Referee Comment 2

Hybrid forest disturbance classification using Sentinel-1 and inventory data: a case study for the Southeastern USA

General comment:

This manuscript combines Sentinel-1 with IDS data for disturbance mapping (wind, bark beetles, defoliators) in a forest region, addressing legacy dataset limitations. However, the text structure is often confusing and lacks explicit research questions. Pervasive formatting inconsistencies further impede readability. Minor revisions for structural clarity, quantitative validation beyond manual polygon delineation using PlanetScope, and thorough clean-up are essential before resubmission.

We will revise the manuscript for clarity and readability, and we will revise the motivation statement in the introduction.

Specific comments:

RC1: The introduction is well explained but provides excessive detail on general topics such as DL training, labeling challenges, and legacy datasets, which are not clearly linked to the study's focus on bark beetle, defoliator, and wind disturbances. The research questions or specific objectives the authors intend to address should be stated explicitly.

We thank the reviewer for this comment. While the Introduction provides important context, we acknowledge that some sections contain general information not directly linked to our study focus. To clarify, we specifically focus on wind, bark beetle, and defoliator disturbances because these disturbance types are particularly challenging to attribute and differentiate in large-scale datasets. For example, in the European Forest Disturbance Map (Senf and Seidl, 2021), only wind and fire disturbances are clearly distinguished, and in the European Forest Disturbance Atlas (EFDA; Viana Soto and Senf, 2024), fire and harvest are emphasized, while the "wind–bark beetle" complex cannot be disentangled. Insects, in particular any insects apart from bark beetle outbreaks, are often underrepresented and bark beetle outbreaks are difficult to separate from wind disturbances. Therefore, our study targets these specific disturbance types to address this critical gap and improve understanding of their dynamics and detectability.

To address this comment, we have rewritten the entire paragraph to clarify the motivation for the selected disturbance types and clearly state our central research question, which now reads:

> *"Specifically, we focus on three key disturbance types: bark beetle, defoliators, and wind. This choice is motivated both by their ecological importance (Seidl et al., 2017; Hicke et al., 2020; USDA Forest Service, 2015; Heaton et al., 2023) and the known challenges and persistent gaps in remote sensing–based classification of these disturbance types (McDowell et al., 2015; Kautz et al., 2017; Schleeweis et al.,2020). For example, bark beetles have killed approximately 3.8 billion trees in western North America between*

1997 and 2018 (Hicke et al., 2020), and the defoliating gypsy moth (Lymantria dispar) has affected over 21.5 million ha in the northeastern United States from 1924 to 2015 (USDA Forest Service, 2015). Insect disturbances are responsible for substantial carbon losses (10 ± 1.3 Tg C yr^{-1}), comparable to those attributed to fire (7 ± 1.0 Tg C yr^{-1}) in the United States (Harris et al., 2016). Wind disturbances, while sparse in time, can be catastrophic, as exemplified by Hurricane Hugo, which damaged around 1.8 million ha of forest in South Carolina (Heaton et al., 2023), and storms have been associated with carbon losses of up to 5 ± 0.7 Tg C yr^{-1} during the period 2006–2010 (Harris et al., 2016).

Due to their extensive impacts, several studies have attempted to map forest disturbances at large scales using remote sensing or to derive large-scale risk assessments, yet gaps in disturbance attribution remain. The North American Forest Dynamics (NAFD; Schleeweis et al., 2020) dataset used Random Forests to classify Landsat pixels into disturbance agents (Removal, Fire, Wind, Conversion, and Stress), with insect disturbances grouped within the broad Stress category alongside drought and disease. Similarly, the European Forest Disturbance Atlas (EFDA; Viana-Soto & Senf, 2025), based on Landsat data from 1985–2023 and using Random Forest classification, maps disturbances such as harvest and fire, but can not disentangle wind/bark beetle compound effects. Both approaches have the challenge of disentangling insects from other disturbance agents (e.g., drought or wind). Previous literature shows that insect disturbances are particularly difficult to detect and differentiate using conventional optical remote sensing, as they typically produce gradual and subtle canopy changes rather than the abrupt spectral signals associated with fire or severe windthrow (McDowell et al., 2015).

