

Article

Stand Properties Relate to the Accuracy of Remote Sensing of *Ips typographus* L. Damage in Heterogeneous Managed Hemiboreal Forest Landscapes: A Case Study

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Abstract

Under the intensifying water shortages in the vegetation season, early identification of *Ips typographus* L. damage is crucial for preventing wide outbreaks, which undermine the economic potential of commercial stands of Norway spruce (*Picea abies* Karst.) across Europe. For this purpose, remote sensing based on satellite images is considered one of the most efficient methods, particularly in homogenous and wide forested landscapes. However, under highly heterogeneous seminatural managed forest landscapes in lowland Central and Northern Europe, as illustrated by the eastern Baltic region and Latvia in particular, the efficiency of such an approach can lack the desired accuracy. Hence, the identification of smaller damage patches by *I. typographus*, which can act as a source of wider outbreaks, can be overlooked, and situational awareness can be further aggravated by infrastructure artefacts. In this study, the accuracy of satellite imaging for the identification of *I. typographus* damage was evaluated, focusing on the occurrence of false positives and particularly false negatives obtained from the comparison with UAV imaging. Across the studied landscapes, correct or partially correct identification of damage patches larger than 30 m² occurred in 73% of cases. Still, the satellite image analysis of the highly heterogeneous landscape resulted in quite a common occurrence of false negatives (up to one-third of cases), which were related to stand and patch properties. The high rate of false negatives, however, is crucial for the prevention of outbreaks, as the sources of outbreaks can be underestimated, burdening prompt and hence effective implication of countermeasures. Accordingly, elaborating an analysis of satellite images by incorporating stand inventory data could improve the efficiency of early detection systems, especially when coupled with UAV reconnaissance of heterogeneous landscapes, as in the eastern Baltic region.

Keywords: false negative; identification error; satellite images; UAV imaging; stand properties; heterogeneous landscape



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1. Introduction

The increasing impact of natural disturbances and their legacy effects, such as pest outbreaks on forests [1], highlight the necessity for early warning systems to mitigate economic, as well as ecological, consequences [2,3]. In this regard, remote sensing is a crucial tool for prompt identification of outbreak sources, aiding timely application of countermeasures or salvaging efforts [4–6]. Satellite images of different spectral composition have been the main

source of data for remote sensing due to availability and cost efficiency, as well as regularity of acquisition [7,8]. This allows for early evaluation of tree stress level based on foliage fluorescence estimates [9,10]. However, due to long-distance estimates, the resolution of civilian commercially available multispectral images is still limited [4,11], raising concerns about their accuracy in highly heterogeneous landscapes [12]. Also, the analysis of satellite imaging is sensitive to artefacts, such as infrastructure objects and cloudiness [13,14].

As an alternative, aerial imaging from high (>3 km) and particularly low altitudes (<3 km) can be used to increase the resolution, although such image acquisition is more resource-intensive and weather-sensitive, with considerably lower coverage [15,16]. Nevertheless, aerial imaging can significantly complement the assessment of problematic spots identified by the satellite [17,18]. On the other hand, aerial reconnaissance with unmanned vehicles (i.e., drones) is becoming increasingly available, automated, and efficient [15,19]. Nevertheless, for the remote-sensing-based early warning system to be efficient in terms of preventive measures, allowing for substantial management of adverse effects, high identification accuracy (e.g., >80%) is needed [19,20]. Furthermore, the structure of the erroneous identifications is crucial, as false positives are less relevant than false negatives due to possible misidentifications of sources (initials) of pest outbreaks [21–23]. False positives, though, can increase management costs due to redundant surveys [6].

In the Baltic Sea region and the Baltics in particular, Norway spruce (*Picea abies* Karst.) is an economically and ecologically important species [24] which occurs in the trailing part of its distribution [25], thus rendering it highly susceptible to climatic and biotic disturbances [2,26,27]. Although growth of Norway spruce has been predicted to increase in response to an extended vegetation period [28,29], the intensifying water deficit and the effect of wind disturbance are drastically increasing the mortality of maturing and mature trees due to outbreaks of European spruce bark beetle *Ips typographus* L. (Insecta, Coleoptera) [2,26]. As successive boosting of several generations of *Ips typographus* over a couple of seasons is necessary for a wider outbreak to develop [30,31], early identification of affected trees (sources) is crucial for effective countermeasures and reduction in economic losses [21,22,32]. This implies the necessity of identification of small-sized damage patches in the forest landscape [31], particularly emphasizing the relevance of false negative errors. Still, due to highly heterogeneous forest landscapes, identification of small-sized damage patches can be particularly challenging [11,12]. Hence, aggregation of several sources of information might be needed for reliable detection [15,19].

