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Review

Early detection of bark beetle (*Ips typographus*) infestations by remote sensing – A critical review of recent research

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ABSTRACT

Bark beetle disturbances increasingly threaten structure and functionality of temperate and boreal forests globally. The early detection of bark beetle-infested trees, i.e. before beetles' emergence from the breeding tree, is essential for an effective outbreak mitigation. Terrestrial control surveys as traditionally employed for infestation detection, however, are resource-intensive and approach their limits in difficult terrain and during mass outbreaks. Developments in remote sensing and detection algorithms are increasingly giving hope that early-infested trees will be detectable remotely, thereby improving control success and management efficacy. Yet, a comprehensive quantitative evaluation of the approaches currently being developed is lacking to date. This review synthesises the state-of-the-art of recent research on early infestation (or green-attack) detection by remote sensing, and places it in the context with underlying biological constraints, technical opportunities and potential management applications. Since each bark beetle-host tree system has specific characteristics and detectability, we focus on the system with the greatest impact on European forests, the European spruce bark beetle (*Ips typographus*), which attacks Norway spruce (*Picea abies*). By screening research published within the period 2000–2022, we included 26 early detection studies in our analyses. All studies reviewed were purely exploratory, testing a variety of data and/or classification algorithms with a relatively limited spatial and temporal coverage. Among tested platforms and sensor types, satellite and multispectral imagery were most frequently investigated. Promising spectral wavelength range or index highly varied among studies and regions. Timeliness and accuracy of detection were found to be insufficient for efficient management, regardless of the tested platform, sensor type, and spatial resolution applied. The main reasons preventing better performance include the rapid development of *I. typographus* in combination with the delayed and highly variable vitality response of the spruce crown, and frequent cloud cover in spruce-dominated regions across Europe. In conclusion, current remote sensing survey methods cannot yet replace terrestrial control surveys for timely bark beetle management. Nevertheless, they might be supportive either as a back-up to regular and frequent terrestrial surveys, or in specific situations, e.g. to detect hibernation trees, in terrain with difficult accessibility, or in extensively managed forests without sufficient survey capacity. We suggest that the term 'early detection' be used consistently as a synonym for 'pre-emergence detection' to avoid ambiguity. Finally, we provide recommendations for future research based on the lessons learned from the studies analysed, namely to use a more rigorous and targeted study design, to ensure interdisciplinarity, and to communicate research results explicitly.

1. Introduction

Global tree mortality induced by bark beetles has substantially increased in recent decades, mainly as a result of climate warming (Fettig et al., 2022). Bark beetle-induced forest decline particularly comprises coniferous tree species such as pine and spruce across North America and Europe, leading to unprecedented disturbance rates at large extents within only a few years (Hicke et al., 2020; Thonfeld et al., 2022). As a consequence, forest structure and ecosystem services are altered at multiple scales, and economic loss may be severe (Hlásny et al., 2021b). Although forestry applies management measures aimed at controlling bark beetle infestations, such interventions often lack timeliness and rigor during mass outbreak periods.

A crucial limitation of management efficacy is the detection of an

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infested tree at an early stage of bark beetle development, which would facilitate its sanitation before the brood starts emerging from that tree. A delayed detection with beetles already emerging from the tree substantially reduces, or even completely impedes sanitation efficacy. Frequently applied terrestrial control surveys allow for a timely and accurate detection of freshly infested trees (Wermelinger, 2004; Kautz et al., 2023), however they are costly and thus challenging to implement area-wide. Particularly in forests that are extensively managed, or difficult to access terrestrially, such control surveys can only be executed with a low frequency (e.g. once or twice a year), which is insufficient for hindering outbreak progression.

Remotely-sensed detection approaches have long been expected to provide a potential solution for improving area-wide detection accuracy and accelerating timeliness, thereby ultimately increasing management efficacy and success. Numerous reviews provide an overview on the general principles of remote sensing regarding bark beetle infestation detection, as well as on potentials and limitations of different approaches for both the North American and European species (e.g., Hall et al., 2016; Senf et al., 2017; Stone and Mohammed, 2017; Hollaus and Vreugdenhil, 2019; Dainelli et al., 2021; Duarte et al., 2022; Luo et al., 2023). Despite intensified research, a breakthrough has not yet been achieved to develop and establish an operational system that enables a reliable detection of bark beetle infestations at an early stage (Marvasti-Zadeh et al., 2023). A fundamental question thus still remains unanswered: Do we long for the unattainable – or will promises soon to be met?

2. Century-long history of research

Historical roots of remotely-sensed bark beetle infestation detection go back almost a century to when in the late 1920′s, small aircrafts became operationable for this purpose in North America (Yuill and Eaton, 1949). Over the following decades aerial imagery improved, e.g. resulting in fairly good detection accuracies for late-stage infestation spots of Ponderosa pine (*Pinus ponderosa*) in the late 1950′s (e.g. up to >80%: Heller et al., 1959). A first comprehensive study for Norway spruce (*Picea abies*) infested by the European spruce bark beetle (*Ips typographus*) was employed in Sweden in the early 1970′s, where a nearly linear correlation between detection rate and time after attack could be revealed (Arnberg et al., 1973). Detectability reached 80% at 60 days after the attack – an impressively high detection rate even from today's perspective (cf. Huo et al., 2023). Such early experimental studies used analog aerial photography taken at a variety of scales from approximately 1:1,000 up to 1:100,000, with the imagery being analysed manually via a stereoscope. Since the mid-20th century, and still to this day, airborne-based surveys (aerial sketch mapping) have been increasingly applied area-wide in the U.S., with the primary aim of documenting yearly forest damage extent and associated damage agents (Coleman et al., 2018). Damage polygons are roughly delineated and attributed manually during the flight by an expert. Ultimately, by the 1990′s, a new era had begun for digital imagery, e.g. image generation from Earth monitoring satellites such as Landsat and Sentinel, and several years later from unmanned aerial vehicles (UAV) as well. Increased spectral range, observation frequency, and spatial resolution of these systems have raised hope that algorithm-based infestation detection will soon become operationable (Chen and Meentemeyer, 2016). This hope has been fulfilled, however, only regarding the detection of late infestation stages (White et al., 2005; Marvasti-Zadeh et al., 2023). Applications include, for instance, the retrospective quantification of bark beetle damage, as well as the mapping and analysis of outbreak patterns (e.g., Fernandez-Carrillo et al., 2020; Migas-Mazur et al., 2021). In contrast, it is significantly more difficult to achieve the remotely-sensed detection of early infestation stages, which would allow for the immediate sanitation of the detected tree. This challenge has gained increasing attention in recent research comprising of different platforms and sensor types, and covering a variety of bark beetle-host systems globally, e.g. *Ips* spp.–*Picea* spp. (Huo et al., 2023), *Dendroctonus* spp.–*Pinus* spp. (Gao et al., 2023) or –*Picea* spp. (Cessna et al., 2021), and *Polygraphus* spp.–*Abies* spp. (Leidemer et al., 2022). Early infestation detection of North American mountain pine beetle (*Dendroctonus ponderosae*) has been reviewed by Wulder et al. (2006, 2009), concluding that operationability was hindered by several biological, logistical, and technological limitations at that time. A more recent synthesis by Zahibi et al. (2021) focused on factors affecting the accuracy of satellite imagery, and pointed to several methodological uncertainties in early detection studies. Ultimately, current advances of remote sensing and machine learning (ML)/deep learning (DL) approaches were reviewed regarding a wide range of pests affecting host tree species worldwide (Luo et al., 2023), as well as more specifically regarding bark beetle infestations (Marvasti-Zadeh et al., 2023). While potentials and limitations of remote sensing and detection approaches have been comprehensively reviewed in above mentioned studies, a quantitative synthesis (e.g. regarding the achieved accuracy and timeliness, potential sensor type, and detection algorithm) is still lacking. However, such a synthesis would be essential to properly evaluate research advances and prospects, allowing for their comparison with alternative detection approaches.

Our review thus aims to synthesise the current state of knowledge regarding remotely-sensed early bark beetle infestation detection in a quantitative manner for the first time. In order to keep the scope, we have not included remotely-sensed susceptibility assessments targeting the identification of at-risk trees before infestations occur (e.g., Kozhoridze et al., 2023; Trubin et al., 2023). Since each bark beetle-host tree system has specific characteristics and detectability, we focus explicitly on the *Ips typographus*–*Picea abies* system here, which is most representative of severe disturbance impacts across European forests (Hlásny et al., 2021a). Furthermore, it is the system that has been investigated most frequently regarding early infestation detection by remote sensing (Luo et al., 2023; Marvasti-Zadeh et al., 2023). It is important to note that species-specificity in our study is not considered a drawback, but rather a required prerequisite to account for species-specific traits. Findings and conclusions can thus not easily be generalised for other agent-host systems such as the North American *Dendroctonus* spp.–*Pinus* spp. or –*Picea* spp. systems.

3. Clarification of terminology

When communicating scientific findings, a clear and unambiguous use of terminology is essential (e.g. Kueffer and Larson, 2014). Unfortunately, previous early detection studies have often failed to do so, presumably without any intention. However, such mis-communication might have likely led to a distorted, mainly too euphemistic perception of study outcome. This may, at least partly, explain exaggerated, unrealistic expectations for the potential of remotely-sensed infestation detection, not only by the scientific community itself, but in particular by practitioners and politicians. Thus, we consider it important to clarify terminology here in order to facilitate a more rigorous communication in the future.

One major source of confusion concerns phenology-based terms, such as 'green-attack stage' or 'early-attack stage' , which are particularly misleading when used across different agent-host systems. 'Green-attack stage' has initially been defined as the 1st year of infestation (=year of attack) in North American *Dendroctonus* spp. (e.g., USDA Forest Service, 1935), which exhibit uni- or semivoltine life cycles (Bentz et al., 2014). In contrast, the life cycle of *I. typographus* is typically bi- or multivoltine (except for high elevations or northern latitudes where it tends to be univoltine), resulting in two or three generations per year (Wermelinger, 2004). With differing development periods of damaging species, decay processes of the respective host trees also differ in time. In the *I. typographus*–*P. abies* system in Central Europe, beetles have typically emerged 6–10 weeks after attack, with the tree crown potentially still appearing as green (Bárta et al., 2022). Hence, while adequate for *Dendroctonus* spp., the term 'green-attack stage' is deceptive for *I. typographus* and should thus not be used to avoid mis-communication. Also subsequent attack stages (yellow-red-grey) are species-specific in time and cannot be transferred from one species to another. For instance, a Norway spruce tree can reach the grey-attack stage as soon as two or three months after attack initialisation by *I. typographus*, while host trees attacked by *Dendroctonus* spp. in North America typically appear to be in that stage only a few years after the attack (Thrower et al., 2004). Attention should likewise be given to the term 'early-attack stage', as it is not strictly defined what *early* is referring to. An 'early-attack stage' is surely a different period in time for *Dendroctonus* spp. (at least several months) than for *I. typographus* (few weeks), and it is highly subjective to the perspective taken. For instance, detecting a spruce tree infested by *I. typographus* 6–10 weeks after the initial attack by means of remote sensing is relatively early, but it is most likely not early enough from the management perspective, i.e. to sanitise the tree in time. To overcome such ambiguity, we define in this study, and recommend to do so in the future, the term 'early detection' in the strict management perspective as 'pre-emergence detection'. That means, that a tree is detected at a point in time before bark beetle offspring start emerging from that tree. 'Post-emergence detection' in contrast, is useless for sanitation of a detected tree, but may still support management of subsequently attacked neighboring trees (see Section 8.3 "Implications for bark beetle management").

