal imaging in agriculture has expanded considerably over the past two decades due to increasing concerns regarding climate change, water scarcity, sustainable crop production, and the growing demand for precision irrigation technologies. Thermal imaging has emerged as an effective, non-destructive tool for monitoring canopy temperature, detecting crop water stress, improving irrigation scheduling, and supporting precision agriculture through remote sensing and artificial intelligence. Therefore, publications published between 2005 and 2025 were considered to capture the evolution of research in this field and identify recent developments and emerging research trends.

A comprehensive search strategy was developed using combinations of keywords related to thermal imaging, canopy temperature, crop water stress, smart irrigation, precision agriculture, unmanned aerial vehicles (UAVs), remote sensing, and machine learning. The search query included terms such as "thermal imaging," "thermal infrared," "infrared thermography," "thermal remote sensing," "canopy temperature," "crop canopy temperature," "crop temperature," "crop water stress," "Crop Water Stress Index (CWSI)," "land surface temperature," "precision agriculture," "precision farming," "smart irrigation," "precision irrigation," "irrigation scheduling," "UAV remote sensing," "UAV," "drone," and "machine learning." Boolean operators (AND and OR) were employed to combine search terms and maximise the retrieval of relevant publications. The complete search query used for data collection is presented in Table 6.

Bibliometric mapping and network visualisation analyses were performed using VOSviewer version 1.6.20. The downloaded Scopus bibliographic records were imported into VOSviewer to examine the intellectual structure, knowledge base, and research trends in the field of thermal imaging for canopy temperature monitoring and smart irrigation. The bibliometric analyses comprised co-authorship analysis (authors), author keyword co-occurrence analysis, bibliographic coupling (countries), and co-citation analysis (cited references). Appropriate occurrence and citation thresholds were applied within VOSviewer to generate meaningful network visualisations by excluding items with insufficient publication or citation frequencies.

The initial search of the Scopus database identified 528 publications related to thermal imaging for canopy temperature monitoring and smart irrigation. The selection procedure followed the PRISMA framework, as illustrated in Figure 1. During the screening stage, predefined inclusion and exclusion criteria were applied to refine the dataset. Only English-language journal articles and review papers published between 2005 and 2025 were considered. Publications belonging

to the Agricultural and Biological Sciences subject area, published in the final publication stage, and available as open-access journal articles were included in the analysis. Conference papers, conference reviews, books, book chapters, book series, editorials, trade journals, articles in press, publications in other subject areas, and non-English publications were excluded to ensure consistency and scientific quality.

Following the application of the inclusion and exclusion criteria, 475 publications remained for further evaluation. These records were subsequently assessed based on their titles, abstracts, and keywords to determine their relevance to thermal imaging applications in canopy temperature monitoring, crop water stress detection, irrigation management, precision agriculture, remote sensing, and related technologies. Studies that did not directly address the objectives of the research were excluded. After the quality assessment process, a final dataset of 115 publications was selected for bibliometric analysis. The selected publications formed the basis for evaluating publication trends, influential authors, leading countries, research hotspots, and the intellectual structure of thermal imaging research in precision agriculture. The bibliometric findings provide a comprehensive overview of the evolution of research in this domain and identify emerging research themes and future directions for canopy temperature monitoring and smart irrigation technologies.

#### **Justification for inclusion criteria**

The inclusion criteria were established to ensure the selection of high-quality, relevant, and scientifically reliable publications for bibliometric analysis. Publications published between 2005 and 2025 were included to capture the evolution of thermal imaging research in precision agriculture. Only peer-reviewed journal articles and review papers within the Agricultural and Biological Sciences subject area were considered to ensure scientific quality and thematic relevance. Furthermore, only English-language, final-stage, and open-access publications were included to improve consistency, accessibility, and reproducibility. Although this approach may have excluded some subscription-based studies, it provided a reliable and consistent dataset for bibliometric mapping and network visualization analyses.

## **RESULT AND DISCUSSION**

### **Evolution of Sensor Platforms**

The first portable infrared thermometers were cheaper and easier to handle and allowed establishing the association between canopy temperature and water status in crops such as cotton and olive [1,27]. However, they are limited to < 10 m<sup>2</sup> per measurement and require 5 to 15 minutes of manual operation. Thus, they could not detect the spatial variability within the field that is the basis of precision irrigation [28]. Low-cost smartphone-connected thermal cameras have been evaluated against professional sensors, showing promising correlations [28,29]. Fixed sensor networks were installed to allow for continuous temporal monitoring and to produce baseline non-water stressed data required for CWSI calculation. Research stations are point locations and they do not take into account the spatial variability of the fields [25,30]. Affordable thermal sensor systems for indoor farming have also been developed [31].

The UAV platforms were developed under the need to have spatial coverage, temporal flexibility and low cost at the same time. Compared to truck-based alternatives, one UAV mission can survey 10–200 ha in <1 hour. UAVs do have a campaign-based capability, but the use of satellite thermal sensors allows continuous surveillance on a regional scale as well. The revisit time of satellite sensors is 1 km for MODIS and 16 days at 60 m for Landsat [24, 32]. The advantage was the possibility of monitoring water stress consistently over the season in time. Poor spatial resolution Satellite data (60–1000 m) cannot discriminate intra-field variability in orchards and vineyards. Clouds reduce the effective temporal resolution [22]. UAV thermal imaging has since been applied to cotton [7], soybean [33], melon [34], taro [35] and coffee [36]. It resulted in the creation of robotic and autonomous platforms in the last years that integrate thermal cameras with mobile irrigation systems [37] or with automated monitoring in greenhouses [12,38] for sensing-based irrigation action. Most systems are prototypes tested in controlled environments, and there is no evidence of integration with commercial irrigation infrastructure [26]. The evolution of sensor platforms used for canopy temperature monitoring is presented in Table 1.

