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Early detection of pine shoot beetle infestation in Yunnan pine forests through UAV-based multispectral and thermal data integration

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The pine shoot beetle (PSB, *Tomicus* spp.) is a destructive stem-boring pest threatening Yunnan pine (*Pinus yunnanensis*), a dominant conifer species in southwestern China. Early-stage infestation is particularly difficult to detect because only 11%–20% of shoots exhibit visible discoloration during the initial attack phase, limiting the effectiveness of conventional field surveys and single-source remote sensing approaches. Reliable early detection is therefore essential for timely intervention and outbreak prevention. This study assessed the potential of integrating unmanned aerial vehicle (UAV)-based multispectral and thermal infrared (TIR) imagery to improve early PSB detection at the individual-tree level. A total of 150 trees representing four damage levels (30 healthy, 50 lightly damaged, 40 moderately damaged, and 30 severely damaged trees) were identified through field-based visual interpretation. Twenty spectral and thermal metrics were extracted from UAV imagery, and commonly used machine learning approaches were applied under three feature scenarios: multispectral only, TIR only, and fused multispectral–TIR features, with 10-fold cross-validation. Most spectral and thermal variables differed significantly among infestation stages ($p < 0.05$). The integration of multispectral and thermal features improved classification performance compared with single-source data. The optimal model (Random Forest) yielded an overall accuracy (OA) of 0.82 and a Kappa coefficient of 0.75. For lightly infested trees, Recall and Precision were 0.72 and 0.74, respectively. Vegetation indices (e.g., GRVI, NDVI, and RVI) were identified as primary predictors, while thermal variability metrics provided complementary information associated with early physiological stress. By enabling detection prior to widespread canopy damage, the proposed multisensor UAV framework supports timely forest health monitoring and provides a tool for integrated pest management under changing environmental conditions.

KEYWORDS

early detection, forest health monitoring, multispectral, pine shoot beetle, thermal infrared, UAV, Yunnan pine

1 Introduction

Forests are a vital component of terrestrial ecosystems, providing a range of critical ecosystem services including soil and water conservation, erosion control, climate regulation, and carbon sequestration (Gao et al., 2023). Despite their significant ecological importance, forests remain vulnerable to various anthropogenic and natural disturbances. Yunnan pine is a key native tree species in southwest China, widely distributed across the subtropical plateaus of Yunnan Province at elevations ranging from 710 to 3320 m. It accounts for approximately 19.63% of Yunnan Province's total forest area (Deng et al., 2013). As a typical pioneer afforestation species on the Yungui Plateau, the Yunnan pine plays a vital role in soil and water conservation while providing substantial timber and non-timber forest products. It plays a crucial role in maintaining regional ecological security and supporting economic development. However, in recent years, frequent severe droughts in southwestern China, particularly in Yunnan Province, have significantly increased both the frequency and scale of insect pest outbreaks in Yunnan pine forests, thereby seriously threatening the stability of forest ecosystems (Zheng et al., 2013). PSB is one of the most common and highly destructive boring pests infesting Yunnan pine. Since the 1980s, Yunnan Province has witnessed two large-scale outbreaks of this pest, which have cumulatively affected over 1 million hectares of forest. Approximately 93,000 hectares of forest were completely destroyed. Once an outbreak occurs, effective control becomes extremely challenging, posing not only a serious threat to regional ecological security but also causing substantial economic losses (Deng, 2016; Ji et al., 2007).

PSB is an endemic forest pest in southwestern China. Belonging to the Scolytidae family within the Coleoptera order, it is mainly distributed in Yunnan, Sichuan, and Guizhou. Its principal primary host species is Yunnan pine (Lu et al., 2010). When monitoring bark beetle damage, the stages of infestation are typically classified based on changes in foliage color from initial attack to final tree death. For example, in trees infested by the mountain pine beetle (*Dendroctonus ponderosae*) or the European spruce bark beetle (*Ips typographus*), the needles typically undergo a progressive color change from green to red and ultimately to gray (Bright et al., 2013; Coops et al., 2006). Numerous studies classify this progression into three attack stages, including the green attack, red attack, and gray attack (Foster et al., 2017; Wulder et al., 2006; Zhan et al., 2020). In contrast to the systemic discoloration induced by *D. ponderosae* and *I. typographus*, infestation by PSB is characterized by heterogeneous discoloration—only the infested pine shoots exhibit discoloration. During the early stages of PSB infestation, a small number of discolored shoots coexist with healthy ones. These subtle initial symptoms lead to no appreciable changes in the overall physiological and structural characteristics of the tree crown (Liu et al., 2025). Timely and effective detection of early PSB infestations, followed by appropriate control measures, is crucial for suppressing population spread and preventing outbreaks. Traditional monitoring methods primarily rely on ground surveys, which are constrained by high labor costs and time delays, making it difficult to meet the demand for early detection amidst rapid PSB spread. Therefore, developing an effective and cost-efficient monitoring approach is necessary.

Remote sensing technology, capable of overcoming temporal and spatial constraints, has been increasingly applied to the large-scale monitoring of forest pests and diseases. It serves as a vital tool for monitoring vegetation health and evaluating the impact of pest infestations (Zhang et al., 2019). Remote sensing data for pest detection can be acquired through multiple platforms, including needle sampling (Abdullah et al., 2018), UAV (Yu et al., 2021b), aircraft (Coops et al., 2006), and satellites (Bright et al., 2017). Among these platforms, satellite imagery has been widely applied to the early detection of bark beetle infestations, owing to its inherent advantage in large-area monitoring. For example, Abdullah et al. (2019a) utilized Landsat-8 OLI/TIRS imagery to acquire spectral characteristics and surface temperature of forest stand canopies for the early detection of *I. typographus* infestations. The results indicated that water stress induced by the infestation leads to elevated canopy temperatures, which can be detected by Landsat-8 satellite imagery. Based on Sentinel-2 imagery, Huo et al. (2021) developed a vegetation index (NDRS) combining red and shortwave infrared bands to improve the detection of spectral differences in stands with early *I. typographus* infestation. Results indicated that this index can effectively discriminate between infested and healthy forest stands while the canopy remains predominantly green, with a detection accuracy that is significantly superior to that of conventional vegetation indices. While satellite imagery holds potential for monitoring early bark beetle infestations, the number of pixels corresponding to early infestation is limited. Only individual pixels where all host trees are in the early infestation stage can be considered valid sample pixels. Furthermore, satellite imagery is highly susceptible to cloud cover, making it difficult to obtain continuous and valid image data for the study area.

In recent years, UAVs have demonstrated tremendous potential in forest health monitoring due to their agility, short revisit cycles, and ability to capture imagery with ultra-high spatial resolution (Manase et al., 2025). Extensive research indicates that drone-based hyperspectral remote sensing technology can capture continuous, narrow-band spectral information to detect subtle spectral variations in vegetation under insect pest stress, thereby accurately characterizing the physiological status of infested trees (Fassnacht et al., 2014; Lausch et al., 2013; Poblete et al., 2023; Pu et al., 2008; Rumpf et al., 2010; Wan et al., 2022). For example, Ma et al. (2023) utilized drone hyperspectral data to achieve precise classification of Yunnan pine damage severity by analyzing spectral sensitivity to PSB infestation in the red edge and near-infrared bands. Lin et al. (2023) further confirmed that spectral reflectance in the red-edge and near-infrared bands serves as key indicators for distinguishing stands with varying PSB damage severity. These studies underscore the crucial role of red-edge and near-infrared bands in the early detection of PSB infestations. The hyperspectral sensor can acquire a large number of spectral bands, thereby enabling detailed characterization of the spectral features of damaged pine trees (Tsai and Philpot, 1998). However, hyperspectral data often exhibit substantial data redundancy in practical applications (Li et al., 2023, 2024; Wang et al., 2024). Excessive spectral bands may introduce irrelevant information, leading to degraded model performance. In addition, the high equipment procurement and operational costs associated with

hyperspectral UAV systems constrain their widespread application in large-scale monitoring scenarios.

In contrast, multispectral UAV systems equipped with the key spectral bands required for monitoring early bark beetle infestations offer greater cost-effectiveness. For example, the DJI M3M UAV is equipped with red-edge and near-infrared bands, which play an important role in the early detection of PSB, and Pine Wilt Disease (PWD; Liu et al., 2025; Yu et al., 2021a). However, multispectral sensors are constrained by their small number of bands and relatively wide bandwidths, hindering their ability to detect subtle variations in vegetation biochemical properties and reducing their effectiveness in early detection of bark beetle infestations. Therefore, to enhance the accuracy and practicality of the early detection of PSB infestations, it is necessary to integrate other technical approaches to compensate for the limitations of multispectral UAVs.