In the Baltics, a few remote sensing solutions based on “Sentinel 2” images are marketed for forest health monitoring, such as “Collective Crunch” (used by the larger-forest management companies) and solutions from the “Baltic Satellite Service LTD”, Latvia, which are marketed to small- and medium-forest management companies. These solutions are based on machine learning and the “Baltic Satellite Service”, including the results from the European Space Agency’s project “EO Baltic platform for governmental services (EO-BALP)”. Both of these are advertised to provide high accuracy (e.g., >80%), though considering the heterogeneity of the landscape [12] and dense infrastructure (artefacts), the accuracy with respect to the demands of the smaller-forest management companies/owners is not yet fully assessed.

This study aimed to evaluate the accuracy of damage identification by remote sensing based on the solutions marketed for small- to medium-forest owners and management companies, focusing on the type of identification errors (false positives and particularly false negatives) in Latvia, Europe. We assumed that the satellite images are suitable for larger outbreaks, while being biased toward damaged patches of smaller size under a highly heterogeneous landscape.

2. Materials and Methods

2.1. Dataset and Sampling

The tested solution provided by the Baltic Satellite Services Ltd. was based on multispectral PlanetScope satellite images. PlanetScope satellite imagery provides high-resolution, high-frequency Earth observation data captured by the PlanetScope constellation, operated by Planet Labs Inc. (San Francisco, CA, USA). The constellation comprises hundreds of small satellites, which collectively enable high temporal resolution, capable of imaging the entire Earth's land surface on a near-daily basis. The high revisit rate is particularly advantageous for time-series analyses. PlanetScope imagery includes four spectral bands at a spatial resolution of 3 m per pixel: blue (455–515 nm), green (500–590 nm), red (590–670 nm), and near-infrared (780–860 nm) [33].

Based on the rasters representing all four bands, a vegetation index was developed in accordance with the general principle, namely statistical scaling, similar to, e.g., NDVI, highlighting the fluorescence of chlorophyll and hence tree stress [34]. However, due to commercial interest, the exact details of the index and processing algorithm are not fully disclosed. The index was developed based on automatically inspected images of good quality (absence of clouds, etc.) acquired for the vegetation season (June–September 2024); forested plots, with Norway spruce as the dominant species, were randomly selected across the country. Still, the images contained small cloud or haze patches (<1.5% of area).

The damage identification algorithm consisted of two main steps. Firstly, pixel-based damage detection, and secondly, stand-level patch identification. The pixel-based workflow analyzed a time series of the developed vegetation index to identify preconditions for crown damage at the pixel level; stability of the changes in the change of state was characterized by the standard deviation. A damage label was assigned to a pixel if a significant deviation (>2 standard deviations) from the background was detected after the damage detection, and such deviations should be consistent in the post-damage images.

Detected patches smaller than 30 m² were excluded from analysis to reduce the noise, even though such patches can be initials of wider outbreaks and infestations [21,22]. In the second step, stand-level analysis was performed by evaluating the spatial extent, shape, spectral characteristics, and additional properties of contiguous pixel clusters (connected components), which have been labelled as damaged using a manually trained machine learning algorithm. The identified patches were considered reliable if the difference from the surrounding pixels within a 12 m buffer (four-pixel sizes) was consistent during the calibration period since the emergence of damage. Hence, the patch very likely represented dead tree crowns. During the calibration, the tested solution has been estimated to be highly (e.g., >80%) accurate in terms of the identification of patches >30 m².

To verify the accuracy of the identification of damage from satellite images, a stratum of 100 Norway spruce stands representing local landscapes with an age of 39–186 years, an area of 0.5–7.2 ha, and where spruce formed 40%–100% of the standing volume of canopy growing in sites with freely draining mesotrophic mineral sandy or silty deep mineral soil were selected from forest inventories from three vicinities in the central part of Latvia (Figure 1). The sites were chosen to represent the local variability of growing conditions and due to accessibility. Such site conditions are typical for the majority of commercial stands of Norway in Latvia. For these stands, damage identification was performed by the developed algorithm based on the satellite image acquired on 30 September. As the control, in the selected stands, aerial reconnaissance flights with DJI P4 Multispectral (SZ DJI Technology Co., Ltd., Shenzhen, China) were made in October and November 2024. Low-altitude photogrammetries were made for each stand (110 m altitude, 85% image overlap, 6 m/s speed). Hence, the most recent satellite images (acquired at the end of September), based on which the damage patches were identified, showed up to a 1.5-month

time gap, during which the symptoms of affected trees could have progressed, even though the trees and pests were becoming dormant.