### **Evolution of Thermal Indices**

The most basic measurement of water stress was the absolute canopy temperature, where elevated temperatures indicated stomatal closure and thus reduced transpiration [1]. The problem was that the absolute temperature depended on ambient conditions, so it was impossible to make reliable comparisons between days or between places. To partially take into account the ambient variability, the difference of the canopy-air temperature ( $T_c - T_a$ ) representing the canopy temperature relative to the air temperature was then used [27, 39]. However,  $T_c - T_a$  was still sensitive to vapor pressure deficit, such that the same value could indicate different levels of stress in different atmospheric conditions. The CWSI gained popularity because it normalized canopy temperature between baselines of non-water-stressed and fully stressed, resulting in a standardized index (0–1) for comparison across crops, environments and seasons. The CWSI and predawn leaf water potential were correlated in olive and almond [27, 4] showed that the CWSI obtained from UAVs could distinguish between three irrigation treatments in olive orchards with more than 85 per cent accuracy. The mean CWSI was 0.0684 and 0.693 for irrigated and water-stressed corn plots, respectively [40]. Time-lag effects between canopy temperature and atmospheric temperature have been shown to influence CWSI accuracy in wheat [41]. Single temperature metrics have limitations including the requirement of non-water-stressed baselines, which may not be commercially available [42], limited windows for measurement [27] and an inability to differentiate between drought, heat, salinity and nutrient deficiency, which have overlapping thermal signatures. Thermal indices of greater sophistication overcome some of these limitations. Thermal Time-Temperature Imaging Method (TTIM) estimates evapotranspiration without crop-specific baselines with a root mean square error (RMSE) of 0.52 mm/day in maize

[43]. Data-driven models instead of theoretical baseline models [42]. Surface energy balance models like METRIC and SEBAL provide spatially distributed ET maps from thermal satellite images [13]. Recent trends include the use of thermal indices in combination with vegetation, hyperspectral and machine learning for the development of multidimensional stress indicators. [44] improved the prediction power of vine water status from  $R^2 = 0.62$  (thermal only) to  $R^2 = 0.81$  (thermal + multispectral). [16] found that the vegetation indices reduced the estimation errors by 15 to 25 per cent compared with models using only thermal data. Machine learning-based spatial prediction of CWSI has been demonstrated in vineyards [45]. Open-source tools for standardized index computation [46] are a sign of the trend towards reproducible and operationally adoptable workflows. Comparison of thermal indices used in canopy temperature assessment is shown in Table 2.

#### **Evolution of Data Fusion Approaches**

Early thermal studies were limited to thermal images which could not differentiate drought from nutrient deficiency, disease or interference from the soil background and it leads to multi-sensor fusion. Thermal and RGB imagery have been shown to improve canopy segmentation and reduce mixed pixel contamination in row crops [47, 48]. The multispectral sensors enabled the calculation of vegetation indices (NDVI, PRI) related to the vigour of the canopy and photosynthetic activity. [49,50] reported the improved discrimination of maize growth stages. Multi-temporal UAV thermal and multispectral data have been used to estimate daily-scale CWSI in cotton [51]. Narrow-band hyperspectral imaging data have been shown to detect early physiological changes prior to the onset of any visible symptoms. Using thermal-spectral correlations, [52] were able to detect early drought stress in turfgrass. Monitoring of water and nitrogen status in cotton based on fusion of hyperspectral and thermal data [53]. The inclusion of LiDAR data provided a third dimension of canopy structure (height, LAI and volume) to improve thermal interpretation by contributing transpiration surface area and shadow distribution. Combining thermal, multispectral and 3D data and the structural data may improve the prediction accuracy for grapevine assessment [54]. Multi-sensor fusion has also been applied to potato [55] and strawberry [20]. The newest technologies are weather networks and soil moisture sensors. For example, [56] proved the higher robustness of the combination of thermal and soil water-content sensors in pear orchards than the usage of each one individually. [13] developed cotton soil moisture maps from Sentinel-2 multispectral and Sentinel-3 thermal data ( $r = 0.909$ , RMSE = 1.98 per cent). Multi-source remote sensing and machine learning have been integrated for root-zone soil moisture prediction in oilseed rape [14]. Different sensors were applied to different parts of the soil-plant-atmosphere continuum. Thermal sensors measured plant response, vegetation indices measured vigour, soil moisture measured supply and weather data measured atmospheric demand. No sensor can measure all the dimensions simultaneously. The irrigation management should be based on the relation of supply, demand and response. A comparison of data fusion strategies is presented in Table 3.

#### **Evolution of Computational Approaches**

Conventional statistical tools like multiple linear regression dominated previous studies establishing fundamental relations between canopy temperature and water status [1]. These methods were interpretable but assumed linearity, limiting their ability to characterize nonlinear interactions among temperature, VPD, soil moisture and phenology. These complicated patterns were learned using machine learning (random forest, SVM, gradient boosting). [50] used random forests to predict maize water status and obtained  $R^2 = 0.62$ . The advantage was that nonlinear relationships could be modelled without physical assumptions and the limitation was reduced interpretability, limiting grower acceptance where it is essential to understand why a zone is stressed. Machine learning has also been applied to tea disease detection [57] and oilseed rape yield prediction [14]. Deep learning, in particular Convolutional Neural Networks (CNNs), made end-to-end feature extraction from raw thermal imagery possible. [58] obtained pixel-level classification accuracy greater than 90 per cent on UAV multispectral data. CNNs were used for thermal super-resolution to boost the accuracy of low-cost cameras [59]. Deep learning outperformed traditional ML for prediction, being 8 to 15 per cent more accurate, but needed more data and computational power, making edge deployment unfeasible without cloud connectivity. Lightweight deep learning models have been developed for real-time stress detection in watermelon [16]. This accuracy-interpretability trade-off is the motivation behind explainable AI (XAI). The Shapley Additive explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) methods quantified the contribution of each input variable to predictions, resulting in feature importance rankings that helped growers identify factors driving irrigation recommendations. But the limitation was computational overhead and approximate rather than exact explanations. The latest evolution is digital twin, which produces virtual replicas integrating real-time thermal data, soil moisture, weather and hydraulic models. This allows you to test out scenarios and optimize schedules before live experimentation. The benefit is that it is proactive management, but the drawback is the computational complexity of maintaining synchronization and the requirement of continuous, high-quality data streams that most commercial farms are not yet able to provide. The evolution of computational methods is presented in Table 4.

#### **Synthesis: Technological Evolution Towards Smart Irrigation**

Each layer of technology solved the problems of the preceding layer. Hand-held thermal cameras defined the relationships between canopy temperature and water status but were spatially-limited. UAV platforms solved the spatial problem, but brought calibration problems. To overcome the limitation of thermal data to discriminate drought from other stresses data fusion of multispectral, hyperspectral, LiDAR and soil moisture data was used. Machine learning and deep learning techniques have proven useful in analyzing high dimensional, multi-source datasets (44,16,50). The most used combination in the present studies is UAV thermal combined with CWSI and random forest or gradient boosting

classification and multispectral indices. This is the most mature path from acquisition to decision using individually validated, commercially available components. However, it remains a research workflow, as the processing, analysis and decision steps are manual and not linked to the irrigation control infrastructure [26]. Technologically mature components that are ready to be deployed include UAV thermal hardware, multispectral sensors and well-established indices such as CWSI and NDVI. New procedures have decreased calibration errors from 3.5°C to 1.1°C [23], and open-source tools for index computation are emerging [46]. In controlled conditions, ML models achieve  $R^2 > 0.80$  [44]. The challenge is how to translate these outputs into automated irrigation controllers that respond to spatially variable recommendations in real time. Four roadblocks are there to implement fully autonomous systems. First, the temporal mismatch between acquisition based on UAV campaigns (weekly–monthly) and daily response time needed to be enabled for responsive irrigation. Fixed sensors could address this mismatch, but they lack spatial coverage. Second, the processing pipeline requires expert intervention in several steps, including radiometric calibration, atmospheric correction, canopy segmentation and zone classification. Third, models are not easily transferable between sites because of the lack of standardized protocols across platforms and environments. Fourth, the thermal processing software does not interoperate with commercial irrigation controllers, so stress maps cannot be directly translated into irrigation actions.