In addition to detection challenges, both approaches rely on manually interpreted disturbance datasets to train their data-driven models. Reference datasets, such as FIA and IDS inventories, can exhibit spatial, temporal, and attribution uncertainties due to human factors (Eifler et al., in press). Furthermore, Andrus et al. (2025) demonstrate additional variability in the spatiotemporal characteristics of tree mortality, specifically regarding duration, severity, and mortality rates, within and among different bark beetle-host trees, highlighting the difficulty of accurately capturing insect-driven disturbances. These challenges are compounded by the limited availability of reference data: Rodríguez Paulino et al. (2024) report that the majority of studies characterizing forest disturbances do not provide accessible datasets, thereby restricting reproducibility and hindering further research. Together, these findings underscore the need for reliable, well-delineated, and publicly available forest disturbance data to enable accurate large-scale mapping.

In this study, we aim to support advances in wind and insect disturbance classification by using remote-sensing to reduce uncertainties in inventory-based datasets. Specifically, we investigate whether C-band Synthetic Aperture Radar (SAR) data from Sentinel-1 can improve the detection and characterization of insect- and wind-related disturbances, leveraging the sensitivity of SAR to structural and moisture changes that are not easily *captured by optical sensors and visual inspection, and Sentinel-1's spatially and temporally continuous, cloud-penetrating structural information. We focus on bark beetle and defoliator disturbances because they are absent from current large-scale attribution efforts, and we include wind disturbances because they frequently co-occur with bark beetle outbreaks and because the EFDA wind–bark beetle complex demonstrates difficulty in disentangling these agents. Wind disturbances also lack consistent, spatially exhaustive mapping products. Together, these three disturbance types provide a critical test case for evaluating radar's ability to reduce spatial and temporal uncertainties in existing disturbance inventories.*

The central motivation for this study is to refine the spatio-temporal characteristics of existing forest disturbance inventories by integrating C-band SAR data from Sentinel-1 at 20x20m spatial resolution, with the long-term, large-scale Insect & Disease Survey (IDS) inventory dataset, which is available for the entire United States since 1997 (IDS; U.S. Forest Service, 2024). IDS offers detailed, aircraft-based disturbance observations, extensive temporal coverage, and information on disturbance agents. However, as discussed above, IDS also suffers from limitations inherent to aerial detection surveys, including human error, inconsistent sampling, coverage gaps, and spatial inaccuracies (Forest Service U.S. Department of Agriculture, 2024; McConnell, 2000; Coleman et al., 2018; Eifler et al., 2024; FAO, 2020; Kautz et al., 2017).

We combine Sentinel-1-based information on the size, location, and timing of disturbances with detailed disturbance-agent information provided by IDS. We further evaluate the spatial agreement between the datasets using independent manual labeling of high-resolution PlanetScope data (Planet Labs, 2025). This integrated approach enables us to refine traditional disturbance mapping and generate a hybrid reference dataset with improved spatial, temporal, and disturbance agent accuracy. In doing so, we provide a semi-automatic framework for bridging information across heterogeneous datasets and supporting the development of algorithms to classify wind, bark-beetle, and defoliator disturbances across large regions."

RC2: [Results] Despite the preprint relying on spatial agreement and manual labels without such metrics, I missed a confusion matrix analysis quantifying omission and commission errors for each disturbance type (wind, bark beetles, defoliators). This quantitative error breakdown is essential for transparent S1DM validation and comparability with IDS/alternatives.

We thank the reviewer for this constructive comment and agree that additional information on omission and commission errors is valuable for understanding the capabilities of Sentinel-1 Change Detection (S1DM) to improve legacy inventory datasets.

Since S1DM is based on overlapping patches with IDS, we are only able to show omission errors - that is, cases where S1DM fails to detect disturbances identified in IDS. Commission errors cannot be directly assessed for several reasons:

1) First, the IDS data does not provide full spatial coverage of the USA territory, but rather of selected areas that are flown-over each year. This means that there might be areas correctly identified by S1CD as disturbed that do not show overlap with IDS because the area has not been flown over (see a more in-depth discussion of the uncertainties of IDS in Eifler et al. (in press)).
2) Second, this means that it is not possible to provide an estimate of commission errors per disturbance type.
3) Finally, the S1CD signal also includes signals from other disturbance types that are not those considered here (fire, drought, other abiotic damage, other biotic damage, harvest), so that a comparison of the aggregated disturbances detected by S1CD and IDS would be meaningless.