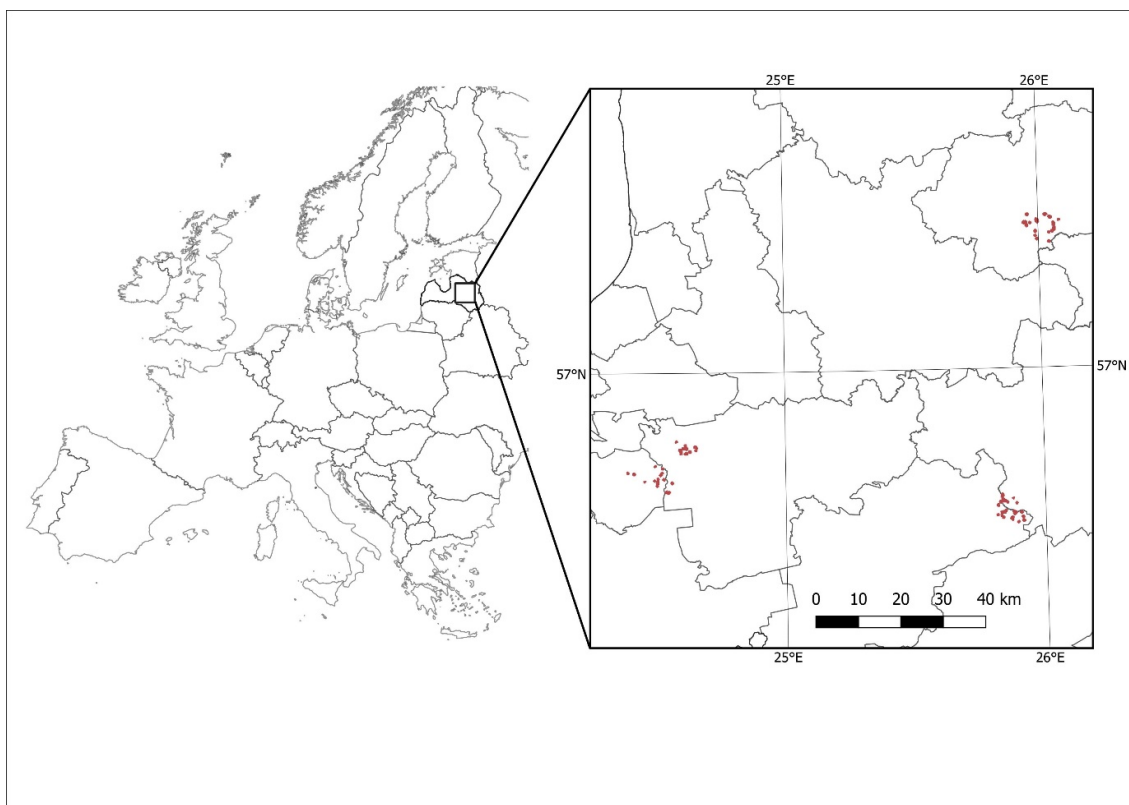


Figure 1. Location of the stands of Norway spruce used for the photogrammetric evaluation of the accuracy of identification of *Ips typographus* L. damage based on the satellite image analysis. Borders of the analyzed forest patches in real size are shown in red.

2.2. Tree Identification, Spectral Indices, and Accuracy Proxies

To identify the location of trees in the studied stands, the difference between the digital elevation model and digital surface model obtained from the Latvia Geospatial Information Agency was derived using Agisoft software (Metashape, v2.2.7), thus identifying apices of the canopy. Based on the aerial reconnaissance multispectral images, the Normalized Difference Vegetation Index (NDVI) raster was calculated based on the intensity of near-infrared (NIR) and red (RED) bands as $NDVI = (NIR - RED) / (NIR + RED)$. This was sufficient to identify dying and dead spruce trees [35,36]. The alignment of the satellite and UAV images was manually inspected, and linear changes in alignment of the latter based on landmarks were introduced if necessary. The alignment was visually evaluated at the scale of forest patches. For each of the selected stands and their surroundings covered by the aerial reconnaissance image, all of the dead and dying Norway spruce trees were identified by manual inspection of photogrammetries. Based on the location and canopy of trees, the patches with dead and or dying Norway spruce were distinguished and measured manually. Satellite images in general covered areas that exceeded the selected stands by at least 150 m.

For the description of the accuracy of satellite identification, the misidentification of the actual damaged tree patches was evaluated in terms of false negatives and false positives. Considering that the patches might also show partial overlap between the satellite and UAV images, the false positive and false negative identification was expressed in three categories (grades). For false positives, the grades were as follows: correct recognition (patches show complete overlap, although sizes might vary <20%); partial mismatch (a few

scattered damaged spruces present in the patch, yet >90% of the trees are healthy); and false positive (no damaged spruces in the patch). Regarding false negatives, the grades were as follows: correct identification (no damaged tree groups outside the identified patch within same forest compartment, although scattered trees might be visible in adjacent stands); partial match (presence of small groups of damaged trees, with the size of group smaller than the adjacent correctly identified patch); and false negative (medium to large groups of damaged trees outside the identified patches).