4. The interplay of beetle phenology, tree physiology, detectability and management

A profound knowledge on coupled processes of bark beetle phenology and host tree physiology over time is crucial to understand their relation to infestation detectability and management efficacy. Principally, three phases I-III can be distinguished following an *I. typographus* attack (Fig. 1): The first phase lasts approximately two weeks after an attack. It consists of beetle-related phenological processes

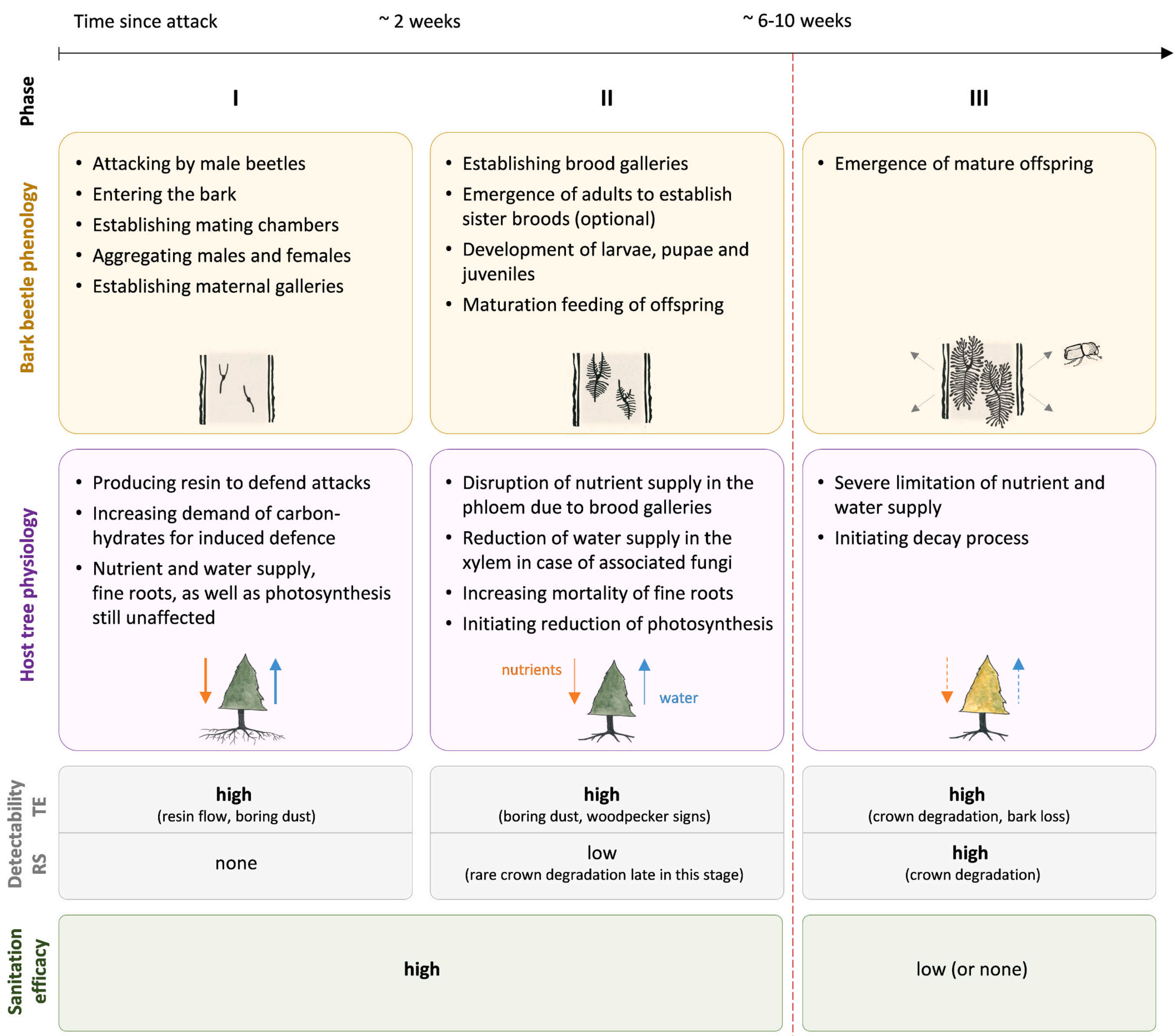


Fig. 1. Schematic overview on interrelations between *Ips typographus* phenology, *Picea abies* physiology, infestation detectability by terrestrial surveys (TE) and remote sensing (RS), and sanitation efficacy over time. Phase I and II are typically called 'green-/early-attack stage', phase III refers to 'red-/grey-attack stage'. The red vertical line highlights the point in time that is critical for an efficient bark beetle management reaction. Note that the scheme relates to the period of *I. typographus* activity only (not considering hibernation within the tree), with time scale representing a typical Central European scenario.

of attacking the tree by male beetles, penetrating through the bark, aggregating conspecifics, establishing the mating chamber in the phloem, and mating with attracted female beetles, which subsequently establish typically two to four vertical maternal galleries. The number of maternal galleries in the phloem depends on the number of copulated females, while the density of established galleries depends on the overall attack density on the tree. Typically, *I. typographus* initiate attacks at easily approachable stem parts below the spruce crown, or at the lower crown with a stem diameter larger than approximately 20 cm. Given a sufficiently high beetle population density subsequent attacks continue downwards, resulting in a full coverage of the stem with galleries in a short timespan (days to a few weeks). During attacks, spruce trees continuously aim to defend against the penetrating bark beetles by constitutive and induced defence mechanisms, such as enhanced resin production (Lieutier, 2002; Krokene, 2015). Intensified defence, however, increases the tree's demands on carbohydrates and may require the re-allocation of carbon reserves (Huang et al., 2020). During drought stress, carbohydrate availability and the generation of hydraulic pressure in resin ducts are further limited, decreasing the likelihood of successfully defended attacks (Netherer et al., 2015). Besides the altered tree carbon investment of primary (growth) and secondary metabolites (defence), tree functioning can be assumed to still be undisturbed in this first stage. Neither transport pathways in the phloem (downward transport of nutrients) and xylem (upward transport of water), nor photosynthesis by the canopy and the uptake of water and nutrients by the fine roots, are negatively affected. Consequently, infestation symptoms merely result from the attack process itself (entrance holes, boring dust), or the immediate tree defence reaction (resin flow), but not yet from subsequent decreases in tree vitality. The only way to detect these early symptoms is through terrestrial surveys (Kautz et al., 2023).

In phase II, horizontal brood galleries are established, where individuals develop from eggs to larvae, pupae, and juvenile beetles. The duration of this phase takes a few weeks depending on temperature (Wermelinger and Seifert, 1998). While offspring are developing, adult beetles may emerge from the tree to establish one or several sister broods elsewhere. The longer the horizontal galleries become over time, and the larger the brood density is at the entire stem or at stem compartments, the more severely nutrient transport in the phloem will be disrupted. In addition to the brood galleries, maturation feeding of offspring further destroys the phloem during the later stage of this phase. As a consequence, tree defence mechanisms collapse and fine root mortality initiates. Subsequently, photosynthesis is limited due to reduced water and nutrient availability in the canopy. In the case of beetle-associated ophiostomatoid fungi, xylem cells can be affected by hyphen, thereby accelerating water deficits in the canopy (Kirisits, 2007). While terrestrially visible infestation symptoms (boring dust, woodpecker-caused small-scale bark loss) appear early in this second phase, changes in the spectral signature that are detectable by remote sensing first initiate with decreasing chlorophyll and/or water content (or associated temperature increase) in the canopy late in this stage. The delay and high variability regarding individual tree's physiological reaction following an attack prevent an accurate detection by remote sensing at this stage. Importantly, sanitation management of the infested tree is efficient only during the first and second phase, as the offspring can be eliminated before emergence.

The third phase begins when the offspring starts emerging from the brood tree, which is the dominant behaviour in *I. typographus* for most of the activity season (i.e., at least until July/August) compared to the offspring remaining in the brood tree for hibernation. Emergence occurs approximately 6–10 weeks after the initial attack in colline to submontane regions in Central Europe (Doležal and Sehnal, 2007; Bárta et al., 2022), and somewhat delayed at higher elevation or in northern latitudes (Fritscher and Schroeder, 2022). Although some infested trees may still remain with a green upper crown early in this stage (Bárta et al., 2022; Huo et al., 2023), canopy degradation gradually amplifies over time as a result of severely limited nutrient and water supply, thus the trees initiate the decay process. At this point, the spruce trees become increasingly easier to detect, for both terrestrial surveys (canopy discolouration, defoliation, extensive bark loss) and by way of remote sensing (notable change in spectral signature). However, a detection cannot be called *early* anymore, as it is too late now for a timely sanitation. Cutting of those trees (i.e., salvage logging) might be even counterproductive both from the bark beetle management (Wermelinger, 2002; Kautz et al., 2013) and biodiversity perspective (Beudert et al., 2015).

In summary, while the detectability of bark beetle-infested trees through terrestrial surveys at any point in time has acceptable success rates, remote sensing approaches first require a significant impact on the tree's canopy functioning. The remotely detectable indicators of canopy vitality (e.g., changes of water and chlorophyll content, cell structure, temperature) are causally influenced only after a chronologically consecutive cascade of several processes initiating during phase II. Hence, remotely-sensed detectability during the activity season is confined by nature, and it thus can be assumed to be rarely feasible before beetle emergence, widely regardless of future technical advances. A promising exception may provide hibernation trees, where a temporal gap in beetle phenology between the phase II (development in autumn) and III (emergence in spring) likely increases the probability of an early detection (see also Section 8.3 "Implications for bark beetle management").

5. Overview of applied detection systems

A detection system consists of a platform, equipped with one or more sensors, and of an analysis workflow. Each platform comes with specific advantages and disadvantages regarding the early detection of bark beetle infestations (Table 1). Out of the four existing platforms, only satellite- and airborne-based systems can be considered suitable for large-scale detection routines due to their ability to provide homogeneous data at large scales. While aerial imagery would be the approach of choice when a flexible image acquisition date or sensor equipment is desired, satellite imagery is beneficial due to the high frequency image acquisition and coverage of up to national or continental scales. Nevertheless, the currently available very high-resolution satellite imagery is costly and typically uses passive sensors that rely on a cloud-free atmosphere. Future developments are likely to reduce the cost of imagery and increase the spatial and temporal resolution, so that high resolution (<5 m) imagery with a frequency of 1–3 days will soon be available at a more reasonable cost. In comparison to the satellite imagery, UAV- and terrestrial-based systems are strongly limited to local- or tree-scale applications, respectively. Terrestrial-based systems and hand-held sensors are typically positioned in the forest at ground level.