To address this, we added Figure R2.1 showing the percentage of IDS events that overlap with S1DM, highlighting omission errors, and included a corresponding paragraph in the Results section.

> *"Figure 3 and Figure R2.1 show that the detection effectiveness of S1DM varies by disturbance type. Wind disturbances have the highest agreement, with 98.1 % of IDS wind events having a corresponding S1DM signal within the 500 m buffer (469 of 478 events). Bark beetle disturbances follow, with 76.3 % of IDS patches matched by S1DM (899 of 1,177 events). Agreement is lower for defoliator disturbances, where only 67.6 % of IDS disturbed areas are captured by S1DM (144 of 213 events). The percentages in Figure R2.1 refer to totals across all years and match the absolute numbers reported in Figure 3."*

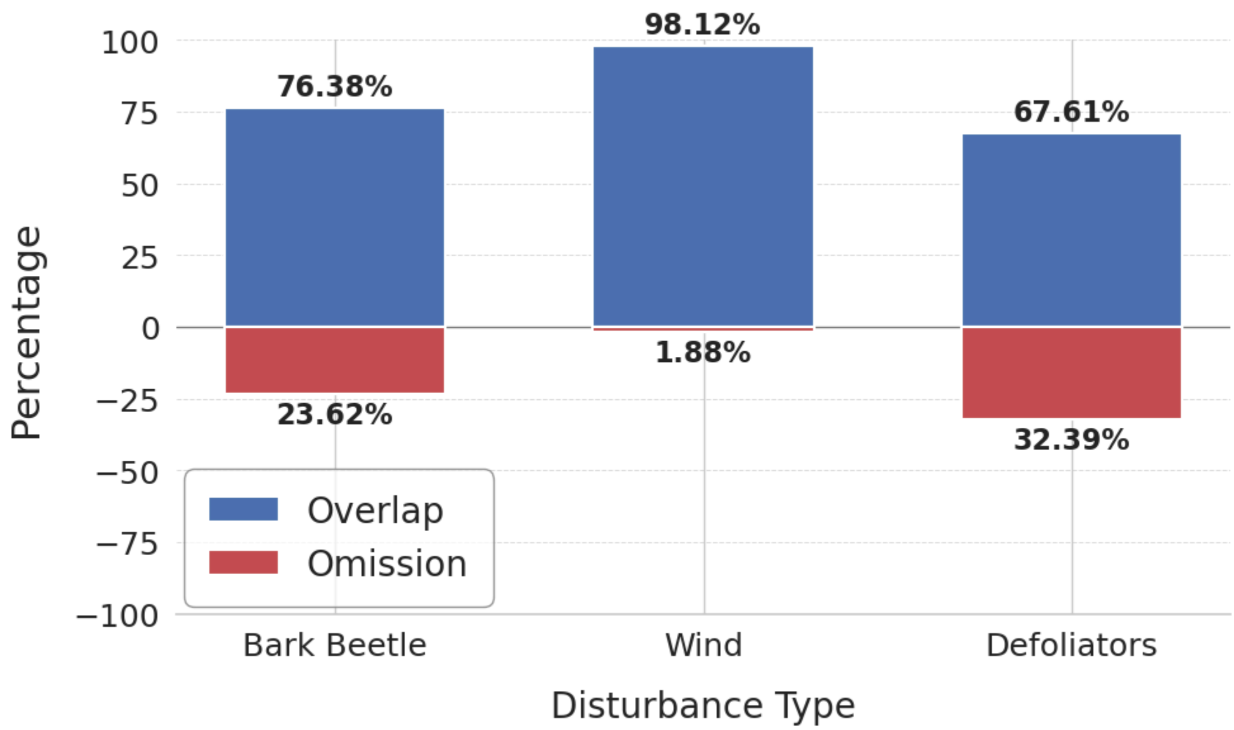

Figure R2.1: Overlap (blue) and omission (red) of IDS disturbance events with Sentinel-1 detections. The x-axis shows disturbance types (Bark Beetle, Wind, Defoliator), while the y-axis indicates the percentage of IDS events. Blue bars represent IDS events with overlapping Sentinel-1 detections, and red bars show IDS events without a corresponding Sentinel-1 detection (omission).