2.3. Data Analysis

To assess the effects of stand properties on the probabilities of false positives and false negatives of the satellite-based recognition of *Ips typographus* damaged Norway spruce, mixed effects ordered binomial regression (cumulative link mixed model) was used. As the criteria for grading the errors, and particularly partial errors, can differ and represent mixed intensities and spatial overlaps, the responses were expressed as ordered categorical variables rather than numerical (parametric) criteria. The tested stand properties (fixed effects) were: stand age, site type, proportion of Norway spruce in the standing stock (degree of admixture), forest stand area, as well as the area of the detected damage patch, number of damaged trees within the patch, and number of damaged trees in adjacent stands (proxies of canopy densities). Interactions were not evaluated due to the limited scope of the dataset, as their inclusion prevented models from converging. To account for the spatial dependencies, vicinity and forest stand were included in the models as nested random effects to account for the differences in the number of damage patches per stand.

As the underlying causes of false negatives and false positives can differ [23,36,37], and the definitions of partial errors vary, they were analyzed separately. However, the set of the tested fixed effects was maintained to highlight the differences in underlying mechanisms. Bidirectional selection of fixed effects based on Akaike Information Criterion and performance metrics was used to eliminate variables lacking significance for either false positives or negatives. The analysis was also conducted for a joint estimate of the co-occurrence of both errors, in which case, the ordering was based on joint ranking, while prioritizing false negatives over false positives (if the co-occurring ranks matched) due to their relevance for management. As the symptoms of affected trees appear rapidly, yet the pest activity in September is low as it becomes dormant [31], the possible effects of a time lag between satellite and UAV imaging, during which new patches might have emerged, were considered negligible. The likelihood ratio χ^2 test was used to evaluate the significance of the fixed effects. Marginal pseudo- R^2 (Nagelkerke; Cragg and Uhler method) was calculated for the description of the overall model performance (goodness of fit statistic), as the conventional estimation of R^2 is not achievable for such models. The data analysis was conducted in R v4.5.2 [38], using the package “ordinal” [39].

3. Results

In total, the accuracy of damage identification was evaluated for 260 damage patches distinguished based on the satellite imaging. The number of damaged patches per forest stand ranged from 1 to 12 (mean of 3.0), yet the area of the identified damaged patches was rather small, ranging from 0.01 to 1.45 ha (mean of 0.13 ha). Accordingly, the damaged patch size relative to the stand area ranged from 0.2% to 71.6% with a mean of 9.1%.

The evaluated satellite estimates were generally biased, as correct (lacking false positives and false negatives) recognition occurred only in 18% of the cases, while the majority of the estimates (55%) were correct regarding one estimate, and erroneous or partially correct regarding the other estimate. In 12% and 15% of estimates, both estimates were erroneous or erroneous and partially correct, respectively. When compared separately,

false positives (28%) and partial false positives (25%) were less frequent compared to false negatives (37%) and partial false negatives (32%). Accordingly, false positives and false negatives separately were not identified in 48% and 31% of cases, respectively.

The misidentification of *Ips typographus* damages was affected by stand properties; the strength of the effects differed by error (Table 1). Hence, the identification models might be improved by supplementation of, e.g., forest service databases. False positives showed the strongest effects of site conditions, as indicated by the highest marginal R^2 value, which, considering that the biological system was evaluated, appeared moderately high. In contrast, false negatives, as well as the co-occurrence of both errors, was considerably less related to stand properties, as the R^2 values of respective models were three times lower (0.115 and 0.105, respectively). The probability of misidentifications was affected by local conditions (forest block), as suggested by the random variances, particularly in the case of false negatives, thus indicating uncertainties due to local conditions, such as artefacts, stand history, and levels of stress for trees.