### **Crop-Specific Applications and Emerging Methodologies**

Thermal imaging is already being used for many more crops than vineyards and olive groves. In staple foods, [60] predicted rice yield ( $R^2 = 0.87$ ) using CNN-LSTM deep learning with multi-temporal UAV thermal and multispectral data. Canopy cooling in wheat is a dynamic trait that is dependent on phenology and time of day [61]. [19] increased the heat extraction by removing three per cent of the extreme pixels. [62] demonstrated that in thermal studies of wheat, more than 96.50 percent of the variance is explained by experimental and confounding variables. Dynamic re-zoning according to CWSI improved water productivity of row crops, e.g., 19 per cent in cotton [63]. [64] predicted the water potential of cotton leaves from thermal images using PSO-LSSVM with  $R^2 = 0.95$ . In [65], canopy temperature and soil properties were included and improved maize soil water content prediction from  $R^2 = 0.42$  (thermal only) to  $R^2 = 0.88$ . [66]. For row crops, [66] used a three-temperature model to estimate soybean transpiration from thermal imagery, while [67] showed that 75 per cent ETc combined with CWSI monitoring balanced processing tomato yield, soluble solids content and lycopene concentration.

In fruit crops, larger grapevine canopies showed greater thermoregulation capacity ( $R^2 > 0.6$ ; [68]. UAV-derived CWSI correlated strongly with almond stem water potential ( $R^2 > 0.85$ ; [69], while CWSI and water use efficiency predicted plum fruit quality [70]. The water status of olive trees was assessed by [71, 72] through thermal and spectral indicators. [73] demonstrated the use of temperature indices for vineyard monitoring at a regional scale. Under severe drought, the best CWSI for Merlot ( $r = 0.84$ ) [74]. The application of kaolin reduced the temperature of the grapevine canopy by 1.9°C [75]. The deep learning model from oblique thermal imaging explained 61.8 per cent of vine stem water potential [76]. In underutilised crops, [77] used UAV multi-modal thermal and multispectral data with deep learning to estimate taro water status, achieving  $R^2$  exceeding 0.91. [78] detected higher canopy temperatures in liana-infested areas of a tropical dry forest, demonstrating thermal imaging applications beyond agriculture. Pest and disease detection is another emerging use case. Thermal photography can detect bark beetle-infested spruce trees seven weeks before multispectral indicators [79]. The bark beetle attack could raise the microclimate by up to 2 °C [80]. [81] used thermal and LIDAR to estimate pine shoot beetle damage ( $R^2 = 0.79$ ). [82] used thermal imaging to phenotype tar spot resistance in maize. [83] used machine learning to identify avocado root rot with thermal and spectral data.

Methodological improvements have addressed key limitations of basic thermal data. [15] proposed a deep learning method for land surface temperature retrieval ( $MAE < 1$  K). [84] achieved a simulation of the directional anisotropy of forest thermal radiation with an RMSE of  $< 1.0^\circ\text{C}$ , and [85] realized a 0.5 K optimization of angular anisotropy correction for row crops. The calculation of the energy balance could be affected by differences of up to 5 °C under the tree canopy of almond orchards [86]. [87] found that structurally complex tree islands within oil palm plantations were associated with lower land surface temperatures, indicating that habitat diversity influences microclimate regulation in agricultural landscapes. [88] applied the UAV-based thermal imaging to locate microclimatic refugia for protecting biodiversity. [89] detected stress in indoor plant factories using thermal imaging and machine learning with an accuracy rate from 81 per cent to 94 per cent. [90] established stomatal conductance thresholds for buffalograss using UAV thermal imagery and random forest, achieving normalised RMSE of 11 to 15 per cent. [91] developed an irrigation optimisation framework for winter wheat by combining UAV multimodal data with an improved evapotranspiration model. [92] showed that the thermal index  $I_g$  had a linear relationship with stomatal conductance, while CWSI had a logarithmic relationship, providing guidance for index selection in irrigation scheduling.

### **Co-occurrence Analysis of Author Keywords**

The co-occurrence analysis of author keywords identified 28 frequently occurring keywords, which were grouped into five thematic clusters, representing the major research domains in thermal imaging for canopy temperature monitoring and smart irrigation (Figure 2). The network reveals that "canopy temperature," "remote sensing," "UAV," "thermal imaging," and "unmanned aerial vehicle" occupy central positions, indicating that these keywords constitute the core knowledge base of the research field. Their strong interconnections demonstrate that thermal imaging technologies integrated with UAV platforms and remote sensing have become the primary approaches for monitoring crop water stress and improving irrigation management.

The red cluster is centred on "UAV," "remote sensing," "thermal imaging," "irrigation," "crop water stress index (CWSI)," "precision irrigation," and "random forest." This cluster highlights the application of aerial thermal imaging and remote sensing techniques for crop water stress detection and irrigation management, with increasing adoption of machine learning algorithms for automated decision-making.

The green cluster comprises "unmanned aerial vehicle," "thermography," "deep learning," and "irrigation management," reflecting recent advances in integrating UAV-based thermal imagery with artificial intelligence to enhance crop monitoring, irrigation scheduling, and precision agricultural practices. The emergence of deep learning indicates a growing research interest in automated image analysis and intelligent irrigation systems.

The blue cluster includes "CWSI," "stomatal conductance," "stem water potential," "soil moisture," "infrared thermography," and "irrigation scheduling," representing studies focused on plant physiological responses to water stress. The close association among these keywords suggests that canopy temperature measurements are widely employed as reliable indicators for evaluating plant water status and optimizing irrigation scheduling.

The purple cluster, comprising "precision agriculture" and "NDVI," emphasizes the integration of thermal imaging with vegetation indices for comprehensive crop health assessment and site-specific crop management. Meanwhile, the yellow cluster consists of "land surface temperature," "evapotranspiration," and "UAS," highlighting research related to estimating evapotranspiration and land surface temperature using thermal remote sensing for efficient agricultural water resource management. Overall, the keyword co-occurrence network demonstrates that research has evolved from conventional thermal imaging-based crop stress detection towards multidisciplinary approaches integrating remote sensing, UAVs, artificial intelligence, deep learning, and precision agriculture. The strong relationships among the identified keywords indicate an increasing convergence of plant physiology, computer vision, remote sensing, and smart irrigation technologies, reflecting the growing emphasis on developing intelligent and sustainable irrigation management systems.