TIR provides a complementary approach for early detection of pests and diseases monitoring by quantifying changes in stand canopy temperature. The physiological basis for this method lies in the fact that water stress is one of the earliest responses in plants facing biotic or abiotic stressors (Jackson et al., 1981). Hais and Kucera (2008) found that satellite-based TIR data can be used to monitor stands affected by *I. typographus*. However, compared to optical imagery, canopy surface temperature derived from satellite data has a much coarser spatial resolution, making it unsuitable for precise analysis at the individual tree level. The emergence of drone technology has facilitated the development of lightweight thermal imaging systems, enabling high precision thermal imaging at centimeter scale resolution (Maes et al., 2018). Calderón et al. (2013) successfully employed drones equipped with thermal imaging cameras to monitor infections of olive tree wilt disease. Zhang et al. (2023) evaluated the role of drone TIR data in the early detection of PWD, demonstrating its promising application potential. PSB feeding directly damages the xylem vessels of trees, obstructing upward water transport. This results in a significant reduction in stomatal conductance and transpiration rates, ultimately causing abnormal elevation in leaf temperature (Jones, 1999). The resulting temperature difference can be detected by TIR imaging. Wang et al. (2019) employed a handheld thermal imager to confirm the existence of a temperature difference between trees severely damaged by PSB and healthy trees. However, whether a similar temperature difference occurs between trees minimally damaged by PSB and healthy trees, and whether such differences can be detected via UAV based TIR imagery, remains unclear.

Early detection of bark beetle damage via UAV technology has long been a research focus. However, few studies have investigated the effectiveness of fusing UAV based multispectral and TIR imagery for detecting early PSB infestations. In this study, spectral reflectance and canopy temperature were extracted from UAV multispectral and TIR imagery, with multiple vegetation indices and temperature related parameters subsequently calculated. A range of ML models were then employed to classify trees by damage severity. The primary objectives of this study are as follows:

- (1) To determine whether a temperature difference exists between early PSB-infested trees and healthy trees.
- (2) To assess the feasibility of detecting early PSB infestations by fusing UAV-based multispectral and TIR imagery.

- (3) To evaluate machine learning models for early damage classification and generate a spatial classification map to support operational forest health monitoring and management.

2 Materials and methods

2.1 Study area

The study area is situated in Zhanyi District, Qujing City, Yunnan Province, China (Figures 1a, b). The region lies in the central Yungui Plateau and serves as a vital ecological barrier for the Pearl River headwaters as well as a core distribution area for Yunnan pine. The terrain is undulating, with elevations ranging from 1,600 to 2,700 m. The area has a subtropical plateau monsoon climate characterized by an average annual temperature of approximately 16°C and mean annual precipitation of about 1,000 mm. Since around 2010, Yunnan pine forests in Zhanyi District have experienced persistent PSB infestations. A field experiment was conducted from June to August 2025, during which five plots were selected (Figure 1c) for acquiring UAV-based visible light orthophotos (Figure 1d), multispectral false-color imagery (Figure 1e), and thermal infrared images (Figure 1f). Sample trees from four plots (red dots in Figure 1c) were used to train the ML models and evaluate their validation accuracy. The trained model was then applied to the remaining plot to assess its application accuracy (green dots in Figure 1c). Furthermore, the study period coincided with the regional rainy season, with cumulative precipitation from June to August reaching 750 ± 50 mm, which constitutes the majority of the annual rainfall. The absence of extreme drought events during the field experiments and image acquisition ensures that the observed physiological stress and canopy thermal anomalies were primarily driven by PSB infestation rather than abiotic water deficits.

2.2 Field research

Detailed field surveys confirmed that Yunnan pines within the study area that were infested by PSB exhibited varying levels of damage severity. PSB is a major boring pest of Yunnan pine. Their life cycle can be divided into two stages: the shoot-feeding stage and the trunk-boring stage (Liu, 2003; Shen, 2017; Smigaj et al., 2019a; Ye, 2000; Ye and Lv, 2004; Zhu, 2003). In late May, adult beetles emerge from tree trunks (Figure 2a) and disperse to the shoots and feed on the pith tissue (Figure 2b). The adults have a body length ranging from approximately 4.3–5.5 mm (Figure 2c). From early December onward, mature adults migrate to the trunks of host trees to complete their reproductive life cycle, which includes egg hatching, larval development (Figure 2d), and adult emergence (Gao et al., 2012; Wang et al., 1997).

To quantitatively assess the damage severity caused by PSB to Yunnan pine, this study classified tree health grades based on the Stand Damage Ratio (SDR) specified in the national standard Criteria for Occurrence and Disaster Severity of Forest Pests (LY/T 1681-2006) issued by the National Forestry and Grassland Administration of China (Table 1). The classification

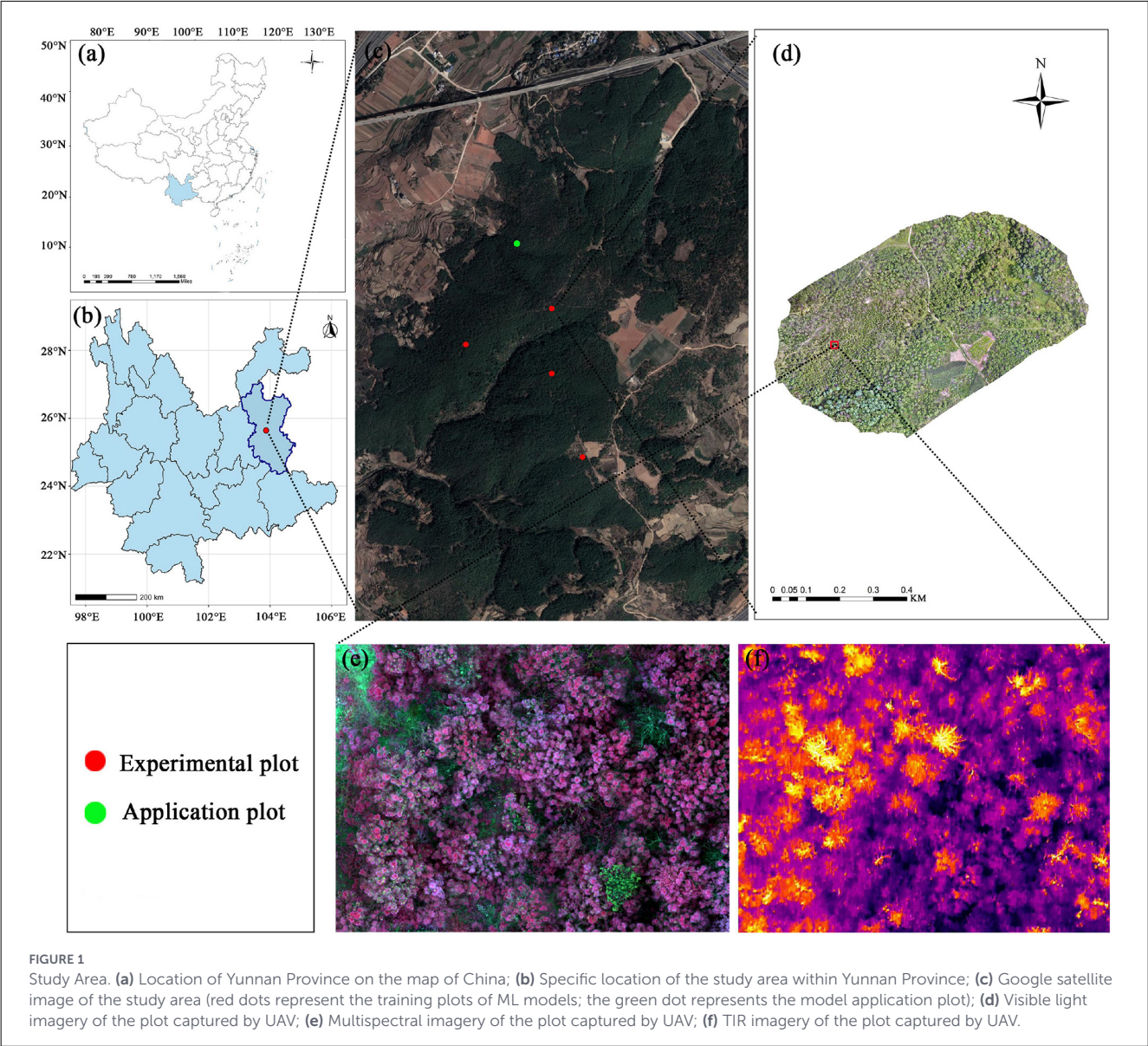


TABLE 1 PSB hazard severity classification standard.