Table 1
Overview of the main potentials and limitations of the different remote sensing platforms for the early detection of *Ips typographus* infestations.

Platform	Potential	Limitation
Satellite	• Up to national-/continental-scale application • Frequent data acquisition • Low costs at medium spatial resolution	• Costly at high spatial resolution • Require cloud-free atmosphere (if passive sensors are used) • Defined sensors
Aerial	• Regional-scale application • High spatial resolution • Flexible data acquisition • Flexible sensor equipment	• Costly at high temporal resolution • Data variability
UAV	• High spatial resolution • Flexible data acquisition • Flexible sensor equipment	• Local-scale application • Data variability • Possible restrictions for application
Terrestrial	• High spatial resolution • Flexible data acquisition • Flexible sensor equipment	• Tree-scale application • Data variability

The advantage of UAV- and terrestrial-based systems, which can be applied flexibly in space and time, comes with the challenge of data harmonisation and large data management – issues that have to be solved for automated detection routines based on such platforms. Moreover, UAV applications are subject to legal constraints, e.g. the prohibition of flights beyond visual line of sight (BVLOS). To date, such systems may thereby support infestation detection only locally and at certain points in time. The future will show how realistic it really is to use autonomous swarms of drones for infestation detection.

Remote sensing sensors can be divided into the groups of active and passive sensors. Active sensors emit their own signals and receive a reflected return signal, which is mainly related to structure. Their performance is less influenced by cloud coverage, weather conditions and atmospheric disturbances in comparison to passive sensors. In forestry applications, two types of active sensors are typically used: Lidar (light detection and ranging), and Radar (radio detection and ranging). Lidar sensors emit laser impulses to detect distances and therefore the surface structure of objects. They provide structural information about the land surface (e.g. forest canopy) and are mainly used to produce 3D-point clouds or digital surface models. In contrast, the reflectance of the microwave signals from Radar sensors is influenced by the surface roughness, geometry and humidity of the surveyed surface. The penetration rate of the signals for vegetation or porous sediments depends on the applied wavelength.

Table 2
List of the 26 reviewed studies in chronological order with its methodological parameters; abbreviations: UAV = unmanned aerial vehicle, Aerial = airborne, Multi = multispectral, Hyper = hyperspectral, RGB = visible light, TIR = thermal infrared; 'Sample size' refers to the number of infested trees observed for validation; 'Extent' classes: Stand = <100 ha, Landscape = ≥100 ha to 10,000 ha, Regional = >10,000 ha; 'Algorithm' refers to the applied detection analysis: x = individual/unspecified algorithm, CNN = convolutional neural network, ID3 = iterative dichotomiser 3, GA = genetic algorithm, GLM = generalised linear model, K-means = K-means clustering, LDA = linear discriminant analysis, LR = linear regression, MAXL = maximum likelihood, ME = maximum entropy, NBayes = naïve Bayes, RFG = random frog, RF = random forest, SAM = spectral angle mapper, Stat = statistical test of difference, SVM = support vector machine, THR = threshold-based classifier; 'Period' refers to months and times of data acquisition.

Study reference	Platform	Sensortype (Sensor)	Spatial resolution	Validation (Sample size)	Extent	Ground truthing	Algorithm	Period
Marx (2010)	Satellite	Multi (RapidEye)	>1–5 m	Cross (>100–500)	Regional	Partial	x	Apr-Jun (2)
Lausch et al. (2013)	Aerial	Hyper (HyMap)	>1–5 m, >5–<10 m	Cross (>100–500)	Landscape	-	SVM, ID3, NBayes	Aug (1)
Ortiz et al. (2013)	Satellite	Multi, Radar (RapidEye, TerraSar-X)	>1–5 m	Cross (≤20)	Stand	Yes	ME, GLM, RF	May (1)
Fassnacht et al. (2014)	Aerial	Hyper (HyMap)	>1–5 m, >5–<10 m	Cross (>500)	Regional	-	GA, SVM	Aug (1)
Immitzer and Atzberger (2014)	Satellite	Multi (WorldView 2)	>1–5 m	Cross (>100–500)	Landscape	Partial	RF, LR	Jun-Jul (2)
Ackermann et al. (2018)[a]	UAV	Multi (Sensor not specified)	≤0.2 m	External (>20–100)	Regional	Yes	x	May-Aug (9)
Latifi et al. (2018)	Satellite	Multi (RapidEye)	>1–5 m	Cross (>500)	Landscape	-	RF	Jan-Dec (46)
Tanase et al. (2018)	Satellite	Radar (ALOS PALSAR)	≥10 m	External (>500)	Landscape	-	x	May-Oct (11)
Abdullah et al. (2019a)	Satellite	Multi, TIR (LandSat 8)	≥10 m	External (>500)	Regional	Yes	LR	May-Aug (3)
Abdullah et al. (2019b)	Satellite	Multi (RapidEye, Spot 5)	>1–5 m, ≥10 m	-	Landscape	-	Stat	May-Sep (12)
Abdullah et al. (2019c)	Satellite	Multi (Sentinel 2)	≥10 m	External (>500)	Regional	-	RFG	Jul (1)
Junttila et al. (2019)	Terrestrial	Lidar (FARO X330, Trimble TX5)	≤0.2 m	Cross (≤20)	Stand	Yes	LDA	Aug (1)
Klouček et al. (2019)	UAV	Multi (Sony Alpha A7, Lumix TZ7)	≤0.2 m	External (≤20)	Stand	-	MAXL	Jun-Oct (4)
Yang (2019)	Satellite	Multi (Sentinel 2)	≥10 m	External (≤20)	Landscape	Partial	RF	Jul-Oct (1–2)
Götz et al. (2020)	Aerial	Hyper (APEX)	>1–5 m	Cross (≤20)	Stand	Partial	RF	Jul (1)
Honkavaara et al. (2020)	UAV	Multi, Hyper, RGB (MicaSense Altum, FPI, Sony A7R)	≤0.2 m	Cross (>20–100)	Stand	Partial	RF	Aug-Oct (7)
Bárta et al. (2021)	Satellite	Multi (Sentinel 2)	≥10 m	External (>500)	Regional	-	RF	Apr-Nov (14)
Hellwig et al. (2021)	Aerial	Hyper (HySpex VNIR 1600)	>0.2–1 m	Internal (≤20)	Stand	Partial	THR, SAM	Jul (1)
Huo et al. (2021)	Satellite	Multi, Radar (Sentinel 1, 2)	≥10 m	Cross (≥100–500)	Landscape	Partial	RF, LDA	Apr-Nov (7)
Minařík et al. (2021)	UAV	Multi (MicaSense RedEdge-M)	≤0.2 m	External (>20–100)	Stand	Partial	CNN, RF	Sep (1)
Bárta et al. (2022)	Aerial	Hyper (CASI 1500)	>0.2–1 m	-	Stand	Yes	Stat	Apr-Sep (7)
Dalponte et al. (2022)	Satellite	Multi (Sentinel 2)	≥10 m	Cross (>20–100)	Stand	-	SVM	Jun-Sep (10)
Huo et al. (2022)	Satellite	Multi (Sentinel 2, WorldView 3)	>1–5 m, ≥10 m	-	Landscape	Yes	Stat	Apr-Oct (9)
Mandl and Lang (2022)[b]	Satellite	Multi (Sentinel 2)	≥10 m	Internal (>500)	Landscape	Partial	RF	Mar-Oct (10)
Safonova et al. (2022)	UAV	RGB (Sensor not specified)	≤0.2 m	External (>20–100)	Stand	Partial	CNN	Aug-Sep (2)
Zakrzewska and Kopeć (2022)	Aerial	TIR (ImageR 9400)	>0.2–1 m	External (>20–100)	Landscape	Partial	K-means	Jun (1)

[a] required an additional inquiry to complete listed data.
[b] see also Mandl and Lang (2023) for details.

Passive sensors detect the reflected or emmited radiation in different spectral ranges from blue up to thermal infrared, which are mainly related to the condition of the vegetation. They register radiation in different bands with specific parts of the spectrum that are visual (blue, green, red; 400–720 nm), red-edge (720–780 nm), near infrared (NIR; 780–1000 nm), short-wave infrared (SWIR; 1000–2500 nm) and thermal infrared (TIR; >3600 nm). According to the captured wavelengths, as well as the composition and spectral resolution of bands, they can be grouped into four distinct passive sensor types: (1) visual sensors using the three bands blue, green, and red, (2) multispectral sensors using at least four different bands, (3) hyperspectral sensors using multiple bands with very high spectral resolution, and (4) TIR sensors using wavelengths >3600 nm.

Pre-processing is an important first step in order to prepare the remotely-sensed data for analysis, e.g., by harmonising it, accounting for atmospheric and topographic influences, and providing georectified information. Such pre-processing is considered essential to obtain enhanced accuracies during the subsequent analysis (Lillesand et al., 2015). The pre-processed data thus describe the spectral signature of the tree canopy, with the aim of detecting changes or differences in biophysical and biochemical leaf parameters between bark beetle-attacked and healthy spruce trees. According to their wavelength range, spectral bands each come with specific potentials and limitations and vary in their ability to detect such alterations following an infestation (Lillesand et al., 2015; Luo et al., 2023). More specifically, bands with visual wavelength ranges are most indicative of reductions in leaf pigments and chlorophyll content. Red-edge and NIR capture alterations regarding the cell structure. SWIR can best be used to detect a reduction in foliar's water content or alteration of its components (biochemicals, proteins, lignin, cellulose). Ultimately, TIR reflects the enhanced temperature of a tree's canopy following an infestation.

Regarding the analysis, there is a wide range of algorithms to be applied for early infestation detection with remote sensing data (Table 2; see also Luo et al., 2023; Marvasti-Zadeh et al., 2023). They can be roughly grouped into three branches: (1) classical methods, such as threshold-based classifiers (THR), linear discriminant analysis (LDA), spectral angle mapper (SAM), parametric classifiers (e.g. maximum likelihood: MAXL) and non-parametric supervised classifiers (e.g. maximum entropy: ME), (2) ML, such as supervised learning classification (e.g. support vector machine: SVM, random forest: RF, naïve Bayes: NBayes, iterative dichotomiser: ID3), supervised learning regression (e.g. generalised linear models: GLM, linear regression: LR), and unsupervised learning approaches (e.g. K-means clustering: K-means, random frog algorithm: RFG), and (3) DL as specific subset of ML (e.g. convolutional neuronal networks: CNN, genetic algorithms: GA). All of these analysis approaches have their specific potentials and limitations (see e.g. Marvasti-Zadeh et al., 2023 for details). Since the applied algorithm may have substantial influence on the detection accuracy, a careful choice of the algorithm is important for obtaining optimal results.

Smoothed time series can also facilitate optimised change detection results. However, it should be noted that an approach such as that proposed by Jamali et al. (2023), while demonstrating the potential of the data and algorithms, cannot be applied to near real-time infestation monitoring since it requires data from an entire growing season for fitting the smoothing function.