[Discussion:] The section effectively highlights S1DM strengths but omits essential components: a dedicated limitations subsection (buffer choices, IDS error propagation, lack of field validation, regional limits); quantitative benchmarking against alternatives such as GLAD/ESDAC; explicit linkage back to the research questions with key results summaries; and implications for operational scalability and DL training. These omissions weaken the broader impact and dataset positioning.

We thank the reviewer for these constructive suggestions, which helped strengthen the Discussion section. To address these points, we have made the following decisions and revisions:

RC3: A dedicated limitations subsection (buffer choices, IDS error propagation, lack of field validation, regional limits)

We would like to note that the implications of buffer choices were already discussed in Section 5.1, *Capabilities and Limitations of Sentinel-1 Change Detection to Improve Forest Disturbance Monitoring*, specifically in Section 5.1.1 *Location and delineation of disturbance patches*.

In response to the reviewer's comment, we have now added a dedicated Section 5.3 *Methodological Limitations*, which consolidates and expands the discussion of limitations across the workflow. This new subsection explicitly addresses buffer selection, error propagation within the IDS framework, and the lack of direct field-based validation. It reads:

> "5.3. *Methodological Limitations*
>
> *In this study, several methodological decisions were made that we would like to clarify. To combine disturbance information, we used a spatial buffer of 500 m and a temporal buffer of ±2 years. These choices were tested against alternative spatial buffers of 100 m, 250 m, 500 m, and 1000 m. Previous work by Eifler et al. (2024) tested larger spatial buffers of 800 m and 1000 m and showed that increasing buffer size introduces additional uncertainty. Our choice of 500 m represents a balance between retaining information and minimizing the risk of introducing spatial uncertainty. Future work could explore in greater detail the impact of spatial uncertainty between inventory datasets and satellite observations to refine buffer selection.*
>
> *Regarding temporal uncertainty, Eifler et al. (in press) found that the mean temporal lag between IDS and satellite-based forest disturbance products can be substantial. Specifically, the mean lag is approximately 0.5 years compared to GFC (±3.7 years) and 1.9 years compared to NAFD (±3.2 years). In all cases, IDS reports disturbances later than both satellite-derived products, highlighting the importance of accounting for temporal offsets when comparing ground-based and remote-sensing datasets. By applying a ±2-year temporal buffer, corresponding to the maximum mean deviation with Sentinel products (~1.9 years), we reduce the risk of falsely classifying disturbances.*
>
> *A key limitation in disturbance detection workflows is the propagation of errors through sequential processing steps; for example, a misclassification in one dataset can influence the final combined disturbance map. Our framework is explicitly designed to reduce error propagation by integrating multiple sources of disturbance information, including Sentinel-1 change detection. While direct field validation would provide the strongest confirmation of disturbances, this is not possible in our case: the events we analyze occurred 5–9 years ago over a very large region, and many affected areas have likely recovered (for example, defoliator impacts often recover within a year). Previous work has explicitly assessed inconsistencies and uncertainties in IDS. Eifler et al. (in press) compared IDS with independent inventory data and found good temporal agreement with FIA, suggesting that temporal errors in IDS are generally low. Our results support this finding, as IDS timing largely aligns with S1DM (Figure R2.1), except that some bark beetle disturbances are detected earlier by S1DM than reported in IDS. However, because FIA lacks sufficiently detailed spatial information, spatial event-level errors cannot be quantified using inventory data alone. To address this limitation, we employed Planet imagery as an independent, spatially explicit proxy for validation. Although this cannot fully replace field observations, it allows us to evaluate the plausibility of disturbances in areas where ground data are no longer available.*

Finally, our study region is limited to the southeastern United States, which is relatively flat and was selected because of its high incidence of wind disturbances. The absence of large mountains avoids topographic-induced uncertainties known to affect Sentinel-1 observations (Borlaf-Mena et al. 2020; Shi et al. 2024). While the framework performs well under these conditions, its application in more mountainous regions would require additional testing."

RC4: Quantitative benchmarking against alternatives such as GLAD/ESDAC.

Thank you for pointing this out. After further investigation, we regret to report that it is not possible to incorporate these datasets into our analysis as a comparable quantitative benchmark.