#### **Co-authorship Analysis of Authors**

Figure 3 illustrates the co-authorship network of authors in the field of thermal imaging for canopy temperature monitoring and smart irrigation, generated using VOSviewer. The analysis was performed using the full counting method with a minimum threshold of one document and two citations per author. Of the 717 authors identified in the dataset, 537 satisfied the threshold criteria, while the 214 authors with the strongest collaboration links were selected for network visualization, resulting in a total link strength of 216.

The network is composed of three major clusters, indicating distinct research communities with strong intra-group collaboration. The blue cluster is dominated by William P. Kustas, who occupies the most central position in the network and serves as a key collaborator linking multiple research groups. Kustas demonstrates strong collaborative relationships with Feng Gao, Alfonso Torres-Rua, Kyle R. Knipper, Christopher Hain, Martha C. Anderson, and Liang Sun, highlighting his significant contribution to thermal remote sensing, evapotranspiration estimation, and precision irrigation research.

The green cluster comprises researchers such as Frank Bai, Yufeng Ge, Christopher M.U. Neale, James C. Schnable, Joe D. Luck, and Tala Awada, reflecting active collaborations in crop phenotyping, UAV-based thermal imaging, precision agriculture, and smart irrigation technologies. The close proximity and dense connections among these authors indicate frequent scientific collaboration and shared research interests.

The red cluster includes authors such as Omar García-Tejera, John H. Prueger, Sebastian J. Castro, María Mar Alsina, Andrew J. McElrone, Lynn G. McKee, Nicolas Bambach, and Einara Zahn. The strong interconnections within this cluster suggest collaborative research focusing on plant physiological responses, crop water stress assessment, vineyard management, and irrigation scheduling using thermal imaging techniques.

Overall, the co-authorship network demonstrates that research on thermal imaging for precision agriculture is characterized by strong international collaboration. William P. Kustas emerges as the principal collaboration hub, connecting multiple research groups and facilitating knowledge exchange across institutions. The presence of well-defined clusters indicates the development of specialized research communities that collectively contribute to advances in canopy temperature monitoring, remote sensing, and smart irrigation technologies.

#### **Bibliographic Coupling Analysis of Countries**

The bibliographic coupling analysis of countries identified 21 countries that satisfied the minimum threshold, forming four distinct clusters that represent the global intellectual structure of research on thermal imaging for canopy temperature monitoring and smart irrigation (Figure 4). The network reveals strong bibliographic relationships among countries, indicating that researchers from different regions frequently rely on similar scientific literature and contribute to common research themes.

Among the participating countries, China occupies the most prominent position in the network, exhibiting the largest node and the strongest bibliographic connections with other countries. Its central location indicates that Chinese publications share substantial reference patterns with the global research community, highlighting China's leading role in advancing thermal imaging, remote sensing, and precision agriculture research.

The red cluster is centred on Spain, which demonstrates strong bibliographic relationships with Brazil, Israel, and several collaborating countries. This cluster reflects extensive research on precision irrigation, crop water stress assessment, and UAV-based thermal imaging applications. Spain serves as one of the major knowledge hubs, contributing significantly to the intellectual development of the field.

The green cluster comprises countries such as the Netherlands and the United Kingdom, indicating strong research linkages in precision agriculture, remote sensing technologies, and environmental monitoring. The close bibliographic relationships within this cluster suggest a shared scientific foundation and similar research priorities.

The yellow cluster is dominated by Germany and the Czech Republic, reflecting collaborative research on irrigation management, thermal sensing technologies, and agricultural engineering. Meanwhile, the blue cluster, led by China, includes France and India, illustrating strong bibliographic similarities in studies related to thermal remote sensing, canopy temperature monitoring, and smart irrigation technologies. Overall, the bibliographic coupling network demonstrates a high degree of international knowledge connectivity, with China, Spain, Germany, the Netherlands, and the United Kingdom emerging as the principal contributors to the intellectual foundation of this research domain. The extensive interconnections among countries indicate that research on thermal imaging and smart irrigation has evolved through global collaboration and shared scientific knowledge, fostering the development of advanced precision agriculture technologies.

#### **Co-citation Analysis of Cited References**

The co-citation analysis of cited references identified 29 highly cited references, which formed three major clusters, representing the intellectual foundation of research on thermal imaging for canopy temperature monitoring and smart irrigation (Figure 5). The network reveals the most influential publications that are frequently cited together, indicating their significant contribution to the development of this research field.

Among the cited references, Jones H.G. occupies the most central position in the network, exhibiting the largest node size and the strongest co-citation relationships with other references. The prominence of this reference highlights its fundamental contribution to the application of thermal imaging and infrared thermography for assessing crop water status and irrigation management. Other highly influential references include Fereres E., Chaves M.M., Hatfield J.L., Tardaguila J., and Fernandez J.E., all of which have played important roles in advancing research on plant water stress, precision irrigation, and physiological responses to drought.

The red cluster represents the core literature related to thermal imaging, plant water relations, and irrigation management. This cluster is dominated by the seminal works of Jones H.G., Fereres E., Chaves M.M., Hatfield J.L., Tardaguila J., and Fernandez J.E., indicating that these publications form the primary scientific foundation for canopy temperature monitoring and crop water stress assessment.

The green cluster consists of references authored by Steppe K., Schmidhalter U., Liu Q., and Zarco-Tejada P.J., reflecting research focused on remote sensing, UAV applications, precision agriculture, and advanced thermal sensing technologies. The strong co-citation links among these references demonstrate their collective influence on the development of modern thermal imaging applications in agriculture.

The blue cluster, represented mainly by Pinter P.J. and Cohen Y., highlights earlier foundational studies on infrared thermography, crop monitoring, and environmental sensing. Although smaller in size, these references maintain strong connections with the other clusters, indicating their continuing relevance in the evolution of thermal remote sensing research. Overall, the co-citation network demonstrates that the intellectual structure of this research field is built upon seminal contributions in plant physiology, thermal imaging, remote sensing, and precision irrigation. The strong interconnections among the three clusters indicate that contemporary research integrates classical studies on crop water stress with recent advances in UAV-based thermal sensing and precision agriculture, thereby supporting the development of intelligent irrigation management systems.