Damage severity	Shoot damage ratio (%)
Health	<10
Lightly damaged	11–20
Moderately damaged	21–50
Severely damaged	>51

criteria are defined as follows: A dead shoot rate below 10% is classified as healthy (Figure 2e); rates of 11–20% indicate light damage (Figure 2g); rates of 21–50% indicate moderate damage (Figure 2f); and rates exceeding 51% indicate severe damage (Figure 2h). Lightly damaged trees represent the early stage of PSB infestation and are therefore the primary focus of this study.

2.3 Image acquisition and processing

2.3.1 Multispectral and TIR image acquisition

This study employed the DJI Mavic 3 Multispectral (M3M, Shenzhen, China) and DJI Mavic 3 Thermal (M3T, Shenzhen, China) drones as data acquisition platforms. The M3M drone incorporates four multispectral cameras covering key bands for vegetation monitoring, including green (560 ± 16 nm), red (650 ± 16 nm), red edge (730 ± 16 nm), and near-infrared (860 ± 26 nm; Figure 3a, Table 2), along with a 20-megapixel visible light camera (Figure 3b). This data collection employed simultaneous multispectral and thermal infrared operations. From August 28 to 30, 2025, multispectral imagery was captured using a DJI Mavic 3 multispectral drone, while TIR imagery of the study area was acquired via a DJI Mavic 3T thermal infrared drone (Figures 3c, d). This specific temporal window was selected to align with the biological cycle of the PSB and the phenological characteristics

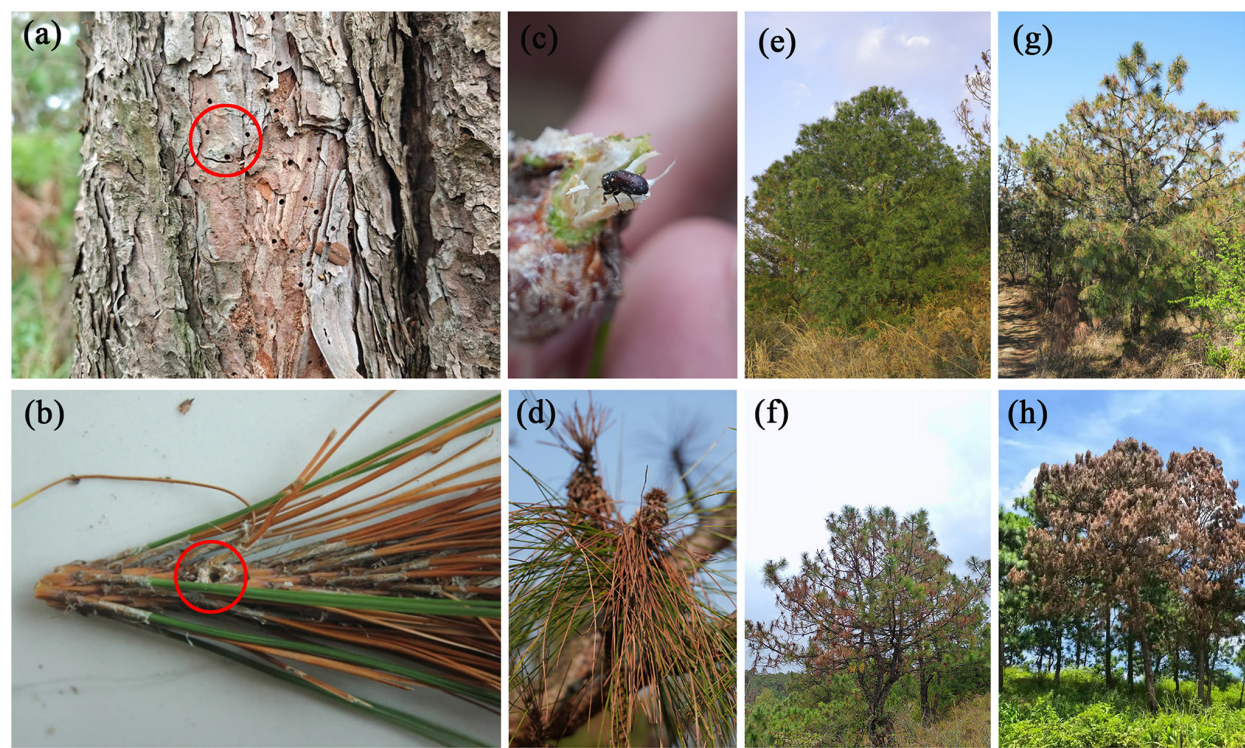


FIGURE 2
(a) PSB emergence hole (red circle); (b) PSB entry hole (red circle); (c) PSB adult; (d) Damaged shoot; (e) Healthy tree; (g) Lightly damaged tree; (f) Moderately damaged tree; (h) Severely damaged tree.

TABLE 2 Multispectral UAV flight parameters.

Parameter	Technical specifications	Unit/description
Spectral bands	Green (560 ± 16) Red (650 ± 16) RE (730 ± 16) NIR (860 ± 26)	nm
Flight altitude	80	m
Spatial resolution (80 m)	0.37	m/pixel
Flight speed	3	m/s
Forward overlap rate	90	%
Lateral overlap ratio	90	%

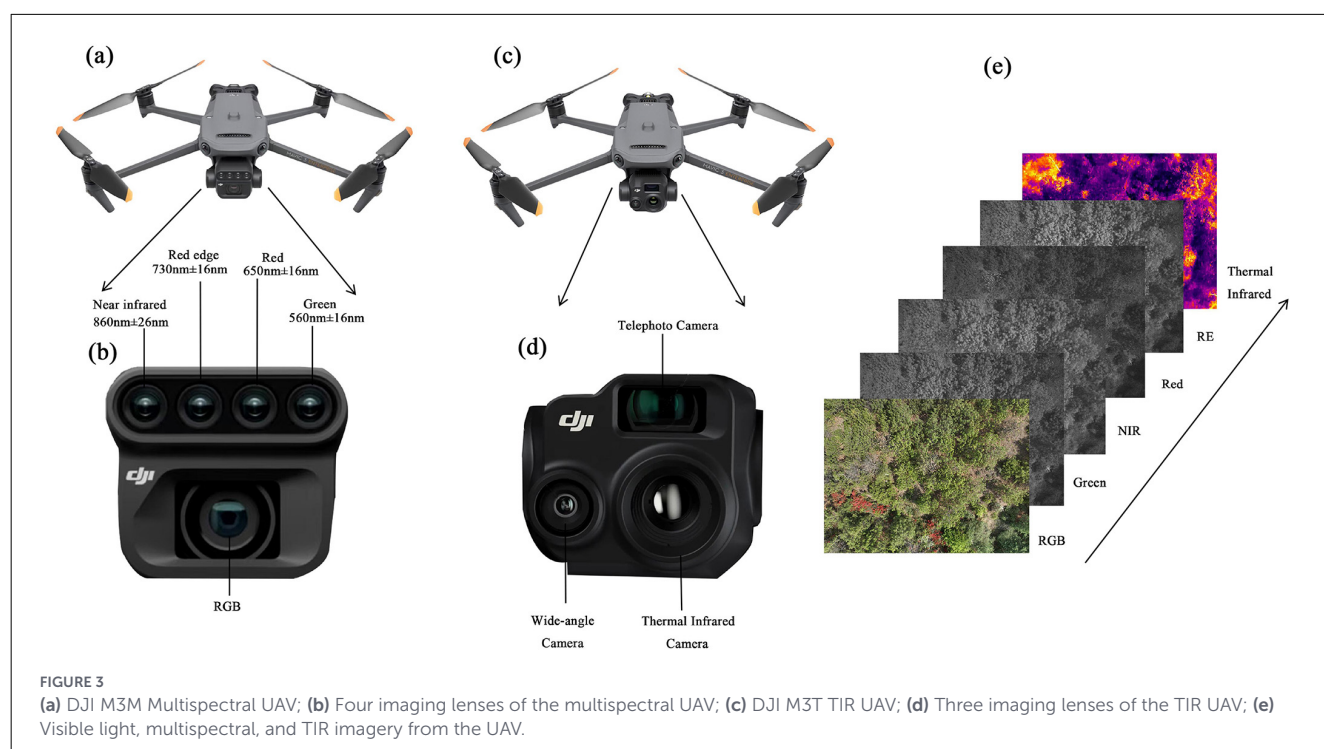
of the host trees. In the study area, adult PSBs emerge from tree trunks in late May to feed on Yunnan pine shoots. By late August, the cumulative physiological stress from months of shoot-boring becomes visually apparent in the field, providing a sufficient number of identifiable samples for model training. Furthermore, this period precedes the natural needle senescence and yellowing that typically occurs after November, thereby minimizing potential phenological noise that could interfere with the spectral and thermal identification of infested canopies.