The GLAD Forest Alerts consists of two alert systems designed to detect tree cover loss. However, both systems fall outside the scope of our study region. GLAD-L provides tree cover loss alerts only between 30°N and 30°S, while GLAD-S2 focuses exclusively on primary humid tropical forests, primarily within the Amazon Basin. As our study area is located in the southeastern United States, neither product provides spatial coverage suitable for direct comparison. However, Eifler et al. (in press) evaluated the consistency of forest disturbance datasets across the continental United States and compared IDS with satellite-based products, including the North American Forest Dynamics (NAFD) and Global Forest Change (GFC) datasets, the latter based on a similar Landsat time-series approach. They found substantial temporal discrepancies between inventory- and satellite-derived disturbances. Specifically, the mean temporal lag of IDS relative to satellite products was approximately 0.5 years compared to GFC (±3.7 years) and 1.9 years compared to NAFD (±3.2 years), highlighting considerable disagreement in disturbance timing between inventory and remote sensing datasets.

With ESDAC, we are not sure if the reviewer was referring to the European Soil Data Centre, which does not directly report forest loss or forest disturbance data. Instead, it serves as a key provider of soil and land-related datasets, often used to analyze or contextualize forest loss processes. Upon reviewing the datasets, we understand that ESDAC primarily hosts datasets with European geographic coverage and does not cover our study region. Furthermore, since ESDAC does not provide forest loss or disturbance products per se, it cannot serve as a quantitative benchmark for our analysis.

Given these geographic and thematic limitations, neither GLAD nor ESDAC datasets can be used as a suitable comparison for our study, which focuses on forest loss dynamics in the southeastern United States. Alternative datasets in the USA (our study area) exhibit substantial uncertainty, whether derived from inventories or remote-sensing classifications (Eifler et al., in press). Studies such as Andrus et al. (2025) further demonstrate that bark beetle-driven disturbances exhibit significant spatiotemporal variability (duration, cumulative mortality area (severity), maximum annual mortality, and mortality rate) that is difficult to capture with broad-scale remote sensing products alone. Together, these findings highlight the ongoing need for improved delineation methods that can accurately capture both the extent and the agent of forest disturbances.

RC5: Explicit linkage back to the research questions with key results summaries

We agree with the reviewer that adding a specific ink back to the research questions will strengthen the discussion. So we reworded the beginning of the discussion:

> "*We aimed to improve forest disturbance mapping by combining IDS inventory data with Sentinel-1 radar change detection, leveraging IDS's detailed disturbance agent information while reducing uncertainties in disturbance size, location, and timing. We find that integrating radar data substantially improves the spatial and temporal characterization of disturbance events, particularly for bark beetle outbreaks and wind damage. The resulting dataset captures both the location and timing of disturbances more accurately than IDS alone. These improvements provide a robust foundation for applications such as training data-intensive, data-driven models for disturbance classification."*

RC6: Implications for operational scalability and DL training

We added a dedicated Section 5.4 *Scalability and Use Cases*, which discusses the implications and benefits of this dataset.

> *"Scalability and Use Cases*
>
> *Scalability, as discussed in Section 5.3 Methodological Limitations, depends in part on the transferability of this approach to regions with complex topography, such as mountainous areas. In addition, differences in forest structure and species composition may require region- or forest-type–specific parameter adjustments, particularly for backscatter dynamics and disturbance signatures. Apart from these terrain- and forest-type–related considerations, Sentinel-1 data are globally available, and the primary constraint on scalability remains the availability of suitable inventory datasets, which currently act as the main bottleneck for applying this method in new regions. With appropriate calibration, however, there are no inherent limitations preventing the extension of the methodology to other regions or larger spatial extents. Apart from these terrain-related limitations, Sentinel-1 is globally available, and the main constraint on scalability is the availability of inventory datasets, which act as the bottleneck for applying this method in new regions. Beyond these considerations, there are no inherent limitations that would prevent expanding the methodology to other regions or larger spatial extents.*

Our study demonstrates that the integration of Sentinel-1 spatio-temporal information can contribute to refining disturbance mapping from inventory datasets. This approach can be applied to other inventory datasets and to other satellite missions, provided they have overlapping spatial and temporal coverage. The structural information inherent in SAR backscatter data and the high spatial resolution of Sentinel-1 offer opportunities to enrich existing forest disturbance inventories, improve temporal and spatial resolution, and reduce uncertainty in forest loss mapping.