#### **CONCLUSION**

Thermal imaging has emerged as a key technology for monitoring canopy temperature and supporting precision irrigation by enabling rapid, non-destructive assessment of crop water status. This review demonstrates a clear technological progression from handheld infrared thermometers to UAV-based thermal imaging, multi-sensor data fusion, and artificial intelligence-driven decision support systems. Among the available thermal indices, the Crop Water Stress Index (CWSI) remains the most widely adopted approach, while the integration of thermal imagery with multispectral, hyperspectral, LiDAR, soil moisture, and meteorological data has substantially improved the accuracy of water stress detection and irrigation scheduling. The bibliometric findings indicate that research in this field is increasingly interdisciplinary, with strong global collaboration and growing emphasis on machine learning, deep learning, and remote sensing technologies. Nevertheless, several limitations continue to restrict large-scale adoption, including the absence of standardized thermal data acquisition protocols, limited model transferability across crops and environments, high computational requirements, and weak integration between thermal sensing platforms and automated irrigation systems. Future research should prioritize the development of standardized calibration procedures, robust and explainable artificial intelligence models, multi-location validation studies, and real-time closed-loop irrigation systems that integrate thermal sensing with IoT-enabled irrigation infrastructure. Greater attention should also be given to economic feasibility and operational scalability under commercial farming conditions. Addressing these challenges will accelerate the transition of thermal imaging from an advanced research tool to a practical technology for improving irrigation efficiency, conserving water resources, and enhancing the sustainability and resilience of modern agriculture.

#### **Supplementary data**

**Table 1. Evolution of sensor platforms used for canopy temperature monitoring**

**Table 2. Comparison of thermal indices used in canopy temperature assessment.**

**Table 3. Comparison of data fusion strategies.**

**Table 4. Evolution of computational methods**

**Table 5. Inclusion and exclusion criteria**

**Table 6. The list of keywords employed during the database literature searches**

**Fig. 1. The PRISMA flowchart.**

**Fig. 2. Co-occurrence Analysis of Author Keywords.**

**Fig. 3. Co-authorship Analysis of Authors.**

**Fig. 4. Bibliographic Coupling Analysis of Countries.**

**Fig. 5. Co-citation Analysis of Cited References.**

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**Table 1.** Evolution of sensor platforms used for canopy temperature monitoring

| Platform                     | Typical Resolution        | Coverage                       | Advantages                                                                    | Limitations                                                                                    | Typical Applications                                            |
|------------------------------|---------------------------|--------------------------------|-------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|-----------------------------------------------------------------|
| Handheld IRT                 | 0.001–0.01 m <sup>2</sup> | <0.01 ha/session               | Affordable, portable, immediate deployment                                    | Limited spatial coverage, manual operation, narrow measurement window                          | Ground truth validation, small-plot water status assessment     |
| Fixed infrared sensors       | 0.01–0.1 m <sup>2</sup>   | 1–10 m <sup>2</sup> per sensor | Continuous temporal monitoring, reference baseline establishment              | Single-location coverage, infrastructure-dependent, limited to research stations               | Diurnal temperature dynamics, CWSI baseline computation         |
| UAV-mounted thermal          | 0.05–0.20 m/pixel         | 10–200 ha/flight               | High spatial resolution, flexible scheduling, multi-sensor payload capability | Flight endurance 20–40 minutes, calibration challenges, weather-dependent, regulatory barriers | Field-level CWSI mapping, precision irrigation scheduling       |
| Satellite thermal            | 60–1000 m/pixel           | Regional to global             | Consistent temporal revisits, large-scale coverage                            | Coarse spatial resolution, cloud contamination, insufficient for within-field variability      | Regional water stress monitoring, large-area drought assessment |
| Robotic/autonomous platforms | 0.01–0.1 m <sup>2</sup>   | Field-scale                    | Integrated sensing and actuation, closed-loop potential                       | Prototype stage, limited scalability, high development cost                                    | Variable rate irrigation, automated greenhouse monitoring       |

**Table 2.** Comparison of thermal indices used in canopy temperature assessment.

| Thermal Index                   | Principle                                                                  | Inputs Required                         | Strengths                                    | Limitations                                                        | Typical Applications                           |
|---------------------------------|----------------------------------------------------------------------------|-----------------------------------------|----------------------------------------------|--------------------------------------------------------------------|------------------------------------------------|
| Absolute T <sub>c</sub>         | Direct measurement of leaf surface temperature; stressed leaves are warmer | Thermal camera or IRT                   | Simplest to acquire, no derived calculations | Highly sensitive to ambient conditions, not comparable across days | Rapid field screening, ground truth validation |
| T <sub>c</sub> – T <sub>a</sub> | Expresses canopy temperature                                               | Thermal camera + air temperature sensor | Simple, low-cost, intuitive interpretation   | Remains sensitive to VPD, same value indicates                     | Quick stress assessment in research plots      |

|                               |                                                                                               |                                                                               |                                                                                              |                                                                                           |                                                                                        |
|-------------------------------|-----------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|
|                               | relative to ambient air temperature                                                           |                                                                               |                                                                                              | different stress levels                                                                   |                                                                                        |
| CWSI                          | Normalizes $T_c$ between non-water-stressed and fully stressed baselines                      | Thermal camera + air temperature + VPD + wind speed + crop-specific baselines | Standardized across crops/environments; widely validated; strong correlation with physiology | Requires non-water-stressed baselines; narrow measurement window; single-stress indicator | Precision irrigation scheduling, deficit irrigation management, spatial stress mapping |
| TTIM                          | Exploits relationship between surface temperature and vegetation index to define triangle     | Thermal imagery + vegetation index + meteorological data                      | No crop-specific baselines required; applicable to any crop; provides actual ET estimates    | Assumes linear relationship; sensitive to image composition and cloud                     | ET estimation, water deficit monitoring in heterogeneous fields                        |
| ML reference curves           | Data-driven baselines replace theoretical Penman-Monteith baselines                           | Thermal imagery + meteorological data + training dataset                      | Eliminates manual baseline determination; adapts to variable conditions                      | Requires sufficient training data; transferability untested                               | Transpiration estimation in orchards with variable microclimates                       |
| Energy balance (METRIC/SEBAL) | Solves energy balance equation at land surface to estimate latent heat flux and ET            | Satellite/UAV thermal imagery + meteorological data + albedo                  | Spatially distributed ET maps; physics-based; field to regional scale                        | Requires accurate LST, albedo, roughness length; computationally intensive                | Regional ET mapping, water balance assessment, irrigation efficiency                   |
| Combined thermal-vegetation   | Integrates thermal and spectral data to capture water status and canopy vigour simultaneously | Thermal + multispectral/hyperspectral imagery                                 | Captures multifactorial stress; reduces false positives                                      | Requires multi-sensor payloads; more complex processing; higher cost                      | Vine water status prediction, multi-stress detection                                   |