Table 1. The strength (χ^2) and significance of the tested fixed effects (stand properties) on the probability of errors in *Ips typographus* L. damage patch identification in Norway spruce stands in Latvia based on satellite imaging and variance of the fixed effects, as well as the pseudo- R^2 value of the cumulative link mixed models. Significance code, p -values: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	False Positive	False Negative	Both Errors Pooled
Fixed Effects, χ^2			
Stand age	1.0	3.9 *	4.5 *
Stand area	3.1	16.0 ***	0.1
Share of spruce in the standing stock	0.2	1.3	0.1
Patch area	20.7 ***	1.8	8.7 **
Number of damaged trees	43.8 ***	1.1	18.2 ***
Number of adjacent damaged trees	18.9 ***	0.8	4.2 *
Random Effects, Variance			
Vicininty	0.240	0.001	0.001
Forest block	0.001	22.09	1.069
Forest stand	0.001	0.001	0.001
Model Performance			
Pseudo- R^2 (Nagelkerke; Cragg and Uhler)	0.379	0.115	0.105

The probability of false positives, which showed the strongest environmental effects (Table 1), was primarily related to the number of affected trees, which generally had an explicit negative effect (Figure 2b). This effect, however, was observed when the number of damaged trees was below 50, after which the accuracy of identification decreased rapidly across the studied gradient. In contrast, the area of the identified patch and the number of adjacent damaged trees had positive effects on the accuracy (Figure 2a,c); however, the effect of the latter was milder, as indicated by a flatter shape and wider confidence intervals of the regression slopes. Regarding the number of adjacent damaged trees, partially correct identification was quite common at the lower end of the studied gradient.

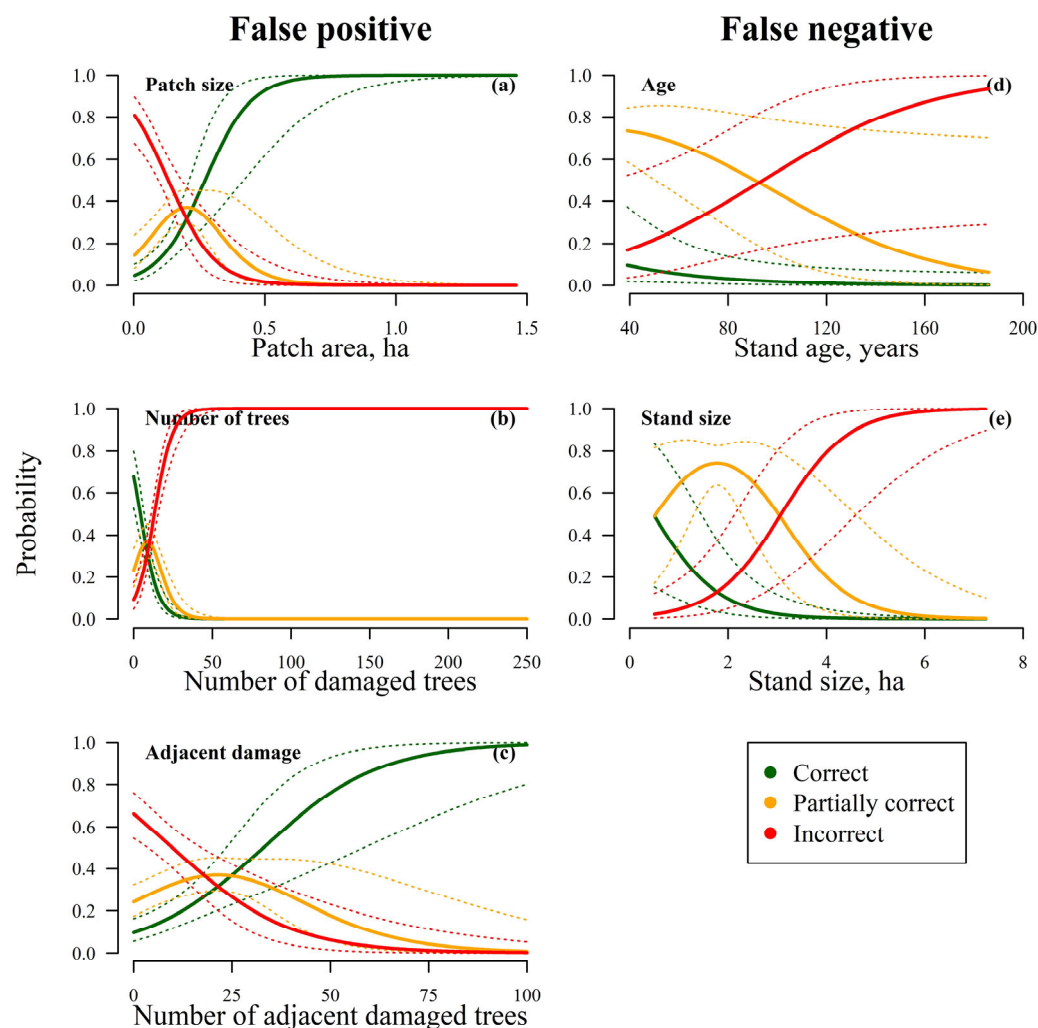


Figure 2. Estimated marginal probabilities of correct and partially correct satellite-based identification of *Ips typographus* L. damage patches larger than 30 m² in conventionally managed maturing to mature hemiboreal Norway spruce stands in terms of false positives and false negatives according to the identified patch and stand properties, as determined by a mixed effects cumulative link model in three vicinities in highly heterogeneous forest landscapes in Latvia, Europe.