The acquisition time and flight parameters for the thermal infrared drone were identical to those of the multispectral drone

(Table 2). Figure 3e displays a sample set of multispectral images of the study area generated following this data acquisition. Data acquisition was conducted under clear, cloudless weather conditions with atmospheric visibility ≥ 15 km, wind speed ≤ 2 m/s, air temperature $27 \pm 0.5^{\circ}\text{C}$, and relative humidity $45 \pm 2\%$. The flight was configured with the following parameters: altitude of 80 m, forward and lateral overlap of 90%, and speed of 3 m/s. Two sets of reference images were acquired both before takeoff and after landing to support radiometric calibration of the multispectral imagery.

2.3.2 Multispectral data processing

Multispectral imagery was preprocessed with DJI Terra 3.5 and ENVI 5.6 software. First, multispectral images were mosaicked into a single orthomosaic in DJI Terra 3.5. Subsequently, a linear regression model was constructed to relate the reference reflectance of calibration panels to the raw digital number (DN) values of the multispectral bands, which was then used to convert the raw DN values of the entire orthomosaic to surface reflectance. While multispectral imagery provides high spatial resolution, this study utilized the multispectral UAV to capture ultra-high-definition visible light imagery visible light imagery (RGB camera) of infested stands (Figure 4). The flight altitude was set to 30 m for this acquisition, aiming to improve the accuracy and reliability of visual interpretation. The visible light imagery had a spatial resolution of 0.05 m, clearly displaying the shoot damage status of



individual tree crowns and providing critical reference for selecting sample trees across different damage severity levels. Through visual interpretation of the visible light imagery, the canopy polygons of trees with PSB infestations were delineated using the Region of Interest (ROI) tool in ENVI 5.6 software. A total of 150 sample trees were selected from the four plots, including 30 healthy trees, 50 lightly damaged trees, 40 moderately damaged trees, and 30 severely damaged trees (Figure 4).

2.3.3 TIR image processing

TIR data were processed with DJI Thermal Analysis Tool 3.0 (DJI Innovation, Shenzhen, China). Systematic sensor-related errors were corrected by converting raw digital number (DN) values to radiance based on the 30% reflectance of a diffuse reference panel (Zhao, 2023). The calibrated data were subsequently converted from 16-bit R-JPEG format to grayscale images (Sun, 2019). The “Iron Red” panel was utilized to calibrate the 0–255 grayscale range to a temperature scale of -10°C to 40°C , thereby enabling both visual and quantitative characterization of canopy temperature.

To obtain accurate spectral and thermal information for individual trees, visible, multispectral, and TIR images were spatially registered in ENVI 5.6. Designating the highest resolution visible light image as the reference image, image registration of multispectral and TIR images was performed using ground control points (GCPs). Then, the tree crown polygons previously delineated on the visible imagery were precisely transferred to the multispectral and thermal layers. Finally, spectral reflectance values per band and canopy temperature values were extracted from the delineated tree crown polygons.

Among the extracted thermal indices, although T_{mean} , T_{max} , and T_{min} represent absolute canopy temperatures, we also included several normalized indices, including T_{std} , ΔT , T_{CV} , and STDA. These indices were normalized relative to the average temperature within the sample tree’s canopy or the temperature within a healthy canopy. This helps mitigate the influence of ambient temperature on these thermal indices to some extent, thereby improving the comparability of thermal signals among different trees within the same flight window.

2.4 Model construction and performance evaluation

The overall workflow of our experiment is illustrated in Figure 5. In this study, 13 multispectral vegetation indices (VIs), and 7 thermal metrics were extracted to characterize the physiological responses of *Pinus yunnanensis* to PSB infestation (Table 3). The selection of these features was primarily guided by their demonstrated sensitivity to the physiological and biochemical changes associated with early-stage bark beetle infestation (Abdullah et al., 2018; Senf et al., 2017). Specifically, the multispectral VIs were derived from visible, NIR, RE spectral bands, each targeting distinct aspects of forest decline. Visible-based indices were used to capture early chlorophyll degradation and subtle needle discoloration, which reflect initial photosynthetic impairment (Curran, 1989; Liu et al., 2021), while NIR-based indices are more sensitive to changes in leaf structure and canopy integrity. Furthermore, red-edge-based indices were incorporated due to the high sensitivity of the red-edge region to subtle variations in pigment concentration and leaf structure. These indices have been shown to detect physiological stress prior to

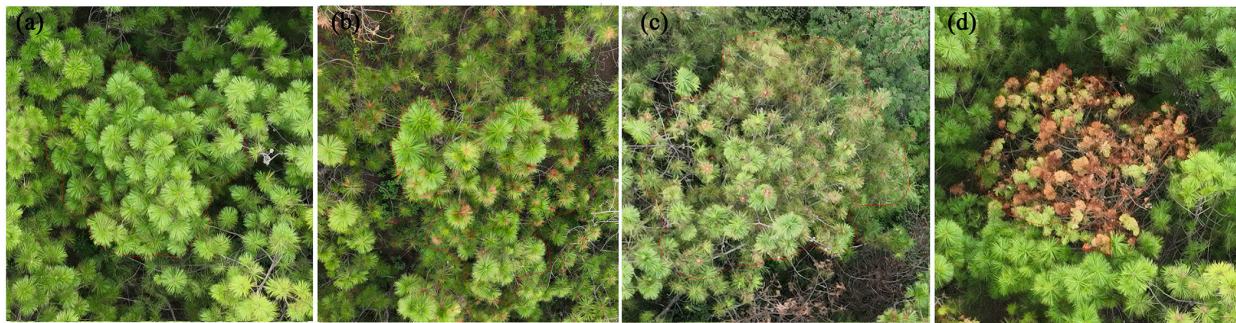


FIGURE 4

UAV visible light images of tree canopies with different damage severity levels. (a) Healthy canopy; (b) Lightly damaged canopy; (c) Moderately damaged canopy; (d) Severely damaged canopy.

widespread visible discoloration, providing a critical window for identifying early-stage infestations (Eitel et al., 2011; Näsi et al., 2015). Regarding thermal metrics, we acknowledge that absolute canopy temperature is highly susceptible to fluctuating ambient meteorological conditions. Prior to model training, one-way ANOVA and Tukey's HSD *post-hoc* tests were performed on the multispectral and thermal features to determine the distribution differences of each feature across the four damage severity levels (Long et al., 2023).

This study evaluated the performance of seven ML algorithms, including Logistic Regression (LR), K-Nearest Neighbors (K-NN), Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), and Extreme Gradient Boosting (XGBoost). For LR, the maximum number of iterations was set to 1,000. The KNN classifier was implemented with five nearest neighbors. The SVM model adopted a radial basis function kernel with probability estimation enabled. For ensemble models, RF, GB, and XGBoost were trained with 100 trees. All other parameters were kept at their default settings.

Three feature sets were used for model training: a multispectral only set, a thermal infrared only set, and a fused set integrating both data types. We adopted a stratified 10-fold cross-validation scheme to ensure that the original proportion of the four damage severity levels was maintained across all folds. For each iteration, seven folds were used for training and three for validation. This process was repeated ten times, and the average performance followed by the standard deviation was adopted as the final evaluation metric to account for variability between iterations. To evaluate the stability of the models and the significance of the performance improvements, both the mean and standard deviation of each metric across the ten iterations were calculated. Furthermore, pairwise Welch's *t*-tests were conducted to determine if there were statistically significant differences ($p < 0.05$) among the different machine learning models and feature scenarios. Different lowercase letters (e.g., a, b, and c) are used to denote these statistically significant differences. Data from four experimental plots were used for model training and validation. Finally, the trained models were applied to an independent application plot, as shown in Figure 1c.