Improved datasets generated through this approach also provide a valuable resource for forest disturbance classification algorithms, for example, based on machine learning (ML) or deep learning (DL) models. The refined IDS-derived disturbance dataset provides more accurate, spatially explicit information about forest disturbances, thereby greatly improving the training of ML and DL models. Reducing noise and uncertainty compared to inventory datasets, it allows algorithms to better learn the characteristic patterns of forest disturbances. This enhanced training data can also support the development of models capable of differentiating disturbance types, particularly when combined with complementary information from other sources, such as vegetation indices reflecting other canopy properties from spectral imagery (Senf et al., 2013; Senf et al., 2015; Senf and Seidl, 2018; Candotti et al., 2022; Hall et al., 2016), or hyperspectral information from new missions such as ENMAP (Vanguri et al., 2024). In this way, the refined dataset not only improves predictive performance but also provides a foundation for adaptive classification frameworks that can generalize across regions, forest types, and disturbance regimes."

[Conclusion:] The conclusion requires substantial restructuring to enhance its impact and avoid redundancy. The first paragraph repetitively restates the global data gap and IDS limitations already discussed in the Introduction and Discussion. While subsequent paragraphs adequately summarize the hybrid S1DM method, they underemphasize the ecological implications—for example, how refined timing enables bark beetle outbreak forecasting, realistic wind patches inform gap dynamics and succession, or defoliator improvements correct carbon flux biases. The authors should explicitly position S1DM as a public benchmark for DL training (linking back to the labeling challenges in the Introduction) and replace vague future work with specific proposals.

We agree with the reviewer and thank them for helping us make a stronger conclusion. We have addressed the individual comments below and added the new conclusion with the changes in bold. at the end.

RC7: Shorten or remove the first paragraph repetitively restates the global data gap and IDS limitations already discussed in the Introduction and Discussion.

We thank the reviewer for this suggestion. We have shortened the first two paragraphs of the Conclusion to avoid repeating points already made in the Introduction and Discussion.

RC8: Emphasize the ecological implications- for example, how refined timing enables bark beetle outbreak forecasting, realistic wind patches inform gap dynamics and succession, or defoliator improvements correct carbon flux biases in the conclusion.

We have added a discussion of ecological implications, highlighting that refined disturbance timing and spatial resolution can support improved modeling of forest dynamics, such as forest disturbance detection and classification, bark beetle outbreak forecasting, and correction of carbon flux changes caused by disturbances.

> "*Improving disturbance mapping allows for constraining downstream calculations, such as quantifying actual forest loss, estimating carbon emissions by disturbance type, and correcting carbon flux biases. The new hybrid dataset proposed here also addresses key challenges in forest disturbance classification and prediction algorithms, particularly those based on machine- and deep learning models (ML and DL, respectively). These data-intensive methods require large amounts of reliable, agent-specific training data. By reducing spatial and temporal noise in IDS, S1DM provides a publicly available, standardized benchmark dataset for training and validating forest disturbance classification and prediction methods. Combined with complementary remote sensing products such as Sentinel-2 or Landsat, this approach has the potential to improve disturbance detection and classification, including the differentiation of subtle disturbance types, such as between different insect disturbance agents or between wind and bark beetle compound events.*"

RC9: Link the DL and ML from the Introduction and explicitly position S1DM as a public benchmark for DL training.

We have strengthened the link to the Introduction and explicitly positioned S1DM as a public benchmark for future forest classification algorithms, including ML and DL model development and evaluation.

New Conclusion (**bold** text indicates changes):

> ***"Reliable, spatially and temporally consistent information on forest disturbances, particularly wind, bark-beetle and defoliator insects, remains a major bottleneck for large-scale disturbance attribution and modeling (Kautz et al., 2017, Rodríguez Paulino et al., 2024). In this study, we directly address this limitation by refining the widely used legacy Insect & Disease Survey (IDS) through the integration of Sentinel-1–based radar change detection (S1DM). This hybrid approach leverages the complementary strengths of both datasets: the long-term, agent-specific information provided by IDS (U.S. Forest Service, 2024) and the spatially and temporally continuous, cloud-independent structural sensitivity of C-band SAR observations.***