Stand size (area) had a negative effect on the accuracy of identification in terms of false negatives, particularly as the partially correct identification probability decreased, with the probability of the false negatives being rather low except for the smaller stands (Figure 2e). This implied effects of artefacts. A similar yet weaker effect was estimated for stand age, for which an even higher probability of partially correct identification of patches was estimated at the lower end of the gradient (Figure 2d).

When the co-occurrence of both errors was analyzed (Figure 3), the effects of site properties were explicit for the strongest contrasts. The number of damaged trees had the strongest (Table 1) negative effect on identification accuracy, which was explicit for the co-occurrence of both errors, for which responsiveness was estimated within the interval of 0–150 trees (Figure 3c). The number of damaged adjacent trees generally had a positive effect on accuracy, particularly regarding absolutely correct identification, yet partially correct identification of patches was related to the lower part of the gradient (Figure 3d). Patch size had a positive effect on accuracy, particularly of the correctly identified patches (Figure 3b). For the other cases, patch size had negligible effects, as indicated by near-flat response curves. Stand age was estimated with the weakest, though negative, effect on the accuracy of damage patch identification (Figure 3a). Even though the regression

slopes were near-horizontal, the erroneously identified patches showed a gradual increase throughout the entire gradient.

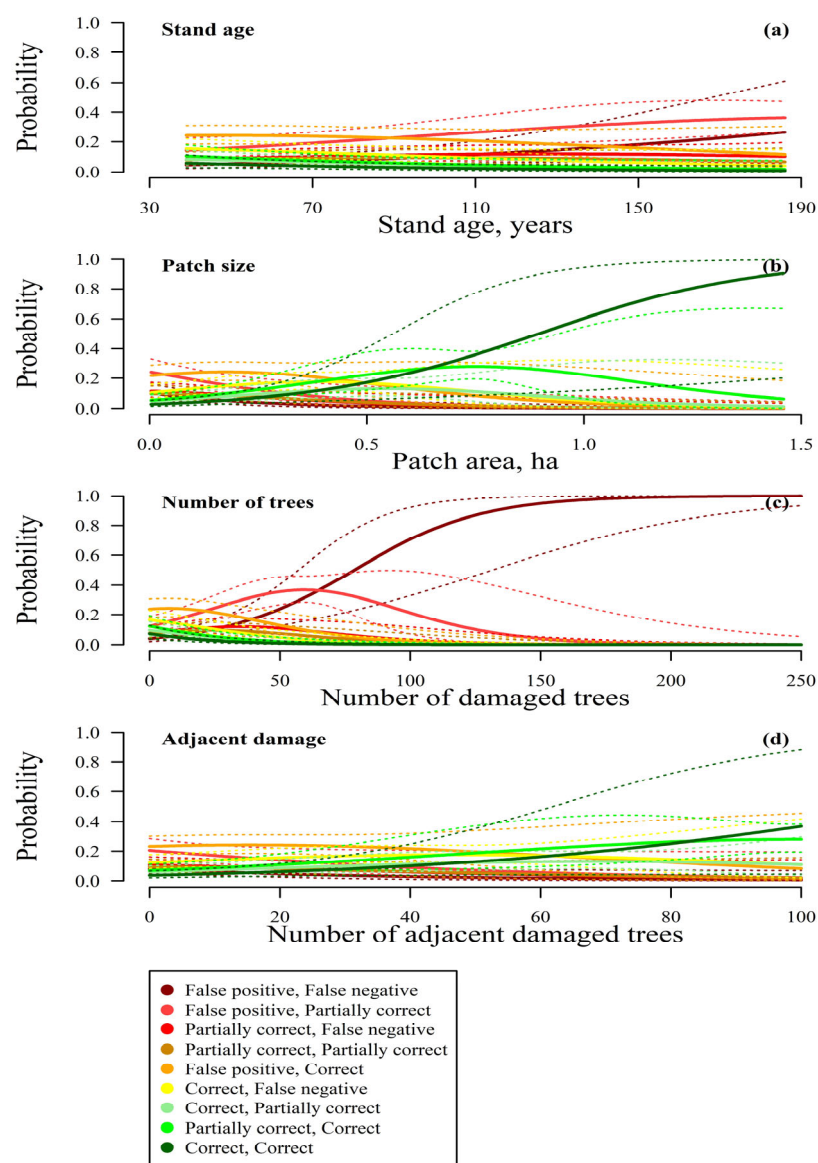


Figure 3. Estimated marginal probabilities of co-occurring false positives and false negatives for satellite-based identification of *Ips typographus* L. damage patches larger than 30 m² in conventionally managed maturing to mature hemiboreal Norway spruce stands according to the identified patch and stand properties, as determined by a mixed effects cumulative link model in three vicinities in highly heterogeneous forest landscapes in Latvia, Europe.