6. Analysis of recent research

We screened existing scientific literature published during the years 2000–2022 that is related to the *I. typographus*–*P. abies* system and to the following keywords: 'early attack', 'early infestation', 'green attack', 'remote sensing'. Thereby we included studies that explicitly focused on the early detection of *I. typographus* infestation by any kind of remote sensing platform, i.e. satellite-, airborne-, UAV- and terrestrial-based sensor systems. In contrast, such studies detecting late infestation stages of *I. typographus* only, infestations caused by other pest species, or purely lab-based studies (e.g. detecting spectral differences between needles related to *I. typographus* infestation), were not considered in our analysis. For each of the selected studies (n = 26) we documented relevant features regarding study extent, sensor, ground truthing, accuracy, among others (Table 2, Appendix A1), to be analysed. Literature published before the year 2000 is scarce and rather outdated, due to the fact that digital imagery only became available afterwards, while methodological advances notably increased post-2000 as well. Hence, the time period considered in our analysis well reflects the recent evolution and current state of research.

6.1. Publication year and distribution of study sites

While between 2000 and 2009 no study was published, the number slightly increased in the following years until 2017 (n = 5), and the majority of studies (n = 21) appeared between 2018 and 2022. This increasing trend demonstrates a quickly growing research interest regarding early infestation detection, which is also associated with improved detection systems and data processing.

All 26 analysed studies were located within European spruce forests that are susceptible to *I. typographus* infestations (Fig. 2). The majority of them pertain to Central Europe (73%; Germany, Czech Republic, Austria, Switzerland, Italy), while 6 studies have been examined in Northern Europe (Sweden, Finland, Poland), and one study in South-eastern Europe (Bulgaria). An obvious cluster (7 studies) relates to the Bavarian Forest National Park in the south-east of Germany, which might be explained by an extensive time-series of yearly aerial imagery that was used for validation purposes.

6.2. Platform, sensor and spatial resolution

Satellite imagery has been most often investigated (54%), followed by aerial (23%) and UAV imagery (19%). Only a single study has applied

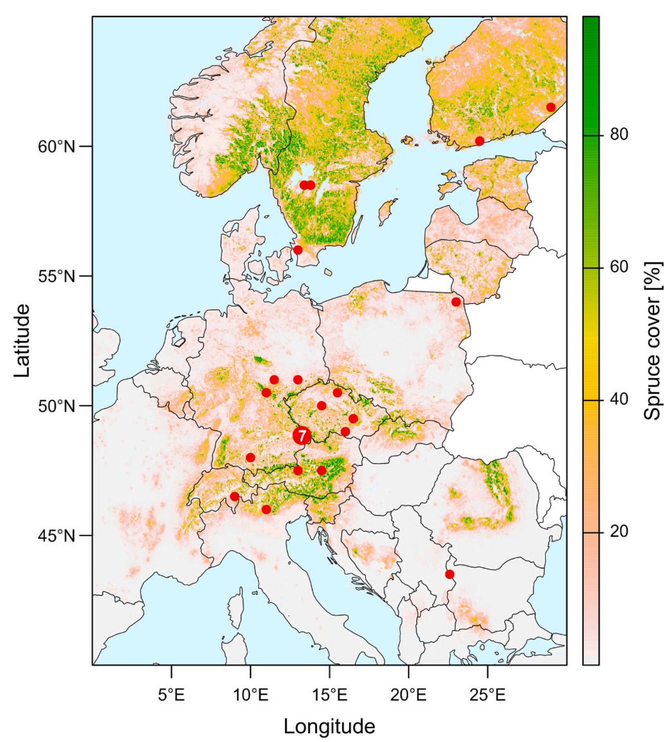


Fig. 2. Recent distribution of Norway spruce (*Picea abies;* according to de Rigo et al., 2016), the major host tree species for *Ips typographus*, and location of study sites as comprised in the analyses (red dots); white areas in Eastern Europe indicate 'no data'.

a terrestrial-based detection approach (Fig. 3a). While satellite and airborne-based studies were examined over the whole analysis period (2010–2022), UAV- and terrestrial-based studies only started in 2018. Passive sensors were the most applied sensor class (87%), with multispectral sensors clearly dominating this group (55%, Fig. 3b). In contrast, active sensors (Lidar, Radar) were only studied 4 times, including 2 times in combination with passive sensors. A clear relation between platform and sensor type was observable: Studied satellite imagery were most frequently from multispectral sensors (Sentinel 2, RapidEye, WorldView 2/3, Spot 5, LandSat 8), and they rarely covered Radar (Sentinel 1, SAR) and TIR (LandSat 8). Aerial imagery typically contained hyperspectral data, while UAV-based approaches mainly used multispectral sensors, and the terrestrial-based approach used a Lidar sensor. Regarding spatial resolution, studied imagery ranged from a few centimeters (UAV, terrestrial) to a few meters (aerial, satellites RapidEye and WorldView 2/3) up to ≥ 10 m (satellites Sentinel 1 and 2, SAR, SPOT 5, LandSat 8). Studies were relatively homogeneously distributed over high-, medium- and low-resolution imagery (Fig. 3c).

6.3. Extent, sample size and frequency, validation and verification

Stand and landscape scale were most frequently addressed for calibration and validation by the analysed studies, when compared to the regional scale (Fig. 3d). Studies validated detections either internally (8%), as cross-validation (42%), or against external data (38%), with the first class being considered the weakest and the latter one the strongest validation method (Fig. 3e). The remaining three studies could not validate their results at all. Out of the 23 studies applying validation, only 30% included validation sample size exceeding 500 infested trees (Fig. 3f). In 26% of the studies the number of investigated early-stage infestations was ≤ 20 trees, which can be considered critically low for training of algorithms and reliable findings. Another critical point is the often very low frequency of observations over time: In half of the studies imagery was acquired and analysed only once or twice during the study period (Fig. 3g). Such low temporal repetition impedes any information on the pre-attack state and the decay sequence. While study periods typically match with the season of potential bark beetle activity (April-September), a smaller part (22%) also considered off-season months (October-March) for acquisition of imagery (Fig. 3h). More than a third of the studies (35%) lack any ground truthing of their remotely-sensed detection results (Fig. 3i). Ground truthing means, that a subset of trees that are remotely classified as ‘infested’ has been terrestrially verified by carrying out control surveys simultaneously, and thereby recording actual infestation symptoms like boring dust, entrance holes, bark loss, crown discolouration or defoliation (Kautz et al., 2023), and/or data on beetles’ developmental stage. Another 42% verified classification only partially, that is for instance by the assessment of external infestation symptoms (but not of beetle development), by applying infrequent or delayed terrestrial verification, or by using auxiliary data such as from phenological models or other remote sensing products. Only the remaining 23% of the studies applied a proper ground truthing – a number that is surprisingly small when considering that ground truthing is a requirement to adequately verify the reliability of classification results.

6.4. Accuracy and timing

To evaluate the achieved accuracy, the user accuracy (or precision) and the producer accuracy (or recall) were extracted from the investigated studies by considering classes ‘early-infested trees’ and ‘healthy trees’ only. User accuracy (UA) is defined as the probability that a value predicted to be in a certain class really is that class. It is calculated as the

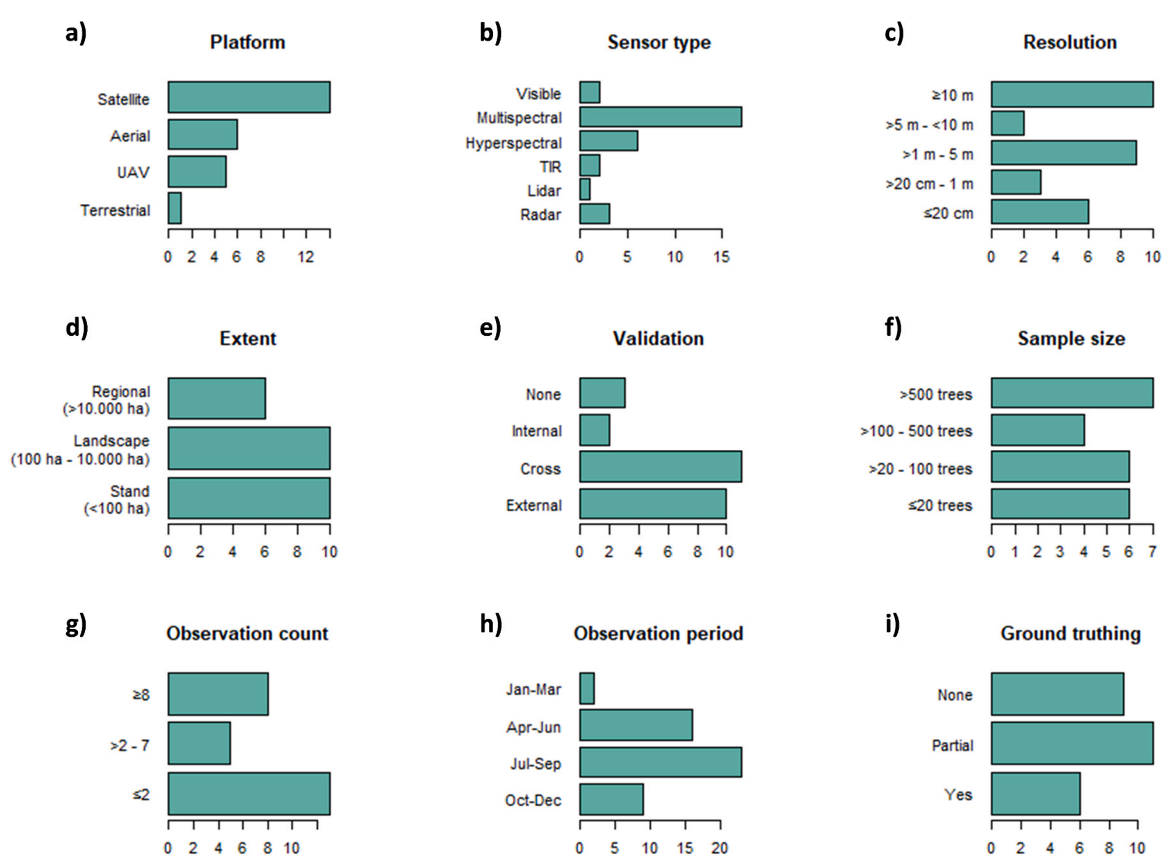


Fig. 3. Frequency of parameters among reviewed studies (n = 26); (a) platform and (b) sensor type used, (c) data resolution, (d) study extent, (e) type of validation, (f) sample size, i.e. number of early-infested trees used for validation, (g) number of acquisition dates within the study season, (h) months of acquisition dates, and (i) ground truthing of early-infested trees. Note that multiple counts were possible in (b), (c) and (h).

fraction of correctly predicted values (true-positives, TP) to the total number of values predicted to be in a class (TP and false-positives, FP):

UA = TP / (TP + FP)

In contrast, producer accuracy (PA) is the probability that a value in a given class was classified correctly. It is calculated as the fraction of correctly predicted values of a class (TP) to the total number of values in that class (TP and false-negatives, FN):

PA = TP / (TP + FN)

The distribution of reference data in the respective classes was assumed to be representative within each study.