Four metrics were used to evaluate model performance: OA, Precision, Recall, and the Kappa coefficient

(Cohen and Measurement, 1960). Among these, OA measures the overall correctness of the model's classifications; Precision reflects the reliability of the model's predictions for the positive class; Recall indicates the model's ability to identify all positive instances, thereby avoiding missed detections; and the Kappa coefficient assesses the agreement between the model's classification results and the ground-truth labels, correcting for the influence of random agreement and providing a more comprehensive reflection of classification accuracy. The formulas for these metrics are as follows:

$$OA = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

$$Kappa = \frac{OA - eAccuracy}{1 - eAccuracy} \quad (2)$$

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

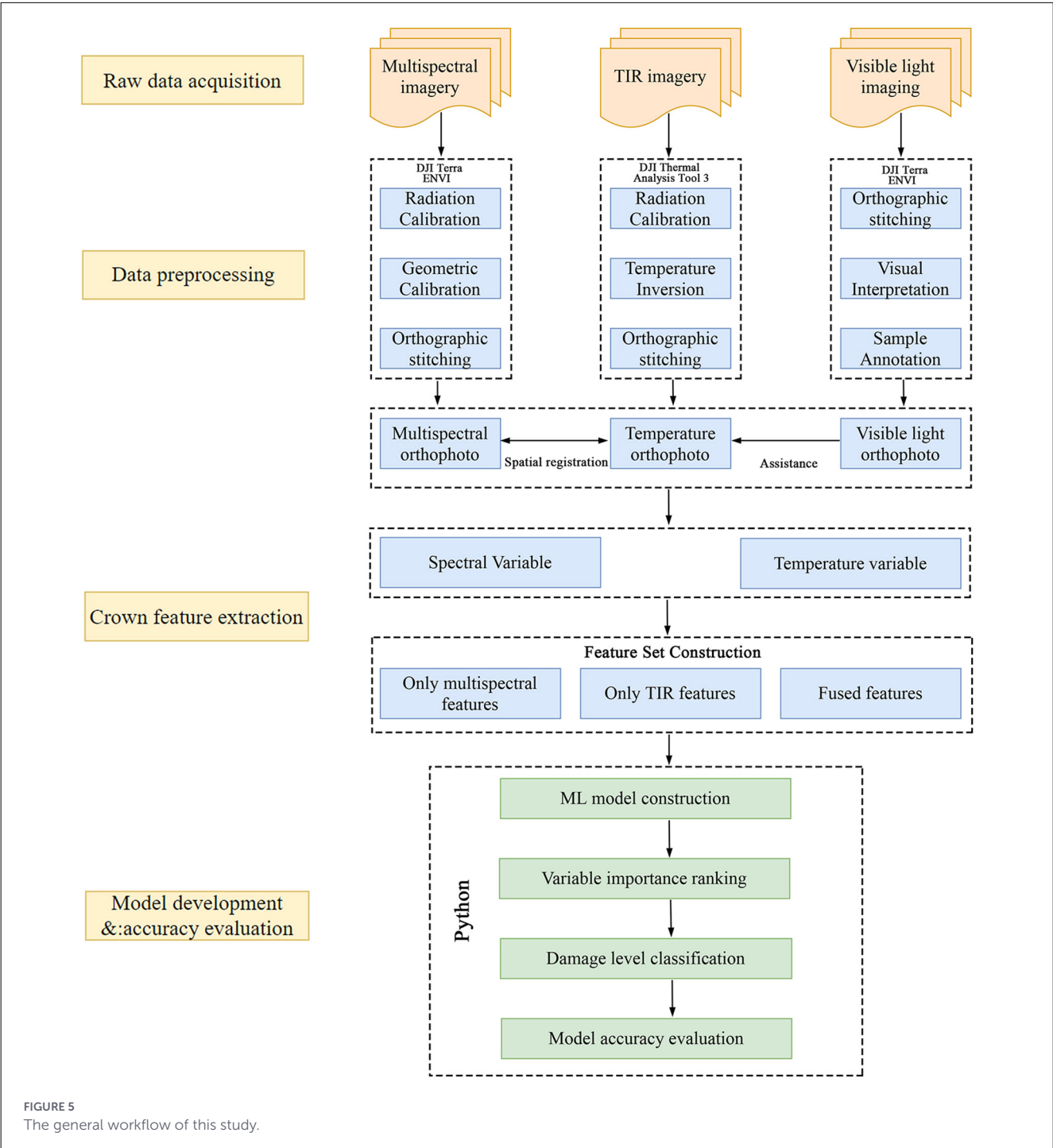
$$Precision = \frac{TP}{TP + FP} \quad (4)$$

Among these, TP, TN, FP, and FN represent the number of true positives, true negatives, false positives, and false negatives in the model's predictions, respectively. These five metrics collectively form a comprehensive standard for model evaluation, reflecting model performance from different perspectives.

3 Results

3.1 Analysis of variable differences among different victimization level trees

One-way ANOVA results indicate that 18 of the 20 features exhibited significant differences among damage



levels ($p < 0.05$). Figure 6 displays box plots for eight features, which show two distinct patterns of change as damage severity increases. The multispectral indices GRVI, NDVI, RETR, and RVI exhibited a significant decline ($p < 0.0001$) as damage severity increased. Conversely, all thermal infrared features (T_{cv} , T_{std} , T_{max} , ΔT) showed a consistent upward trend ($p < 0.05$) with increasing damage severity.

Post-hoc tests (Tukey HSD) revealed significant differences ($p < 0.05$) between healthy trees and lightly damaged trees in

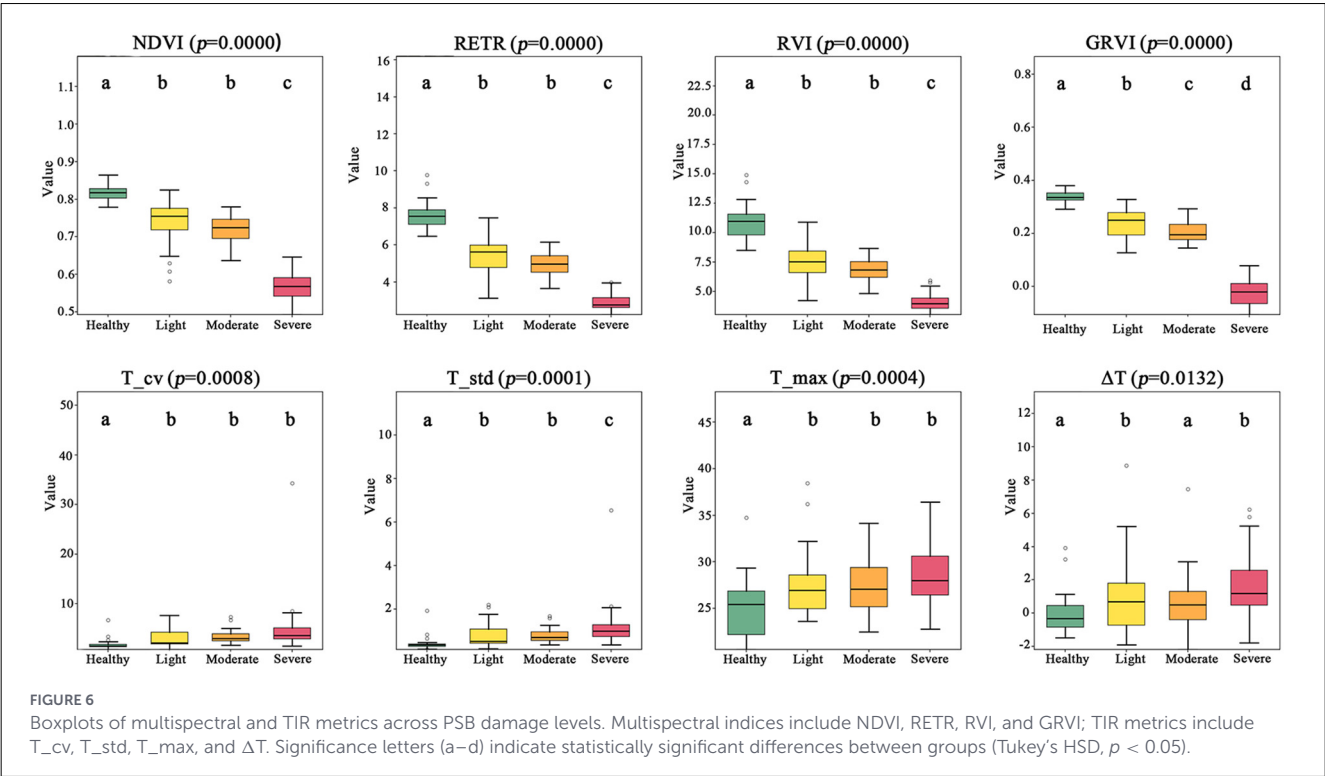
four multispectral vegetation indices (GRVI, NDVI, RVI, and RETR) and thermal infrared indicators T_{cv} , T_{std} , T_{max} , and ΔT .