**Table 3.** Comparison of data fusion strategies.

| <b>Data Fusion Strategy</b> | <b>Additional Information</b>                                                         | <b>Advantages</b>                                                                    | <b>Challenges</b>                                                                  | <b>Irrigation Applications</b>                                             |
|-----------------------------|---------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|----------------------------------------------------------------------------|
| Thermal only                | Canopy temperature as proxy for water status                                          | Simplest setup, lowest cost, well-established indices (CWSI)                         | Cannot distinguish drought from nutrient/disease stress; mixed-pixel contamination | Basic deficit irrigation scheduling, ground truth validation               |
| Thermal + RGB               | High spatial resolution context for canopy segmentation                               | Improved canopy boundary detection, reduced soil background noise, low-cost addition | RGB provides no physiological information beyond visual structure                  | Canopy segmentation, image masking, improved thermal pixel classification  |
| Thermal + Multispectral     | Vegetation indices (NDVI, PRI) capturing vigour, chlorophyll, photosynthetic activity | Captures both water status and canopy vigour                                         | Requires multi-sensor payloads, co-registration complexity, higher cost            | Vine water status prediction, multi-stress detection, precision irrigation |
| Thermal + Hyperspectral     | Narrow-band spectral data detecting early physiological changes                       | Early stress detection, simultaneous water and nutrient monitoring                   | High data volume, complex processing, expensive sensors                            | Pre-symptomatic stress detection, water and nitrogen management            |
| Thermal + LiDAR             | 3D canopy structure (height, LAI, volume)                                             | Improved accuracy accounting for canopy architecture variability                     | Expensive sensors, heavy payloads, limited UAV flight time                         | Structural variability mapping, improved prediction in                     |

|                         |                                                      |                                                                        |                                                                           |                                                                          |
|-------------------------|------------------------------------------------------|------------------------------------------------------------------------|---------------------------------------------------------------------------|--------------------------------------------------------------------------|
|                         |                                                      |                                                                        |                                                                           | heterogeneous canopies                                                   |
| Thermal + Soil Moisture | Direct measurement of water availability             | Links plant response to water supply; more robust than either alone    | Requires ground sensor installation, limited spatial representativeness   | Irrigation scheduling based on both soil water status and plant response |
| Thermal + Weather       | Atmospheric demand parameters (VPD, wind, radiation) | Enables CWSI computation, corrects for ambient variability             | Requires co-located weather station, temporal alignment needed            | CWSI-based scheduling, reference baseline computation                    |
| Multi-source fusion     | Comprehensive soil-plant-atmosphere continuum        | Captures supply, demand, and response simultaneously; highest accuracy | Complex data pipelines, multi-platform integration, high operational cost | Closed-loop smart irrigation, variable rate irrigation                   |

**Table 4.** Evolution of computational methods

| Approach               | Typical Algorithms                                          | Strengths                                                                                       | Limitations                                                                        | Typical Applications                                                          |
|------------------------|-------------------------------------------------------------|-------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| Traditional Statistics | Multiple linear regression, correlation, ANOVA              | Transparent, interpretable, low computational cost                                              | Assumes linear relationships, cannot model complex interactions                    | Establishing fundamental temperature–water status relationships               |
| Machine Learning       | Random forests, SVM, gradient boosting, k-NN                | Models' nonlinear relationships, handles multi-dimensional data, moderate training requirements | Reduced interpretability, requires feature engineering, limited generalization     | ET estimation, water stress classification, yield prediction                  |
| Deep Learning          | CNNs, U-Net, autoencoders, RNNs                             | End-to-end feature extraction, highest accuracy (8–15% improvement), handles spatial patterns   | Requires large datasets, high computational cost, poor interpretability            | Image classification, thermal super-resolution, pixel-level crop mapping      |
| Digital Twins          | Physics-based models, Kalman filters, agent-based modelling | Scenario testing, predictive management, real-time synchronisation                              | High complexity, requires continuous high-quality data, synchronisation challenges | Real-time irrigation monitoring, predictive maintenance, optimised scheduling |

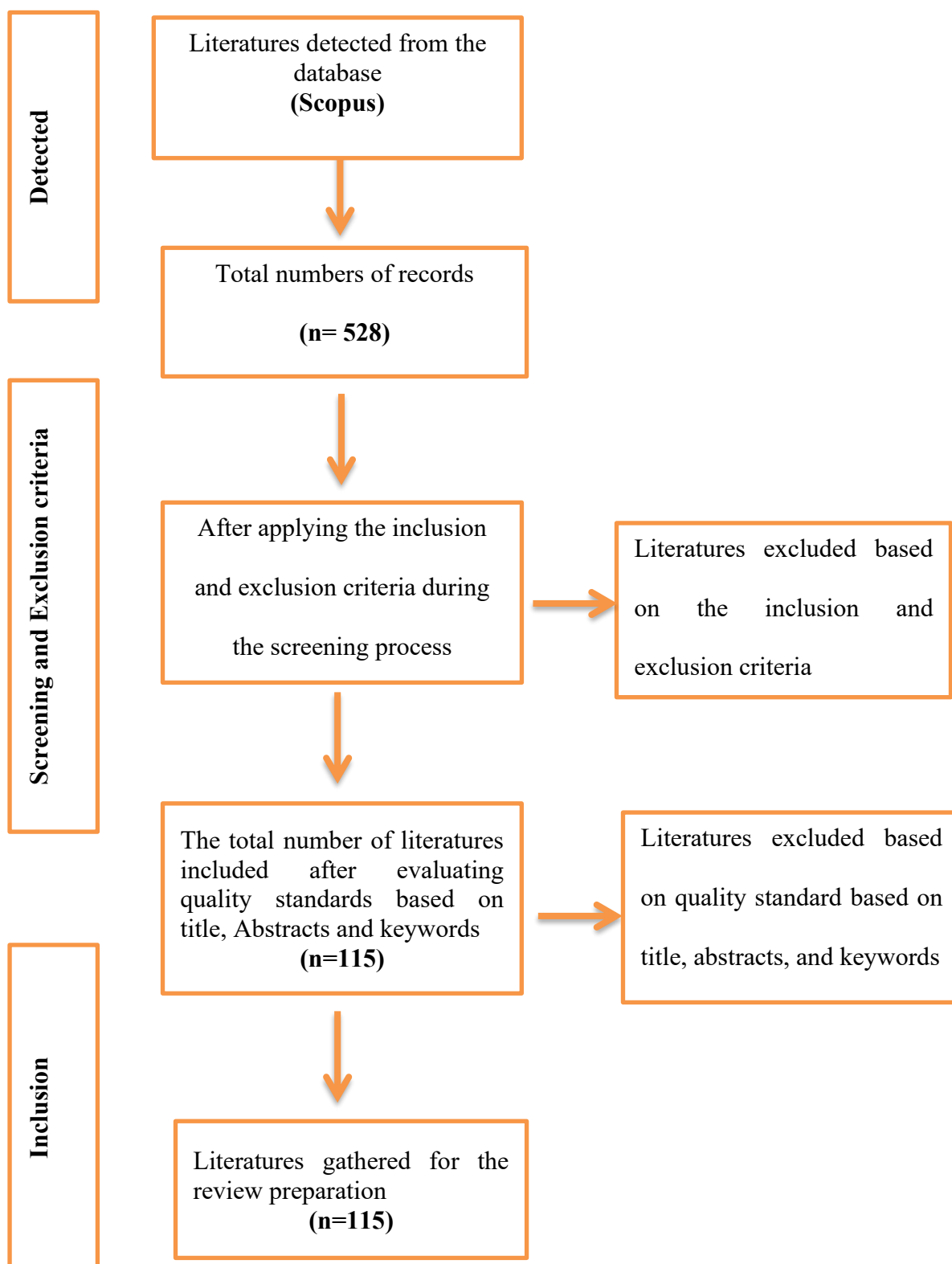
**Table 5.** Inclusion and exclusion criteria