Among all studies, UA and PA of early infestation detection was reported in 17 studies. UA ranged from 23% to 79%, with an extreme lower outlier of 2% (mean ± SD 59 ± 20%, median 62%; Fig. 4). Unfortunately, none of the studies exceeded 80% – a threshold based on practical experience and modelling (Pietzsch et al., 2023), which is considered indicative for a robust and beneficial operational system. The highest UA could be achieved with high- to medium-resolution imagery (≤ 5 m) and with the multispectral sensor type, once combined with Radar. Low-resolution satellite imagery (≥ 10 m) resulted only in fair UA values of 53–68%, regardless of sensor type (Appendix A2). PA reached a higher maximum value (95%), but showed basically a similar level (mean ± SD 63 ± 23%, median 67%; Fig. 4). Although UA and PA values reported here might be interpreted as promisingly high at first glance, it is important to note that these values represent the best obtained single result from a range of results documented within each study. This could refer, for instance, to a certain spectral range or to a subset of sample trees.

Moreover, neither UA nor PA alone suffice for an evaluation, but should rather be used in combination. Contrasting values point to an unbalanced adjustment to the reference data. For instance, the combination of high PA but low UA regarding infested trees (e.g., PA = 95%, UA = 23% in Zakrzewska and Kopeć, 2022) indicates that almost all infested trees were detected, but with many false-positives, where healthy trees were classified as ‘infested’. Viceversa, when UA is high, but PA is low (e.g., UA = 76%, PA = 41% in Marx, 2010), a high ratio of detected infestations were correctly detected, however, many infestations failed to be detected. Hence, a valuable detection approach is characterised by relatively high values for both UA and PA. Only three studies achieved ≥ 70% in both metrics and can thereby be considered as most accurate, i.e. Minařík et al. (2021) with UA = 79% and PA = 86%, Immitzer and Atzberger (2014) with 70% and 76%, and Ortiz et al. (2013) with 79% and 73%. In comparison with detection accuracy achieved by frequent terrestrial surveys (e.g., UA = 91% and PA = 93% as reported by Kautz et al., 2023), this is clearly lower (Fig. 4). Interestingly and in contrast to expectation based on previous findings (cf. Luo et al., 2023), the accuracy of hyperspectral sensors (UA = 62 ± 8%, PA = 50 ± 19%, n = 3) is not found to be superior to multispectral sensors (UA = 60 ± 23%, PA = 64 ± 25%, n = 10). The only study, that directly compared these two sensor types, however, revealed slightly more accurate detections using hyperspectral imagery (Honkavaara et al., 2020). Overall, technical advances in very recent years did not lead to drastically more accurate detection. Several studies obtained best accuracy late in the season, i.e. September and October (e.g., Latifi et al., 2018; Huo et al., 2021; Bárta et al., 2022). However, this pattern probably does not result from the more accurate detection of early

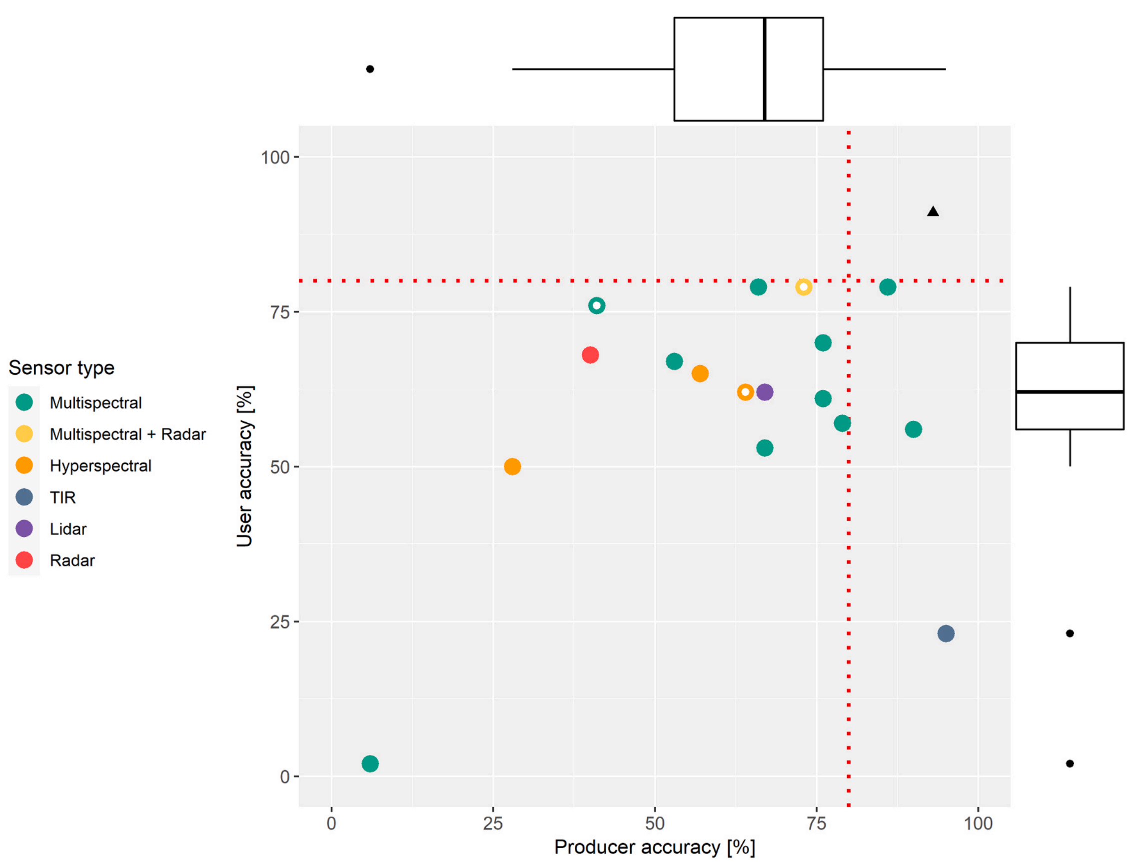


Fig. 4. Accuracy metrics for early detection among reviewed studies (n = 17, see also Appendix A1 and A2 for details). If multiple accuracies were reported within a single study (e.g., by comparing different spectral ranges, indices or sites), only the best-performing experiment is shown. Colour differentiates between sensor types applied, and white dots denote those studies where timeliness of detection proved to be likely. Dotted red lines indicate 80% accuracy as practitioner-based threshold for reliability of the detection. The black triangle represents detection accuracy as achieved by frequent terrestrial surveys (Kautz et al., 2023), and is added for comparison.

infestation stages in autumn. Rather it is based on the more accurate detection of late-stage infestations with beetles having emerged already, which becomes increasingly detectable later in the season. Ultimately, image segmentation, such as tree crown delineation and tree species classification, has been revealed to be an important analysis step before applying the proper detection algorithm, so as to enhance detection accuracy (e.g., Hellwig et al., 2021; Minařík et al., 2021). While UA and PA concerning the detection of healthy trees (Appendix A1), and of trees at a late infestation stage (red/grey), showed typically higher values than the aforementioned UA and PA for early-infested trees, these metrics were not the focus here. Likewise, overall accuracy (OA, Appendix A1) is not appropriate for our purpose, as forest management applications are interested in distinguishing between optimised detection of early infestation (PA) and the reliability of remotely classified early-infested trees (UA). Furthermore, OA is considered to be particularly misleading when the classes of infested and healthy trees are highly unbalanced, as is typically the case in early infestation studies.

Both parameters, accuracy and timing of the infestation detection, are by nature strongly related to each other. That is, the earlier the infestation stage (= short time period after initial attack), the lower the probability that the tree is accurately detected as infested (= worse detection accuracy). As described above, timing is defined here from the management perspective. This means that detection is considered timely as long as the tree is detected as 'infested' *before* the bark beetle brood has emerged. In such cases, immediate sanitation of the tree would be an efficient management measure (vertical red line in Fig. 1). For 19 of the 26 studies it was considered feasible to evaluate whether or not the remotely-sensed detection was done in time in order to relate accuracy and timing. Finally, for only 5 of those 19 studies (Marx, 2010; Ortiz et al., 2013; Honkavaara et al., 2020; Huo et al., 2021; Bárta et al., 2022) timeliness proved to be likely. This means, that only a fifth of all reviewed studies (5 out of 26) likely achieved a timely detection, and that consequently most of best-case UA and PA values given above likely refer to a too-late detection (Fig. 4). In conclusion, shown detectability of infestations can be considered strongly limited as far as regarding both accuracy and timing, and thus insufficient for application to support bark beetle management.

Despite this sobering evaluation, roughly half of the studies (54%) claimed a successful, or at least potentially successful detection approach concerning an early infestation stage (Appendix A1). Reasons for such overly enthusiastic interpretation by the study authors might be twofold: First, remote sensing experts are likely less familiar with the biological background and management requirements (see Section 4 "The interplay of beetle phenology, tree physiology, detectability and management"), thus they may be putting their results in the wrong context. Second, researchers, project funding and scientific journals tend to be interested in publishing 'positive' results (accurate detection), rather than 'negative' results (failed detection). The resulting publication bias towards higher accuracy and timeliness ultimately leads to an overestimated potential of early infestation detection by remote sensing. Our analysis similarly reflects such bias, however, we aimed to reduce it by considering grey literature as well (Fig. 4, Appendix A1 and A2).

6.5. *Spectral range*

Of the 26 studies reviewed, the importance of spectral ranges in differentiating between early-infested and healthy trees was explicitly investigated 23 times. While roughly half of those studies only focused on the differentiation within certain wavelength ranges (bands), including Lidar and Radar, the other half tested spectral indices as well, i.e. combinations of two or more bands. Depending on the sensor used different wavelength ranges were tested and compared. Visible light to NIR (400–1000 nm), followed by SWIR (1000–2500 nm), were most frequently investigated in contrast to TIR (>3600 nm), as well as Lidar and Radar data (total columns in Fig. 5). Regarding the early-detection potential, the blue wavelength ranges clearly falls behind the other studied wavelengths, as demonstrated by the fact that from all of the studies testing such wavelength ranges, only 23% assigned potential to it. Taking into account, that high-scoring TIR, as well as Lidar and Radar, have all been significantly less studied, SWIR appears to be the most promising with 75% relative importance among the well-studied ranges (Fig. 5, Appendix A1). This is in line with findings from a laboratory study that shows differences in spectral reflectance between needles from infested and healthy trees within the NIR and SWIR range