3.2 Model performance evaluation

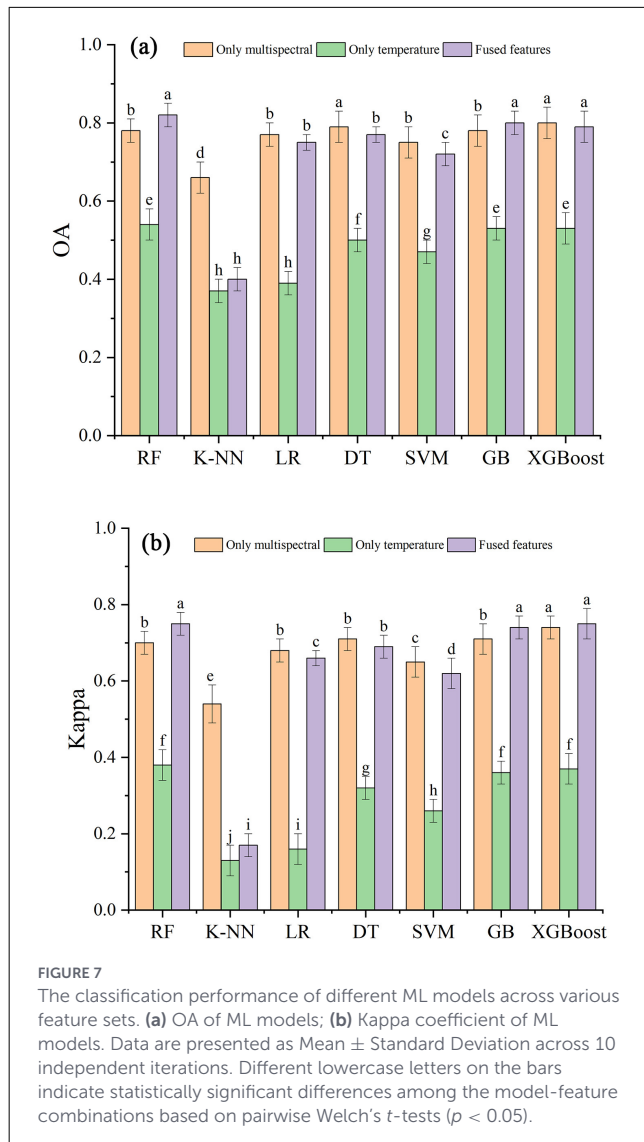
This study systematically compared the performance of seven classification models for PSB detection using feature sets derived from UAV multispectral and thermal infrared imagery. Results

TABLE 3 Multispectral and TIRFeature extraction methods for PSB detection.

Abbreviation	Name	Equation	Reference
NDVI	Normalized difference vegetation index	$\frac{NIR-R}{NIR+R}$	(Sha et al., 2020)
RVI	Ratio vegetation index	$\frac{NIR}{R}$	(Zhou et al., 2022)
DVI	Difference vegetation index	$NIR - R$	
GRVI	Green-red vegetation index	$\frac{NIR-G}{NIR+G}$	(Motohka et al., 2010)
NRTG	Near-infrared to green light ratio	$\frac{NIR}{G}$	(Cotrozzi, 1970–2020)
RENDVI	Red edge normalized vegetation index	$\frac{NIR-RE}{NIR+RE}$	(Yu et al., 2021a)
REP	Red edge position	$705 + 35 \frac{NIR+RE-RE}{NIR-RE}$	(Pan et al., 2023)
NDRE	Normalized difference red edge index	$\frac{NIR-RE}{NIR+RE}$	(Wu et al., 2023)
RETR	Red edge to red light ratio	$\frac{RE}{R}$	(Gitelson et al., 2003)
T_mean	Average temperature	Mean temperature of all pixels within the ROI	(Sagan et al., 2019)
T_max	Maximum temperature	Maximum temperature of all pixels within the ROI	
T_min	Minimum temperature	Minimum temperature of all pixels within the ROI	
T_std	Temperature standard deviation	Standard deviation of temperature pixels within ROI	
ΔT	Temperature variation	$T_mean - T_healthy_mean$	
T_cv	Temperature coefficient of variation	$\frac{T_std}{T_mean} \times 100\%$	(Sagan et al., 2019)
STDA	Standardized temperature difference anomaly points	$\frac{\Delta T}{T_healthy_std} \times 100\%$	

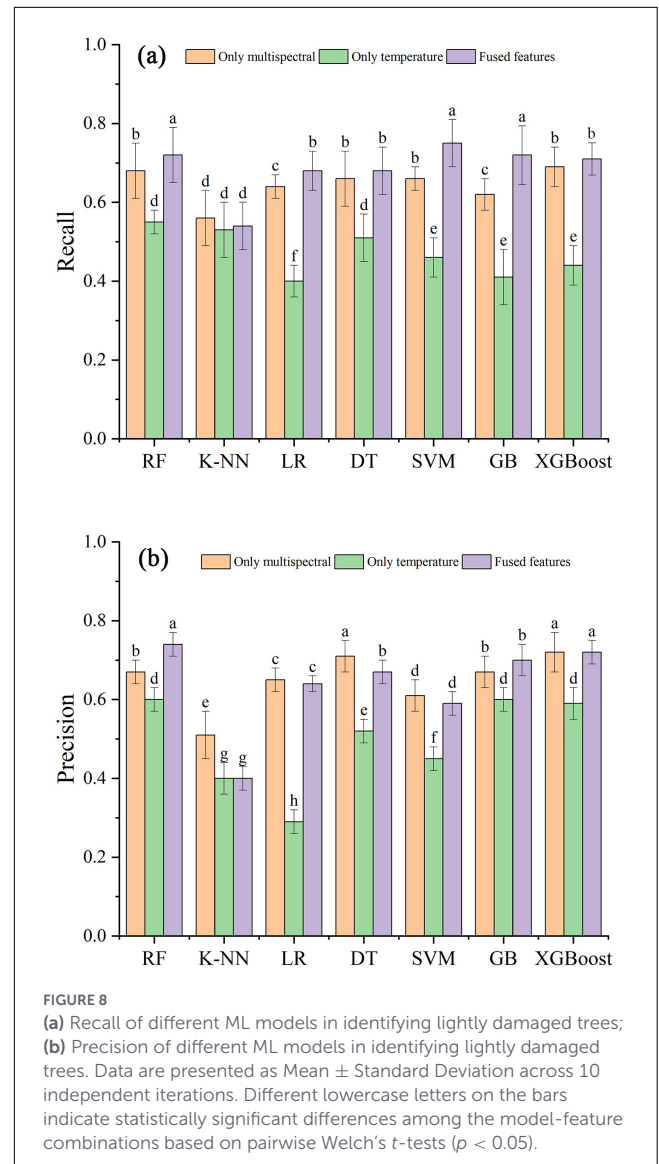


show that overall model performance varies across the feature sets (Figures 7, 8). Under the multispectral only feature set, the XGBoost and DT models achieved the highest accuracies, with OA values of 0.80 ± 0.04 ($Kappa = 0.74 \pm 0.03$) and 0.79 ± 0.04 ($Kappa = 0.71 \pm 0.03$), respectively. When the only TIR feature set was applied, the overall performance decreased markedly across all models, although the RF model reached the highest accuracy in this scenario, its performance remained limited ($OA = 0.54 \pm 0.04$; $Kappa = 0.38 \pm 0.04$), confirming that TIR data alone is insufficient for reliable PSB identification. Integration of multispectral and TIR data in the fused feature set yielded the most robust results, with the RF, GB, and XGBoost models exhibiting the strongest performance. While no statistically significant differences in OA were observed among these three models ($p > 0.05$), the RF



model achieved a mean OA of 0.82 ± 0.03 . Notably, for the RF and GB models, the OA and Kappa values obtained using fused features were significantly higher than those achieved using the only multispectral feature set ($p < 0.05$), a trend that was not observed for the XGBoost model.