| Databases         | Inclusion                            | Exclusion                                                               |
|-------------------|--------------------------------------|-------------------------------------------------------------------------|
| year              | 2005 – 2025                          | <2005                                                                   |
| Subject area      | Agricultural and Biological sciences | Others                                                                  |
| Document type     | Articles, Review                     | Conference papers, Book chapters, Books, Editorials, Conference reviews |
| Languages         | English                              | Non- English<br>And others all                                          |
| Source type       | Journal                              | Trade journal<br>Book series<br>Book<br>Conference proceeding           |
| Publication stage | Final                                | Article in press                                                        |
| Open access       | All open access                      | Others                                                                  |

**Table 6.** The list of keywords employed during the database literature searches

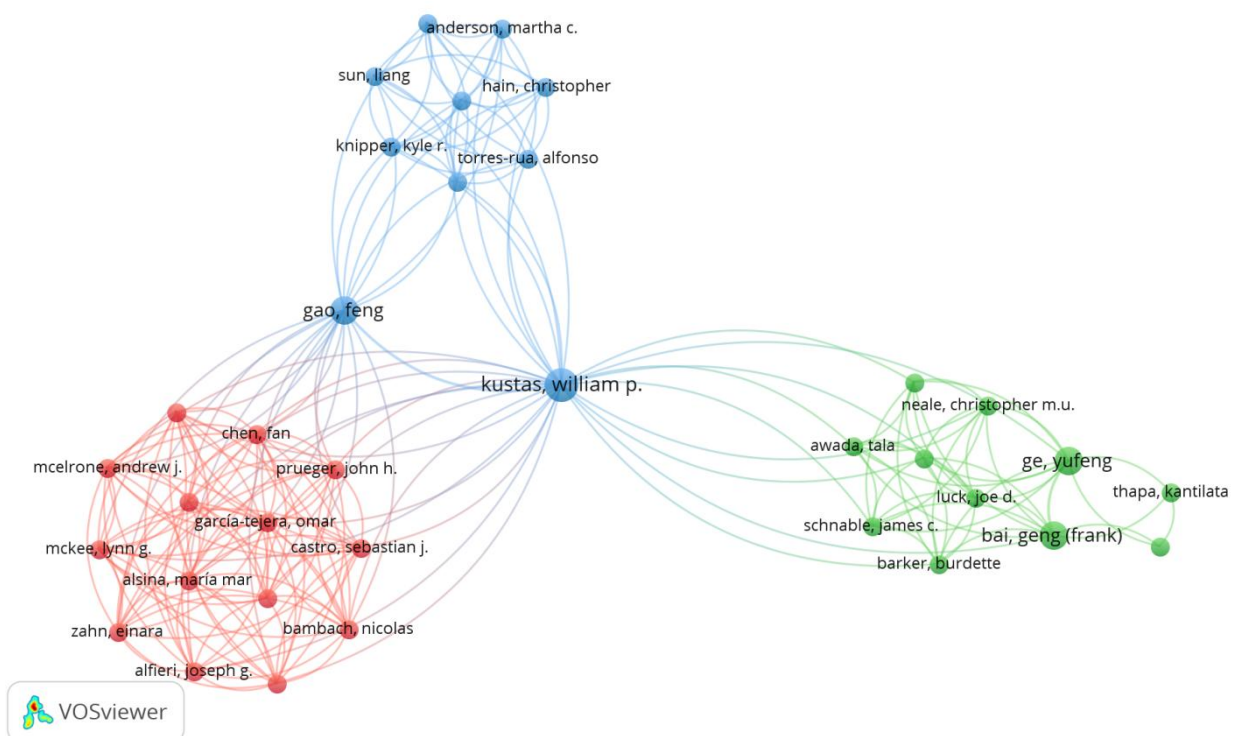
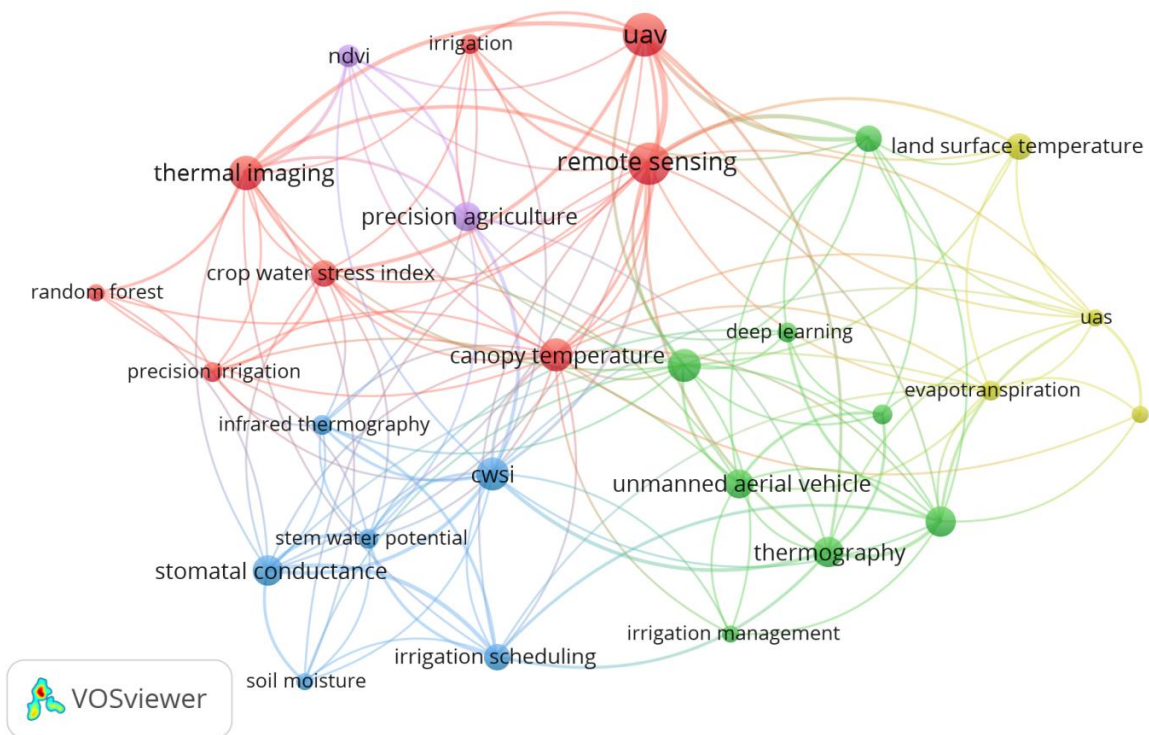
| DATABASES | KEYWORDS                                                                                                                                                                                              | TOTAL NUMBER OF ARTICLE |
|-----------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------|
| Scopus    | "thermal imaging" OR "thermal infrared" OR "infrared thermography" OR thermography OR "thermal remote sensing" "canopy temperature" OR "crop canopy temperature" OR "crop temperature" OR "crop water | 528                     |