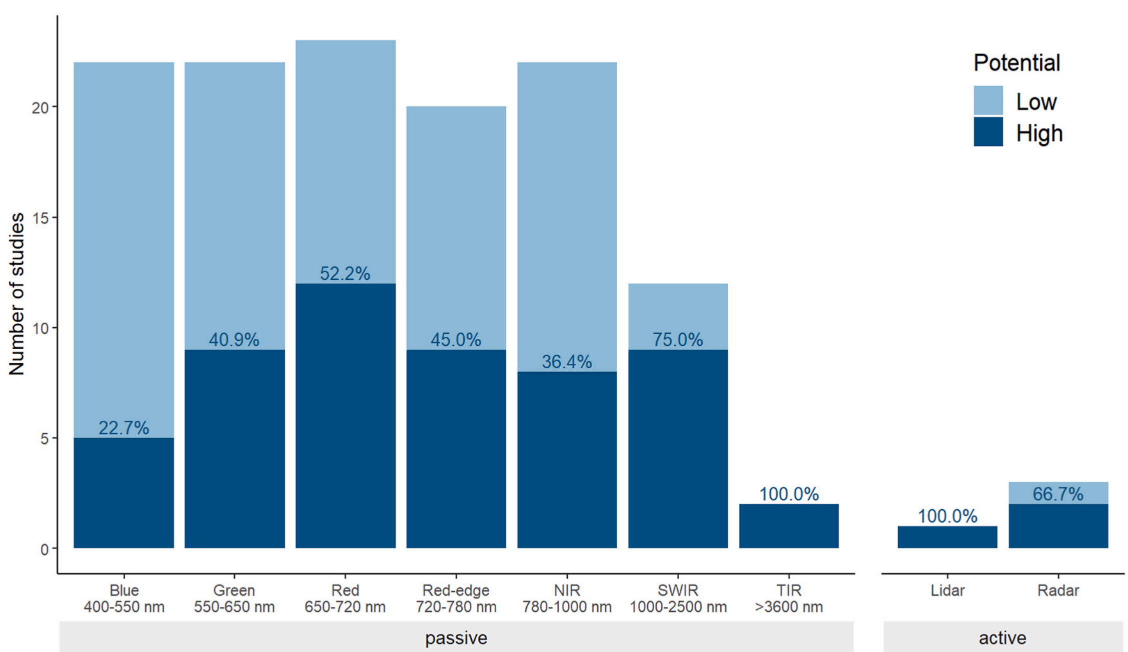


Fig. 5. Relative importance of different wavelengths for the early detection of *Ips typographus* infestation by remote sensing. Total bars represent the number of studies investigating the wavelengths, with light and dark blue shading differentiating between assigned low and high potential, respectively. Figures on top of the dark blue bars quantify the relative importance as ratio between high potential studies to the total number of studies testing such wavelengths.

(Abdullah et al., 2018). Radar data was evaluated with potential both alone (L-band; Tanase et al., 2018), or in combination with multispectral data (X-band; Ortiz et al., 2013). In contrast, Radar (Sentinel 1) was revealed with less potential when compared to multispectral wavelength ranges (Sentinel 2; Huo et al., 2021). Beside single bands of different sensors, numerous spectral indices considering the spectrum from red to SWIR (650–2500 nm) have been identified with high potential (Appendix A1). In particular, two water-related indices (Normalised Difference Water Index: NDWI, Disease Water Stress Index: DWSI) and one "greenness" index (Normalised Difference Vegetation Index: NDVI) were most often revealed with high potential for early infestation detection. Interestingly, studies typically indicated more than one wavelength range or index with high potential, and wavelength ranges or index preferences were not consistent among studies (Appendix A1).

In summary, for the detection of early infestation of spruce trees by *I. typographus*, a certain potential has been attributed to sensors with sensitivity in a wide range of wavelengths, that are related (*i*) to a reduction of chlorophyll mainly affecting the visible green and red light (550–720 nm), (*ii*) to a reduction of water mainly affecting the red-edge, NIR, and SWIR wavelength ranges (720–2500 nm), and (*iii*) to an increase of canopy temperature as a consequence of reduced evapotranspiration and photosynthetic activity affecting TIR (>3600 nm). This outcome is in line with previous knowledge on North American bark beetle-host systems (Mullen et al., 2018; Marvasti-Zadeh et al., 2023), and causally related to physiological processes occurring within trees following an infestation (see Section 4 "The interplay of beetle phenology, tree physiology, detectability and management"). Nonetheless, notable inconsistencies among studies also emphasise the critical challenge to specify sensors and spectral ranges that reliably work across different years and regions.

6.6. Detection algorithms

RF was by far the most often applied algorithm (38% of all studies). This supervised ML algorithm is considered to be robust to overfitting and performs well on high-dimensional data. However, when directly compared with alternative approaches (as done in three studies), RF performed equally well to LR (Immitzer and Atzberger, 2014), or was outperformed by ME (Ortiz et al., 2013) and CNN (Minařík et al., 2021). Since algorithm performance largely depends on the structure and size of the data set (Marvasti-Zadeh et al., 2023), testing and comparing various algorithms on data sets seems advantageous for obtaining optimal detection results. Besides the aforementioned algorithms, there have been numerous others applied, ranging from simple statistical tests for differences, over threshold-based classifiers, to ML/DL approaches (Table 2). The fact that only two studies used advanced DL-based methods such as CNN (Minařík et al., 2021; Safonova et al., 2022) suggests that the limited amount of training data may still pose a substantial obstacle for application. Nevertheless, although being computationally expensive and requiring large data sets, it will likely be the most promising detection algorithm type in future (Marvasti-Zadeh et al., 2023).

7. Cloud cover analysis

We used available data on cloud cover (Finkensieper et al., 2016, 2018, 2020) and surface radiation (Pfeifroth et al., 2018, 2019) from the recent years spanning from 2011 to 2021 to map monthly fractional

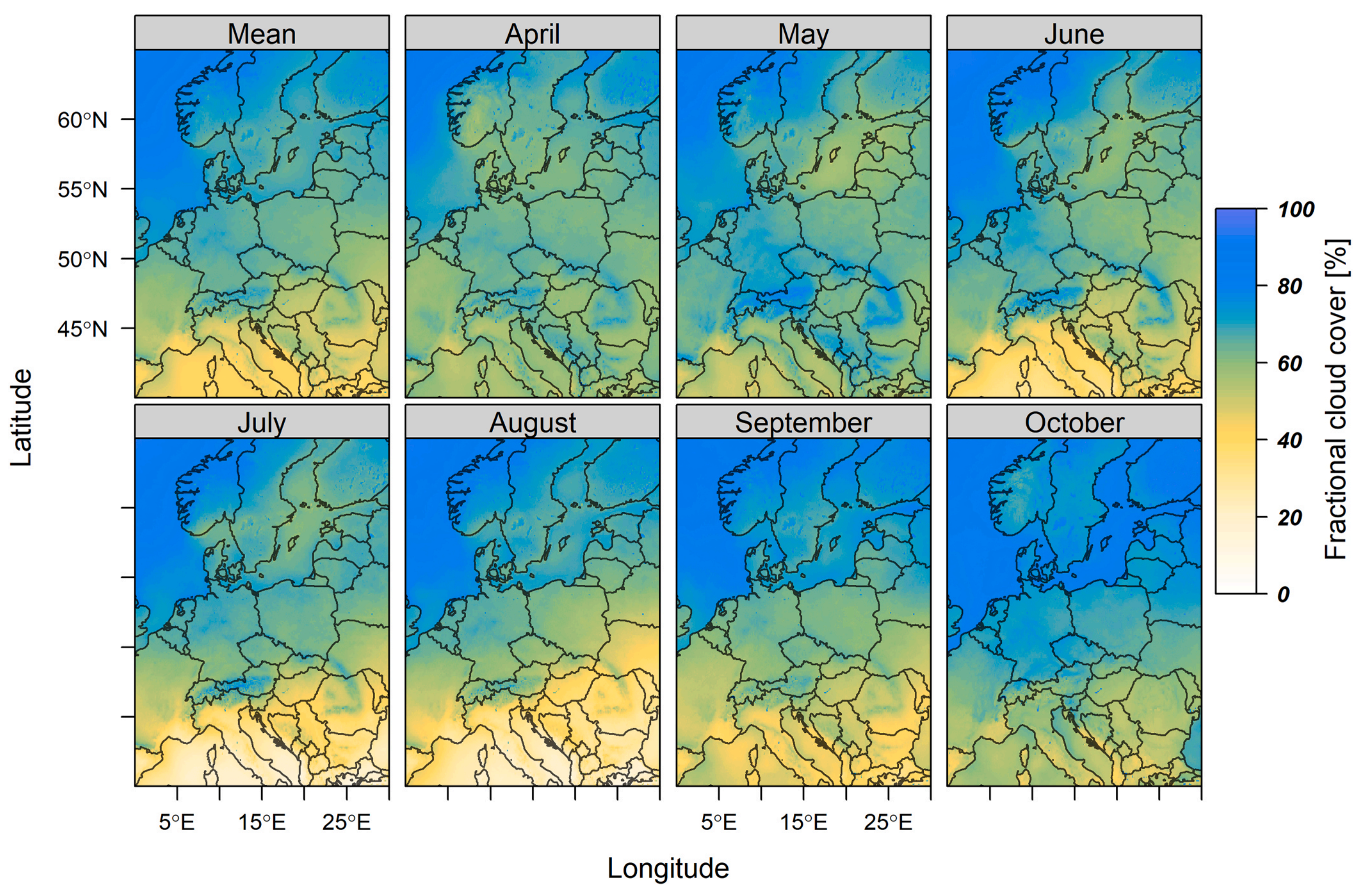


Fig. 6. Monthly mean fractional cloud cover [%] for the period most relevant for early infestation detection (April-October, shown as total and separated for single months) in years 2011–2021 across Europe. Fractional cloud cover represents the percentage of each pixel (0.05° x 0.05°) covered with clouds.
Data Source: Finkensieper et al. (2016, 2018, 2020).