4. Discussion

4.1. Overall Identification Accuracy

Although significant differences in canopy reflectance spectra even during the “green-stage” of *Ips typographus* attacks have been reported [5,40,41], it remains challenging to use vegetation indices to reliably (e.g., with the accuracy of >80% of cases) distinguish healthy, susceptible, and green-attacked trees with decent accuracy [7]. Accordingly, the identification accuracy of damaged patches, particularly small-sized ones, was generally biased, as indicated by the occurrence of errors (Figure 2). A high percentage of erroneously or partially correctly detected patches based on the satellite imaging can be linked to the heterogeneity of the eastern Baltic forest landscapes [11,12], even though the resolution of

the used satellite images has increased compared to, e.g., Landsat images. Nevertheless, similar levels of errors have been previously reported for similar endeavours [42].

The potential effects of false negatives in detecting spruce damage are often overlooked [23]. From a forest management perspective, false positives are less detrimental than missing information (false negatives) about the actual infestations that could lead to substantial economic losses due to potential unaccounted sources of outbreaks [21,22,32]. For *Ips typographus*, false negative results remain a critical issue during endemic population phases, when early identification of initial damage patches, often preceded by dry and hot weather conditions, is essential to minimizing economic losses [4]. Hence, such an identification error would facilitate *Ips typographus* spread, causing economic losses due to an excessive number of spruces killed before countermeasures are implemented [21,23,32]. Still, false negatives and false positives, however, can be inherently linked, hence improving accuracy to reduce false negatives could increase false positives and vice versa [6], indicating trade-offs and limitations for optimization based on satellite imaging alone.

Differing underlying ecological causes of false negatives and false positives [23,36,37] were explicitly indicated by the sets of significant stand and patch variables (Table 1). Furthermore, the stand and patch variables had a considerably stronger effect on false positives, as indicated by the R^2 values of the calibrated models, suggesting the possibility of using forest registry data [14] as a considerable amplifier of their predictability by remote sensing [4–6]. Although bearing significant effects, the stand and patch variables were weaker predictors of false positives, as the R^2 values were lower. The local specifics in the probability of false negatives were related to the forest block, as indicated by the variances of random effects, implying effects of medium-scale drivers, which were not captured by the tested effects, such as history or local specifics in management approaches, as well as the proportion of spruce in the landscape. This also highlights the high spatial heterogeneity of the identification accuracy. Given the limited scope of this study, these effects could not be reliably evaluated.

The local variability of false positives was considerably lower, as indicated by much lower variance, the highest share of which was related to vicinity (Table 1). False positive rates may also depend on the regional overall level of pest infestation, suggesting that remote sensing approaches may be more useful for decision-making during large-scale outbreaks [43]. In turn, false positive error rates in the heavily infested stands can be as low as 10%, but identification reliability can decrease when infestation intensity within spruce stands is low [44], as in the case of this study.

4.2. Stand- and Patch-Level Effects on Identification Accuracy

The explicit positive effect of patch size on identification accuracy in terms of false positives (Figure 2a) can be explained by the efficiency of the satellite images for the identification of individual trees [45]. Still, the estimated frequency of false positives was high in the smaller patches (<0.1 ha), which often correspond to individual trees and are more likely to be misidentified, mistaking small forest openings for dead spruce trees [46]. The positive effect of the number of adjacent damaged trees on identification accuracy (Figure 2c) implies relationships with the spatial clustering of damage, which is affected by stand density and the canopy status of trees [32]. The rapidly increasing frequency of false positives in relation to the number of damaged trees within a patch (Figure 2b), again, could be related to clustering of the damaged trees [30]. Apparently, in larger clusters, some small groups of trees can survive [26,47] which were not clipped from the patch during the identification [42].