|  |                                                                                                                                                                                                                                                                    |  |
|--|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|
|  | stress" OR CWSI OR "crop water stress index" OR "land surface temperature" "precision agriculture" OR "precision farming" OR "smart irrigation" OR "precision irrigation" OR "irrigation scheduling" OR "UAV remote sensing" OR UAV OR drone OR "machine learning" |  |
|--|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--|

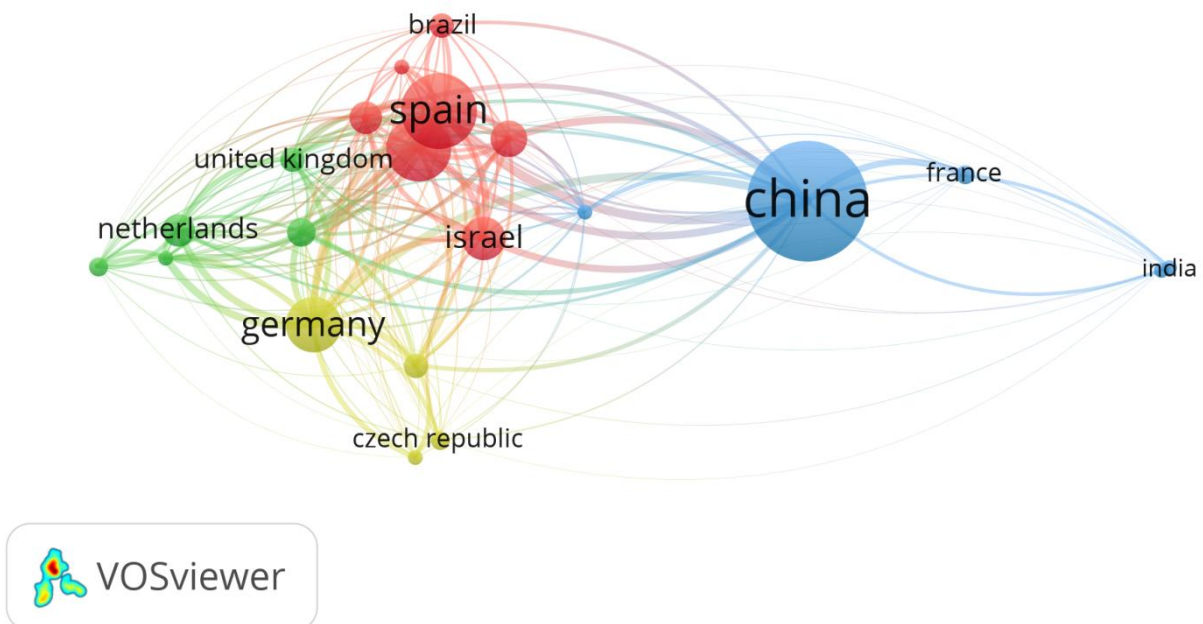


**Fig. 1.** The PRISMA flowchart.

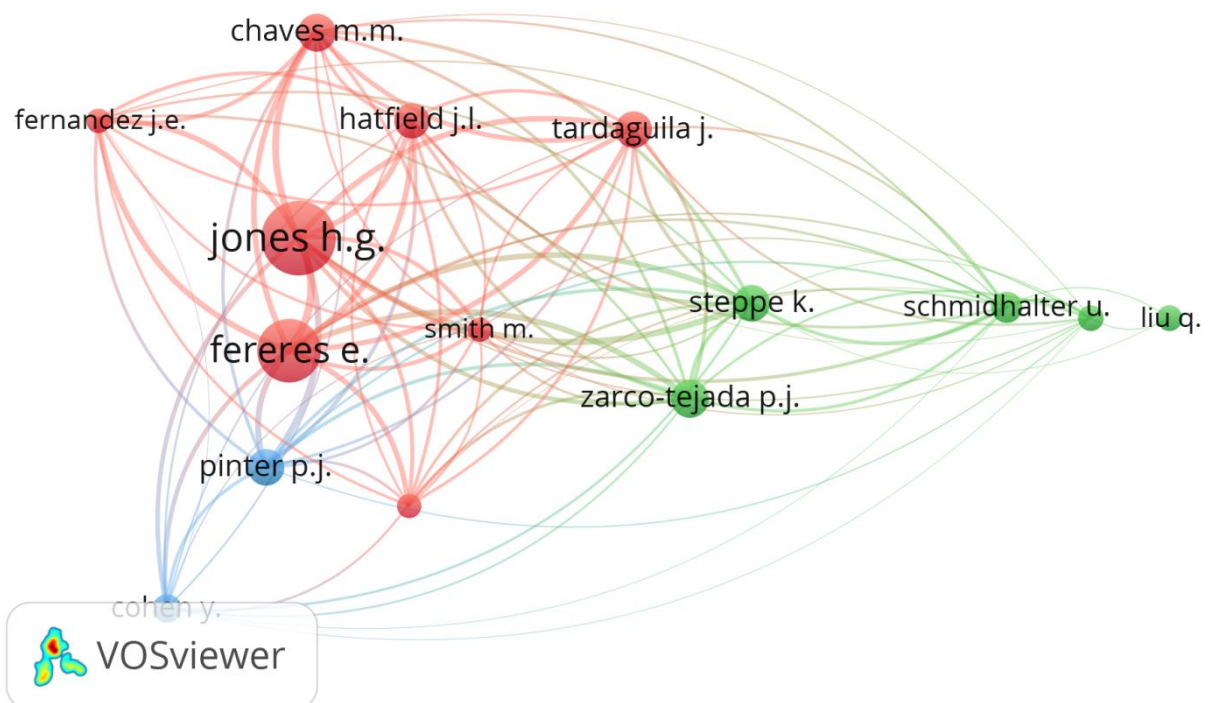
**Fig. 2. Co-occurrence Analysis of Author Keywords.**



**Fig. 3. Co-authorship Analysis of Authors.**



**Fig. 4. Bibliographic Coupling Analysis of Countries.**



**Fig. 5. Co-citation Analysis of Cited References.**