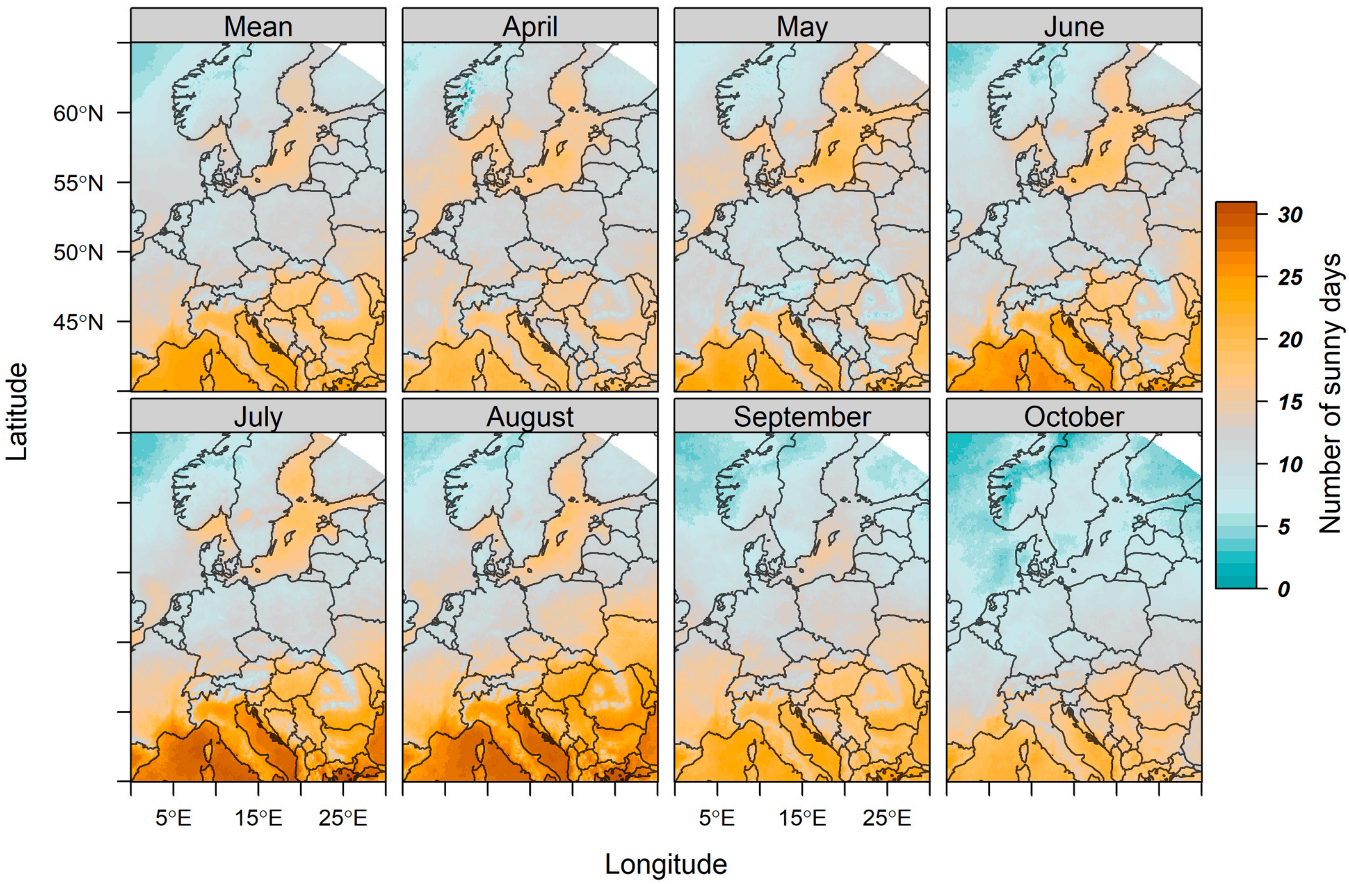


Fig. 7. Monthly mean number of sunny days for the period most relevant for early infestation detection (April-October, shown as total and separated for single months) in years 2011–2021 across Europe. Sunny days represent days with at least 80% of the potential surface downwelling shortwave radiation (100% = completely blue sky) of each pixel (0.05° x 0.05°). The white upper-right corner lacks data.
Data Source: Pfeifroth et al. (2018, 2019).

cloud cover and the amount of sunny days for major parts of Europe. It allows for evaluating the potentials and limitations of obtaining cloud-free satellite imagery for infestation detection. Results show an average cloud coverage of approximately 50–80% in regions significantly affected by *I. typographus* infestations (Fig. 6, see also Fig. 2), depending on location and month. In Central Europe, for instance, lower elevations were less frequently cloud-covered (60–70%) than mountainous regions (70–80%), with the month of April, as well as the months from July to September, being the months least frequently cloud-covered. In Northern Europe there was generally greater cloud coverage (70–80%), in particular for the late season (September, October). In contrast, regions in Southern Europe clearly showed a decreased cloud coverage (40–60%), however, they are also far less affected by *I. typographus* due to the widespread absence of spruce forests (Fig. 2). In relation to cloud coverage, the amount of sunny (largely cloudless) days per month ranged from 7 to 12 days on average in Central and Northern Europe (Fig. 7). Only temporarily and in certain regions were 15 days per month reached or slightly exceeded. Our findings refine and agree well with a previous study analysing global Sentinel-2 imagery taken in 2017 (Sudmanns et al., 2020).

As demonstrated by both metrics, the availability of cloud-free imagery for early-infestation detection is strongly limited by weather conditions in Central and Northern Europe. This means that there is a critical disadvantage for passive sensors (visible, multispectral, hyperspectral and TIR sensors; e.g. as reported by Candotti et al., 2022), which would require a cloud-free atmosphere as a prerequisite. The limiting effect can be illustrated by an example: 60–70% cloud coverage reduces the potential 5-day frequency of Sentinel-2 imagery to a 15-day frequency on average. Given the short time window between the initiation of crown degradation following an attack and beetle emergence (Fig. 1), such delay is almost prohibitive for a timely infestation detection. Moreover, data gaps could be considerably larger than such an average estimate, with the length of the gap difficult to predict. As a consequence, early detection approaches based on passive sensors are relying on a very frequent image acquisition (1–3 days) to potentially overcome this disadvantage.

8. Synthesis, research needs and application

8.1. Substantial challenges remain for early infestation detection

Despite intensified research and increasing technical advances over recent years, there are still numerous challenges to overcome regarding the development of an operational system that reliably detects *I. typographus* infestations at an early stage, i.e. before brood emergence. Some of these challenges represent rather fundamental obstacles, that seem to be very likely impossible to overcome even with consideration of future developments:

- Previous study outcomes were indecisive regarding a spectral range or index best suited for detection. The fact that a certain spectral range or index may work well only for a specific area or year, makes it difficult to develop a high-performing system applicable at any location and time. The transferability of the results is further limited by the lack of physical reference or model for most sensor data. Therefore, calibration needs to be done by empirical models, which require additional normalisation. Only future research considering large-scale und multi-year sampling will be able to prove to what extent higher robustness can be achieved.

- Accuracy and timing of detection is insufficient for timely sanitation, regardless of the platform, sensor type, and spatial resolution applied in the investigated studies. This limitation mainly relies on preset environmental factors regarding the specific bark beetle-host system, such as the rapid brood development of *I. typographus* and delayed crown degradation of *P. abies* following an attack, as well as the high probability and variability of cloud cover in affected areas across Europe. The latter limitation could be solved by using detection systems being less dependent on weather conditions or cloud cover, i.e., active sensors like Lidar or Radar. Aerial or UAV systems flying below cloud level might be advantageous as well, but harsh weather conditions (wind, rain) may complicate or even impede its application. Furthermore, aerial and UAV imagery tend to vary with regard to light conditions (position of the sun, insolation), which complicates any automated detection, and requires additional corrections and/or manual adaptations.
- Applied algorithms detect a reduction in tree vitality – however, such reduction is not necessarily related to bark beetle attacks. In other words, algorithms can detect stressed trees, but they can hardly distinguish between stressors. For example, drought-stressed spruce trees can show similar signatures to trees that have been attacked by bark beetles (e.g., decreasing NDVI and NDWI; Vicca et al., 2016), due to similar physiological restrictions of tree functioning from both stressors. To at least partially control for non-bark beetle related stress, it would be useful to use a continuous time series that also includes the pre-season condition of the trees (Huo et al., 2021).
- Remote sensing approaches rely exclusively on detecting canopy changes (e.g., water and chlorophyll content, or temperature), that exceed the range of natural variability or measurement inaccuracy. Such canopy symptoms typically indicate a late stage of infestation, and can thus be considered unreliable for an early detection. Even by applying high-resolution imagery and most recent DL-based algorithms (e.g., Kanerva et al., 2022) it is hardly possible to detect crowns of infested trees earlier than with the human eye. That is particularly the case, for when crown degradation starts at the lower crown with the crown top still remaining green (Bárta et al., 2021, 2022; Huo et al., 2023). Moreover, remote sensing is completely incapable of detecting early infestation symptoms appearing below canopy, such as boring dust or fallen bark patches due to woodpeckers feeding on bark beetle larvae. Its detection absolutely requires terrestrial surveys, optionally supported by trained sniffer dogs (Kautz et al., 2023; Vošvrdová et al., 2023).
- Ultimately, the cost-benefit ratio provides a relatively tight margin for any potential detection system. Since bark beetle management is most efficient with high sanitation rates of approximately $\geq$ 80% of infestations detected and removed in time (e.g., Pietzsch et al., 2023), the benefit of a system providing only a low- to medium-ranged detection accuracy and timing will be strongly limited in supporting bark beetle management to mitigate infestation progression.

8.2. Lessons learned and future research directions

Multiple lessons can be learned from reviewing past studies on remotely sensed early infestation detection, and used in order to accelerate scientific outcome as well as to facilitate its communication:

Apply a rigorous and target-oriented study design

We strongly encourage further studies on early infestation detection that enable validation of detection results, comparison among approaches, and evaluate the potential for application. In detail, we urge for (*i*) considering a sufficiently large sample size (regarding number of trees, sites, seasons and years), (*ii*) verifying detection results terrestrially (ground truthing), and (*iii*) reporting accuracy metrics (UA, PA) related to early infestation stages. Moreover, testing and comparing different detection algorithms is highly recommended. Precise tree species maps would also be supportive for future detection studies by facilitating the correct choice of classes in the accuracy assessment. Following the strict definition of 'early infestation', the development of brood stages within the detected tree is the most valid reference. Unfortunately, external infestation symptoms, or even auxiliary data such as from phenological models, harvesting or other remote sensing products, have often been used for validation, most likely because they were more readily available. Future studies will need more rigor to advance our current knowledge. Only by employing studies rigorously, the achieved detection accuracy and timing can be compared with alternative remote sensing approaches or terrestrial surveys.

Ensure interdisciplinarity

Conceiving, employing and documenting an early detection experiment is anything but a trivial task to be done by remote sensing scientists alone. Rather it requires a bunch of expertise from different fields, that is of course remote sensing (e.g., for data acquisition and analyses), but also deep data science (e.g., for selecting appropriate ML/DL-based algorithms), forest entomology (e.g., for sampling and ground truthing), and forest management (e.g., for result interpretation). As such experiments are typically part of a scientific project, it is recommended to involve scientific experts from all relevant fields already at the project proposal stage. Finally, results should be discussed with practitioners from bark beetle management, in order to relate scientific output with demands for application.

Communicate explicitly

Unfortunately, research reporting often seemed to be partly driven by creating expectations. Future studies should pay particular attention to a clear and explicit communication of their results. This point not only includes the usage of adequate, species-specific terminology, but also encourages a more balanced interpretation of mixed results and the communication of 'negative results'. Otherwise, the perception of the results remains distorted. Result transfers or generalising conclusions across pest-host systems, e.g., regarding potential spectral ranges for detection, should be avoided when species/genera are characterised by different behaviour and phenological traits.

Our synthesis clearly shows that we have yet to make the important step from individual exploratory studies to research aimed at developing operational detection systems to support bark beetle management. So far, research has addressed the question 'How early infestations can be detected at best?'. While this continues to be an important question, future studies might amplify their focus given towards a more applied perspective and prioritise the robustness of a detection system. Here, robustness means that a near real-time detection system, while not optimal, is reliable in terms of accuracy and timing across regions and years. More precisely, answers are expected to questions such as 'Which spectral bands or indices provide a robust signal for attacked spruce trees?' and 'At which infestation stage is the signal sufficiently robust?'. Then it will be up to the practitioners to decide, whether and to what extent such a system may support their bark beetle management. For such decisions, comparative studies will be most meaningful, i.e. studies comparing accuracy and timing among different detection approaches (such as different remote sensing approaches vs. terrestrial surveys) at the same study site and period. Experimental set-ups as e.g. applied by Einzmann et al. (2021) –although not focusing on early infestation detection–, Dalponte et al. (2023) and Huo et al. (2023) provide promising examples regarding such aspects.