This study primarily focuses on identifying early-stage PSB damage (lightly damaged trees). Figure 8 illustrates the Recall and Precision performance of different classification models for lightly damaged trees under various feature set conditions. In terms of Recall, the RF (0.72 ± 0.07), SVM (0.75 ± 0.06), and GB (0.72 ± 0.07) models exhibited relatively strong performance and their recall values with fused features were significantly higher than those using only multispectral features ($P < 0.05$). Regarding Precision, the RF (0.74 ± 0.03) and XGBoost (0.72 ± 0.03) models outperformed others. Specifically, the Precision of the RF model improved significantly after integrating TIR features ($P < 0.05$), whereas the XGBoost model showed no such significant improvement ($P > 0.05$). In conclusion, the RF model demonstrated the most robust performance across all evaluation



metrics, making it the optimal model for detecting early PSB infestation. Furthermore, the fusion of multispectral and TIR features led to a significant 4% increase in the RF model's Recall compared to the multispectral-only approach ($P < 0.05$).

The confusion matrix of the optimal model (RF) for identifying PSB damage under feature fusion is presented in Table 4. Each cell value represents the cumulative sum of 10 independent experiments. The model exhibited excellent performance in distinguishing healthy trees from severely damaged trees. For healthy trees, the Precision and Recall reached 0.89 and 0.97, respectively. The identification accuracy for severely damaged trees achieved excellent performance, with Precision and Recall at 1.0 and 0.97. Moderately damaged and lightly damaged trees exhibited moderate identification accuracy, with Precision and Recall at 0.74 and 0.72, respectively. Lightly damaged trees were prone to misclassification as healthy or moderately damaged trees. Nevertheless, the overall classification results for lightly damaged trees remained within an acceptable range.

TABLE 4 Confusion matrix for PSB hazard detection using random forest models with feature fusion.

Class	Healthy	Light	Moderate	Severe	Recall
Healthy	87	3	0	0	0.97
Light	11	108	29	0	0.72
Moderate	0	32	86	1	0.72
Severe	0	2	1	87	0.97
Precision	0.89	0.74	0.74	1.00	
OA	0.82				
Kappa	0.75				

Rows represent the true values and columns represent the predicted values.

3.3 Feature importance analysis

Higher feature importance values indicate greater contribution to model classification. Feature importance analysis based on the RF model reveals that vegetation indices play a significant role (Figure 9). The importance values for GRVI, NDVI, and RETR reached 0.175, 0.173, and 0.135, respectively. Next in importance were the thermal infrared features T_{std} and T_{cv} , with importance values of 0.062 and 0.057. By contrast, REP, NRTG, red band reflectance, and ΔT contributed relatively little to model performance.

3.4 Model application and thematic mapping

To validate the applicability of the RF model in practical monitoring, this study selected an application plot (Figure 1c) for model application. This plot consisted of 280 Yunnan pines with a diverse distribution of damage levels, including 57 healthy, 90 lightly damaged, 67 moderately damaged, and 66 severely damaged trees. Figure 10 illustrates the distribution of damage to Yunnan pines caused by PSB infestation. Most lightly damaged trees within the stand were correctly identified, while a few early-damaged trees were misclassified alongside healthy and moderately damaged trees. The Recall and Precision for identifying early-damaged trees were 0.72 and 0.81, respectively (Table 5). The RF model based on the UAV multispectral and TIR fusion dataset demonstrated not only good performance in the experimental plots but also strong classification capabilities in the application plots.

4 Discussion

This study evaluated the feasibility of drone multispectral and TIR imagery for early-stage monitoring of PSB damage. Results indicate that fused multispectral and TIR imagery can enhance the accuracy of early PSB damage detection. Multispectral vegetation indices play a crucial role in early PSB damage monitoring, while TIR features provide substantial supplementary support. Multispectral vegetation indices are sensitive to chlorophyll content, while TIR data reflect changes in canopy temperature.

During the early stages of PSB damage, affected trees exhibit yellowing of pine tips, decreased chlorophyll content in needles, and increased levels of carotenoids and anthocyanins. These physiological changes induce spectral response variations that can be captured by vegetation indices (Liu et al., 2021). Simultaneously, PSB damages the phloem tissue in pine tips, obstructing water transport and reducing transpiration in the canopy needles. This leads to elevated needle temperatures, and the resulting water stress signals can be sensitively detected by TIR sensors. Multispectral and TIR data can identify distinct anomalies during the early stages of tree damage, forming a complementary approach that significantly enhances the accuracy of drone imagery in monitoring early PSB damage.

Following PSB infection of Yunnan pine, NDVI, GRVI, RETR, and RVI vegetation indices showed a significant decline as the severity of damage increased. This trend aligns with studies on PWD and *I. typographus* (Abdullah et al., 2019b; Yu et al., 2021b). The calculation of NDVI, GRVI, and RVI relies on the reflectance of the red, green, and near-infrared bands. The decline in vegetation indices directly reflects changes in reflectance across these spectral bands. On one hand, insect pest stress reduces chlorophyll content in needles, shifting reflectance peaks in the green region, absorption troughs in the red region, and reflectance in the red edge region (Abdullah et al., 2018; AHERN, 1988; Curran, 1989; Reichmuth et al., 2018). On the other hand, changes in needle water content and other physiology substances (e.g., starch, proteins, lignin, and cellulose) possibly affect scattering, thereby altering reflectance in the near-infrared region (Curran, 1989). Additionally, stomatal closure to conserve water might also contribute to reduced near-infrared reflectance (Abdullah et al., 2019b).

T_{std} , T_{cv} , T_{max} , and ΔT significantly increase with escalating damage severity, exhibiting notable differences even during the healthy to lightly damaged stage. This trend aligns with prior research (Lin et al., 2017; Smigaj et al., 2019b), indicating that trees infected by PSB enter a “stress state.” To reduce water loss, they close stomata, diminishing canopy heat dissipation capacity and leading to elevated temperatures. In contrast, healthy trees maintain normal “transpiration cooling,” resulting in lower canopy temperatures. The sensitivity of temperature characteristics such as T_{std} , T_{cv} , and T_{max} to the early stages of PSB damage may be related to the non-uniform distribution of affected shoots within the canopy. During the initial phase of PSB infestation, only a portion of the needles are infected, and the temperature difference between healthy and damaged shoots increases the overall temperature variability within the canopy.

This study compared the accuracy of seven ML models in identifying early-stage damage caused by PSB. The results revealed that the RF model demonstrated statistically significant and robust advantages in the multispectral and TIR feature fusion datasets. Its mean OA and Kappa coefficient significantly improved to 0.82 and 0.75, respectively, while Recall and Precision for the light damage stage increased to 0.72 and 0.74. While algorithms like SVM achieved a high absolute Recall for lightly damaged trees under feature fusion, they suffered from significant trade-offs with low Precision, indicating a high rate of false positives. In contrast, the RF model was the only algorithm to achieve