The significant negative effect of stand age on damage identification accuracy in terms of false negatives (Figure 2d) can be related to the explicit age and size-related increase in susceptibility of Norway spruce to biotic stresses [26,32]. Accordingly, the

spontaneous mortality of scattered individuals/small groups increases under the endemic pest populations, while the small scale of the groups of the dying trees have been often overlooked based on satellite images alone [23]. The negative effect of stand size on the identification accuracy in terms of false negatives (Figure 2e) can be related to the typical management specifics, namely, formation of homogeneous spruce stands [12]. Under such conditions, the number of individuals/small groups of the dying trees, which can be overlooked [23], depends on size under the endemic pest population [32]. Similar yet flatter effects were observed for identification accuracy when both errors were considered simultaneously (Figure 3a), which can be explained by the involvement of either error types, for which the set of significant fixed effects was specific (Table 1). Hence, the synergy of the effects underlying identification types can be suggested as the cause of the low proportion of absolutely correctly identified damage patches. Hence, explicit evaluation of interactions between site characteristics and patch properties could be suggested as the focus of further research.

As the response curves of the patch identification errors were non-linear (sigmoid or bell-shaped; Figures 2 and 3), it is possible to evaluate thresholds of stand and patch properties for reliable patch identification under the highly heterogeneous landscape [11,12]. When considering false positives individually, the patch size of 0.5 ha appeared as the threshold for highly reliable identification (>95%), exceeding it. In turn, the minimum number of adjacent trees that resulted in 80% accuracy of identification was 59, while the number of damaged trees within a patch above 10 was almost certainly causing a false positive misidentification. When both errors were considered together, the estimated thresholds were up to threefold higher (Figure 3), indicating the necessity for inclusion of the systemic effects of stand properties in identification algorithms. Simultaneously, the negative effect of the number of damaged trees was also flatter, suggesting 50 tree groups to be likely erroneously identified.

4.3. Limitations, Uncertainties, and Prospects

The suggested stand and patch size thresholds (Figures 2 and 3), however, exceeded the mean and the median stand size in Latvia (1.154 ± 0.002 and 0.73 ha, respectively, according to data from <https://data.gov.lv/dati/lv/dataset/meza-valsts-registra-meza-dati>, (accessed on 15 October 2025), as well as the mean identified patch size, rendering satellite-only based identification less reliable [12,22,30,37]. Considering the high resolution of the satellite images, the estimated thresholds appear quite excessive, indicating the necessity of more elaborate damage identification systems, incorporating UAV and inventories [17,18]. The estimated threshold values, in turn, can be used as the benchmarks for prioritizing stands for UAV surveillance [15].

An additional potential approach to improve *Ips typographus* damage identification accuracy is the use of extended time-series remote sensing data to capture the spatiotemporal dynamics of *Ips typographus* spread [47,48], thus highlighting the changes in spruce health. Also, the time-series approach could help to minimize the influences of environmental artefacts such as forest roads, ditches, and local windthrows, which can interfere with spectral identification. Detected changes in vegetation indices between and within the growing season would strongly indicate possible changes in tree health irrespectively of environmental artefacts [5,17].

Even though only 100 stands were analyzed, the explicit systematic effects of stand and damage patch properties on the probability of false positive and, particularly, more influential false negative errors suggested that regional trends have been captured. This is supported by the variability of size, age, and structure of the analyzed stands. As the stands represented highly heterogeneous seminatural forest landscapes [12], the observed results

should be considerable for the hemiboreal forest of the Eastern Baltic region. Considering the relevance of small-sized patches as sources of potential outbreaks [4,21,22,32] and the estimated patch size thresholds (Figure 3b), the potential underestimation of the false negatives resulting from the $<30\text{ m}^2$ cutoff-level for damage patches likely had a negligible influence on the results. Furthermore, the main differences would refer to false positives, the effect of which is less relevant for outbreak prevention, but rather would result in additional management costs. Furthermore, small patches could be increasingly affected by the sensor noise.

Considering differences in the dating of the images, as the latest satellite images were acquired in September, yet UAV imaging was performed in November, the rate of false negatives might be partially related to the time gap and phenology, as the health of affected trees deteriorated [17,41]. On the other hand, September is the beginning of autumn, when the activity of the pest species decreases explicitly [30,31], while November is already a dormancy period.

5. Conclusions

To improve *Ips typographus* damage identification using satellite data, we recommend focusing on two key aspects. Firstly, the damage identification system would highly benefit from the supplement of UAV reconnaissance, while stand properties, which are acquirable from inventories, could be used for prioritization of UAV flights. Second, regional pest pressure information should be integrated into identification algorithms. A local/national pest and disease monitoring programme, which tracks *Ips typographus* flight dynamics and damage annually as part of the National Forest Monitoring Program, could provide valuable input for such regional risk assessments. Additionally, incorporating time-series remote sensing data would allow for the assessment of temporal changes in stand condition both within and between growing seasons.

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Data Availability Statement: Due to legal (commercial) issues, data are available on request from the authors.

Conflicts of Interest: Authors Ilze Bargā and Linda Gulbe-Viluma were employed by the company Baltic Satellite Service Ltd. The remaining authors declare that the research 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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