Besides future technical developments regarding detection systems (expected to further increase data availability and quality), parallel advances in ML- and DL-based detection algorithms will also likely contribute to increased infestation detectability (Marvasti-Zadeh et al., 2023). However, small and unbalanced data sets for training of detection algorithms remain a crucial challenge in early infestations. Digitising bark beetle management processes, e.g. App-based infestation documentation, could likely be a way towards obtaining better training data.

8.3. Implications for bark beetle management

As synthesised above, an early detection of *I. typographus* infestations (i.e., before brood emergence) with sufficient accuracy is still not feasible. The extent to which future advances in both remote sensing imagery and detection algorithms can approach or achieve this goal remains uncertain. Most promising for a large-scale operational detection system seems to be imagery with (*i*) sensors with sensitivity in wavelengths from the red to SWIR spectra (possibly with additional structural information from Radar or Lidar), (*ii*) a high spatial resolution, i.e. <5 m, to record single tree crowns or groups of trees, (*iii*) a frequent data acquisition, i.e. every 1–3 days, and (*iv*) advanced methods of ML and DL for calibration and data analysis (e.g., YOLO network architectures; Marvasti-Zadeh et al., 2023).

Regardless of the future prospects, the question remains as to how far remote sensing can support bark beetle management in the present. Although current approaches are unlikely to detect *I. typographus* infestations early enough for sanitation, they can guide terrestrial surveys and thus facilitate timely sanitation of subsequent infestations in the vicinity of the detected tree(s). Subsequent infestations typically occur within short distances (~100–300 m) from previous infestations, with adult beetles establishing sister broods or emerging filial beetles establishing broods of the next generation (Kautz et al., 2011). It is therefore possible to detect infestation spots terrestrially at a relatively early stage of their spread and while they are still small. Infestation detection by remote sensing can be considered supportive either as a back-up to regular and frequent terrestrial surveys, or as stop-gap solution in cases where terrestrial surveys cannot be applied on a regular and frequent basis, e.g. in terrain with difficult accessibility, or in extensively managed forests without sufficient survey capacity. It is important to note that careful terrestrial surveys are still fundamental and without any alternative for an effective outbreak mitigation. While remote detection cannot replace terrestrial surveys, it can be a useful complement to them.

Remotely detected infestations typically lag behind one bark beetle generation during spring and summer (April/May-August) due to the fast development and emergence, but the likelihood for a timely detection increases in autumn (September, October). During this period, the vast majority of *I. typographus* initiates hibernation within the tree and will not emerge until the following spring (Schebeck et al., 2017). Consequently, the excretion of boring dust –a reliable indicator of early infestation in terrestrial surveys– is diminished drastically. For these reasons, remote sensing may be particularly helpful in detecting hibernation trees that are attacked in late July/August, and become detectable in September/October (Dalponte et al., 2023). After that, the time window gradually closes as the sanitation efficacy decreases, because beetle-filled bark patches become loose and drop either passively or during sanitation felling (Kautz et al., 2023).

Ideally, remotely-sensed information on recent infestations, or on reduced vitality/increased temperature of the spruce canopy as a predisposing factor for subsequent infestations (Huo et al., 2021; Kozhoridze et al., 2023; Trubin et al., 2023), can be integrated into dynamic risk assessment applications. Such tools are currently under development (Hallas et al., 2020), which will more accurately assess the risk of *I. typographus* infestation based on daily and forecast weather data, thereby supporting foresters to prioritise terrestrial control surveys and management measures in time and space. Previous approaches used annual data, some including remotely sensed infestations, to predict bark beetle damage within the next season (e.g., de Groot and Ogris, 2019; Duračiová et al., 2020). However, a more timely risk assessment would further accelerate the workflow, make predictions more accurate and ultimately increase management efficacy.

CRediT authorship contribution statement

Markus Kautz: Conceptualisation, Methodology, Investigation, Writing – original draft. **Joachim Feurer**: Investigation, Visualisation, Writing – review & editing. **Petra Adler**: Methodology, Investigation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Data availability

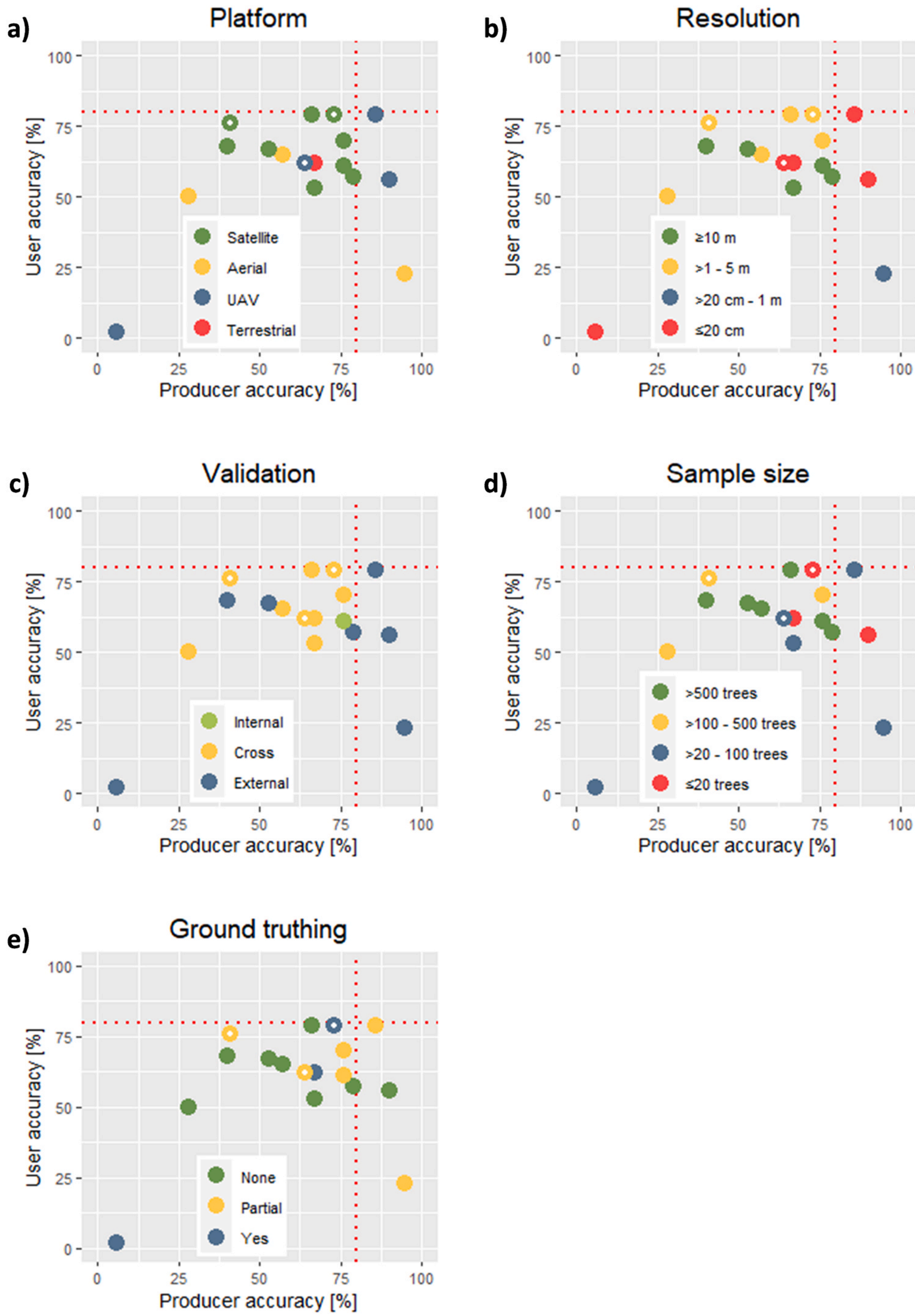
Data will be made available on request.

Appendix

A1. List of the 26 reviewed studies in chronological order with the reported accuracy and spectral performance; PA = producer accuracy, UA = user accuracy (each for early-infested/healthy trees, respectively); OA = overall accuracy (including only relevant classes early-infested and healthy trees); for abbreviations of spectral ranges see Section 5, and for abbreviations of spectral indices see individual studies; light grey shading indicates that the sensor type/spectral range has been studied, and dark grey shading indicates that the study assigned potential for early detection of *Ips typographus* infestations.

Study reference	Accuracy			Early detection claimed?	Sensor type / Spectral range									Spectral indices assigned with potential
	PA (%)	UA (%)	OA (%)		BLUE	GREEN	RED	RED-EDGE	NIR	SWIR	TIR	LIDAR	RADAR	
Marx, 2010	41/100	76/87	-	No										-
Lausch et al., 2013	28/62	50/62	-	No										-
Ortiz et al., 2013	73/99	79/98	97	Yes										NDVI
Fassnacht et al., 2014	57/79	65/69	75	No										-
Immitzer and Atzberger, 2014	76/65	70/72	73	Yes										-
Ackermann et al., 2018 [a]	6/94	2/98	92	No										-
Latifi et al., 2018	66/-	79/-	70	No										-
Tanase et al., 2018	40/91	68/76	74	No										-
Abdullah et al., 2019a	-	-	-	Yes										-
Abdullah et al., 2019b	-	-	-	No										DSWI, LWCI, NDWI, NDRE, NGRDI
Abdullah et al., 2019c	53/-	67/-	-	Yes										NDRE 2, NDRE 3, SR-SWIR, NDWI, DSWI, LWCI, RDI
Junttila et al., 2019	67/75	62/75	-	Yes										-
Klouček et al., 2019	90/83	56/97	84	Yes										GI
Yang, 2019	-	-	88	Yes										DSWI, MSI, NDWI, VM1, water-related VIs
Götz et al., 2020	-	-	-	No										PRI, REP, NDNI, WBI
Honkavaara et al., 2020	64/67	62/55	55	Yes										-
Bárta et al., 2021	79/76	57/80	78	Yes										TCW, NDVI
Hellwig et al., 2021	-	-	-	Yes										own index (HI1)
Huo et al., 2021	-	-	80	No										own index (NDRS)
Minařík et al., 2021	86/69	79/90	82	No										-
Bárta et al., 2022	-	-	-	Yes										REIP, PRI, ANCB$_{650-720}$
Dalponte et al., 2022	67/76	53/66	74	Yes										CLRE, GNDVI, NBRI, NDREI2, NDVI, NRVI, REIP, SLAVI
Huo et al., 2022	-	-	-	No										-
Mandl and Lang, 2022 [b]	76/-	61/-	-	Yes										DSWI, NDI45, NDWI
Safonova et al., 2022	-	-	-	No										-
Zakrzewska and Kopeć, 2022	95/67	23/100	60	Yes										-

Footnote: [a] required an additional inquiry to complete listed data, [b] see also Mandl and Lang (2023) for details



A2. Accuracy metrics for early detection among reviewed studies (n = 17). If multiple accuracies were reported within a single study (e.g., by comparing different spectral wavelength ranges, indices or sites), the best-performing experiment is shown only. Colour differentiates between (a) platform, (b) data resolution, (c) type of validation, (d) sample size (i.e., number of early-infested trees) used for validation, and (e) ground truthing applied. White dots denote those studies with timeliness of detection proved to be likely. Dotted red lines indicate 80% accuracy as practitioner-based threshold for reliability of the detection.

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