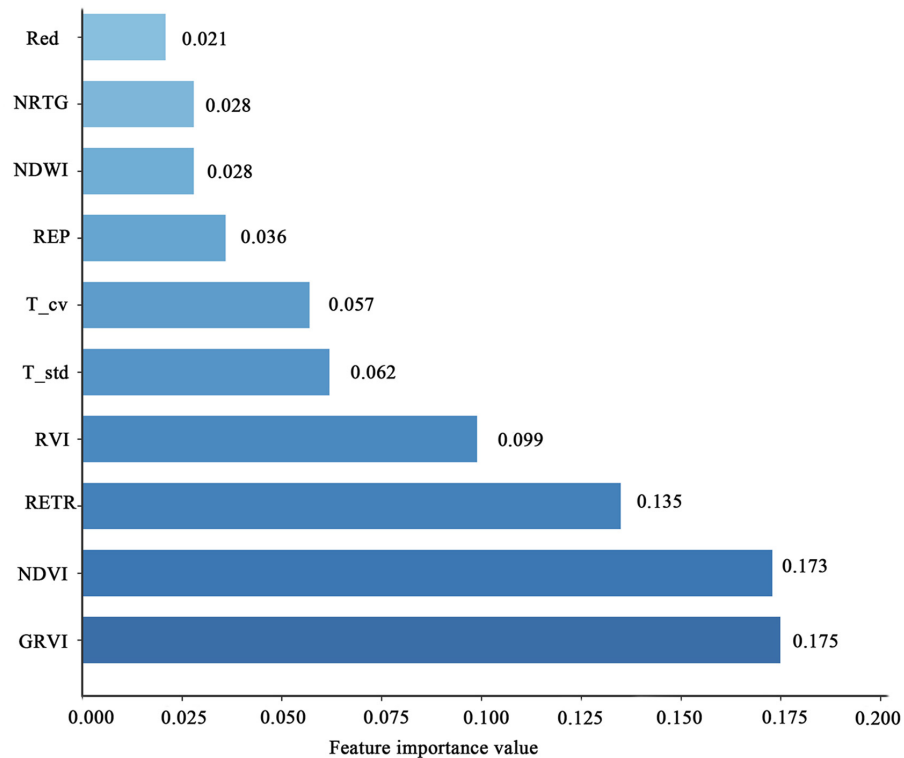


FIGURE 9

Feature importance ranking of RF Models on the fusion feature dataset (Only the top 10 most important features are listed).

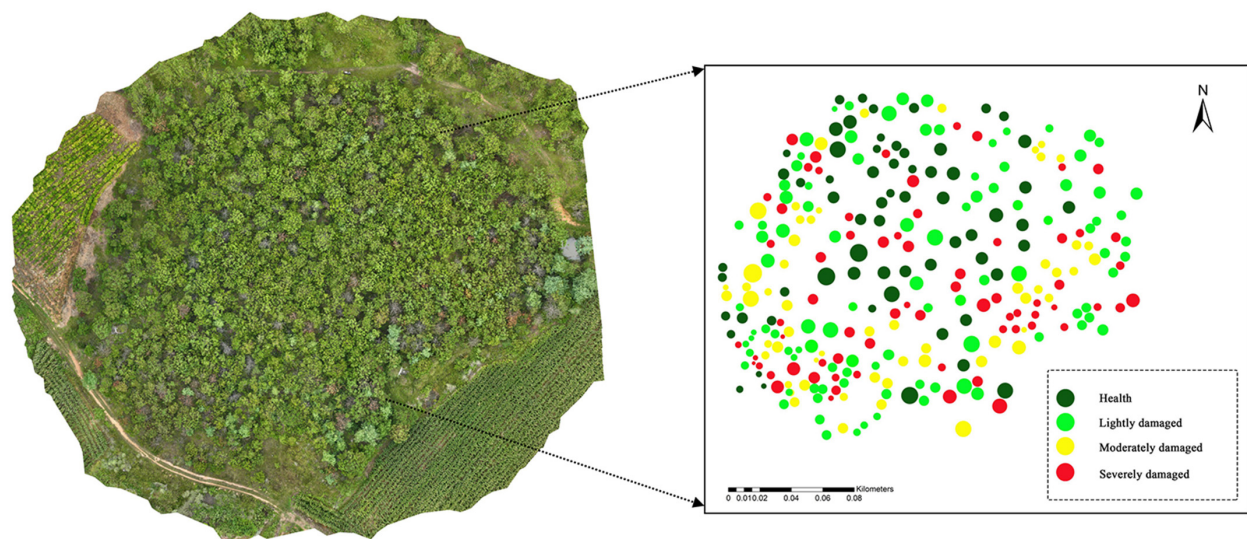


FIGURE 10

Classification map of pines with different PSB damage severity levels.

significant simultaneous improvements across all core metrics. This result aligns with findings in [Bi et al. \(2024\)](#), both indicating that the RF model exhibits high robustness when integrating multi-source remote sensing features. The primary reason for the superior and balanced performance of the RF model lies in its ability to handle nonlinear relationships among multi-source features.

When reflecting early-stage PSB damage, multispectral vegetation indices and TIR temperature features characterize vegetation spectral response and canopy thermal state, respectively, with differences in information sources and spatial scales. Traditional linear models (such as LR) struggle to effectively describe these relationships. In contrast, the RF model automatically

TABLE 5 Confusion matrix for identifying different damaged trees using RF models in applied plots.

Class	Healthy	Light	Moderate	Severe	Recall
Healthy	55	2	0	0	0.96
Light	4	65	18	3	0.72
Moderate	3	13	48	3	0.72
Severe	0	0	0	66	1
Precision	0.88	0.81	0.73	0.92	
OA	0.83				
Kappa	0.78				

Rows represent the true values and columns represent the predicted values.

learns complex relationships between multispectral and TIR features without requiring complex feature transformations by integrating multiple decision trees (Breiman, 2001). During the light damage stage, where pest signals are weak and susceptible to background noise, the RF model's ensemble mechanism enhances result stability, enabling more reliable identification of early-damage samples.

Compared to previous studies, this research employs a more cost-effective and easier-to-deploy dual-sensor approach combining multispectral and TIR sensors, rather than expensive hyperspectral systems with massive data volumes. This enables effective identification of early-stage PSB damage before widespread shoot discoloration occurs (Ma et al., 2023; Pan et al., 2023; Wang et al., 2022). Achieving precise monitoring of early PSB damage is crucial for timely pest control, helping reduce the risk of pest spread, and lowering the economic costs of management. Despite these achievements, several limitations remain. First, the relatively small sample size ($n = 150$) may partially affect the model's generalization ability in more complex scenarios. While we validated the model's generalization using an application plot, achieving a Recall of 0.72 for early-damaged trees, this plot was geographically close to the training site. The model's generalization ability across different elevations, slope orientations, and vegetation compositions remains to be verified. Future research could expand the sample size to validate the model's stability in identifying early PSB damage under diverse stand conditions. Second, this study utilized single-temporal UAV imagery collected within a narrow time window under consistent meteorological conditions. Although this ensured that trees across all damage levels were exposed to nearly identical ambient temperatures, the absolute thermal metrics T_{mean} , T_{max} , T_{min} remain inherently sensitive to measurement timing. While we mitigated this by incorporating normalized indices like T_{std} , ΔT , and STDA, the current model's performance is primarily reflective of the physiological state during this specific seasonal window (August). Future research should employ multi-temporal data to identify the optimal detection window, which will require more rigorous temperature normalization protocols to decouple environmental fluctuations from true infestation-induced stress signals. Third, this study relied solely on two-dimensional image data, neglecting the

modulating effects of canopy structure parameters (e.g., leaf area index, branch density) on light-heat signals. Integrating LiDAR data could further enhance the model's capability to detect early PSB damage.

Overall, this study demonstrates that combining multispectral and thermal data improves early detection of PSB infestation. The integration of these data sources helps capture canopy responses that are not easily identified using a single sensor.

5 Conclusions

This study demonstrates the feasibility of integrating UAV-based multispectral and TIR imagery for early detection of pine shoot beetle (PSB) infestation at the individual-tree scale. Significant canopy temperature anomalies were observed even during the early damage stage, suggesting early stress-related responses that can be detected through thermal imaging.

The fusion of multispectral vegetation indices and thermal metrics improved classification performance compared with single-source data. The RF model showed robust performance when applied to the fused feature set, achieving an OA exceeding 0.80 and maintaining reliable detection capability for lightly infested trees. The trained model was further validated in an independent application plot, demonstrating stable generalization performance.

Overall, this multisensor UAV framework enables earlier identification of PSB infestation and provides actionable information for forest health monitoring. By facilitating detection prior to extensive canopy damage, the proposed approach supports integrated pest management strategies under increasing environmental stress and contributes to adaptive forest management.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

SH: Writing – original draft, Formal analysis, Visualization, Data curation, Conceptualization, Methodology, Investigation. SZ: Writing – original draft, Data curation, Investigation. LC: Investigation, Writing – original draft, Validation. LG: Resources, Writing – review & editing, Investigation. NL: Supervision, Writing – review & editing. SY: Writing – review & editing, Software, Validation. LW: Writing – review & editing, Data curation, Visualization. ZZ: Supervision, Project administration, Writing – review & editing, Conceptualization, Funding acquisition.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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