Our analysis specifically targets three key sources of uncertainty in legacy disturbance inventories: disturbance location, disturbance outline, and disturbance timing ***(Eifler et al., in press; Coleman et al., 2018; Andrus et al., 2025)****.*

*Although S1CD shows reduced sensitivity to subtle canopy changes such as those associated with defoliator activity, it performs well for structurally significant disturbances, including wind damage and bark beetle outbreaks****, a performance consistent with Bruggisser et al. (2021), who demonstrated that Sentinel‑1 can reliably detect decreases in forest height greater than 10 m.*** *Spatially, disturbance centers were generally within 200–950 meters of one another. Although the overall disturbed area remained similar, the S1DM dataset identified more physically plausible disturbance patterns, with Wind and Bark Beetle showing significantly improved agreement with independent manual reference data compared to IDS* ***(see Figure 8)****.*

Improving disturbance mapping allows for constraining downstream calculations, such as quantifying actual forest loss, estimating carbon emissions by disturbance type, and correcting carbon loss uncertainty (Harris et al., 2016). The new hybrid dataset proposed here also addresses key challenges in forest disturbance classification and prediction algorithms, particularly those based on machine- and deep learning models (ML and DL, respectively) (Rodríguez Paulino et al., 2024). These data-intensive methods require large amounts of reliable, agent-specific training data. By reducing spatial and temporal noise in IDS, S1DM provides a publicly available, standardized benchmark dataset for training and validating forest disturbance classification and prediction methods. Combined with complementary remote sensing products such as Sentinel-2 or Landsat, this approach has the potential to improve disturbance detection and classification, including the differentiation of subtle disturbance types, such as between different insect disturbance agents or between wind and bark beetle compound events. Previous studies have demonstrated that such distinctions are possible at local or site scales for individual events using optical or multi-sensor data (Senf and Seidl, 2018; Candotti et al., 2022). However, the systematic and large-scale application of these approaches remains challenging due to limited reference data and the complexity of disturbance dynamics. In this context, S1DM provides a resource that supports the development of scalable, automated disturbance classification frameworks and facilitates the study of ecologically relevant disturbance processes across broader spatial and temporal extents.

Despite these advances, some uncertainties remain, particularly regarding the precise timing and duration of gradual disturbances. Future work could explore the integration of additional data streams, such as Sentinel-2 time series, and advanced learning strategies, to further reconcile information from IDS, S1DM, and optical observations, particularly for cases where neither dataset fully captures the disturbance signal.

Overall, our approach offers a scalable and substantially less labor-intensive alternative to manual labeling and is readily transferable to other regions and legacy inventories

> ***(FORWIND; Forzieri et al., 2020; DEFID2; Forzieri et al. 2023).*** *By improving the reliability of disturbance reference data, this work lays the groundwork for more robust data-driven analyses of forest disturbance dynamics across large spatial and temporal scales."*

RC10: [General formatting:] Please ensure consistent paragraph indentation (either all first-line indents or none) and uniform spacing between paragraphs throughout the manuscript. Currently, indentation is inconsistent, and spacing varies. Additionally, fix inconsistencies such as missing figure citations in the text (e.g., L427 "Panel a" without "Figure 5"), incorrect numbering in subsections (e.g., "5.1.2 (2)" in the Discussion), and other formatting artifacts. A thorough clean-up is essential for readability.

We thank the reviewer for pointing out these formatting inconsistencies. We have thoroughly revised the entire manuscript, correcting paragraph indentation, spacing, figure citations, subsection numbering, and other formatting issues. The manuscript should now be consistent and fully aligned with standard formatting conventions.

Minor comments:

*L16: The acronym "Sentinel-1 Disturbance Mapping (S1DM)" should be introduced when it first appears (around line 12), rather than later in the abstract. Define the term before using the abbreviation.

Thank you for noticing. We have now introduced the acronym appropriately at first use in Line 16.

*L40: Clarify early in the paragraph that these percentages refer to the coverage of disturbance reports (i.e., data availability) rather than the actual affected forest area, to avoid possible misinterpretation.

We have revised sentences in L39–41 to clarify this point and it now reads:

> *"However, the quality and extent of reporting vary significantly across regions. As shown by FAO (2020), the coverage of disturbance reports (i.e., data availability) differs substantially by disturbance type and geographic region. From 2002 to 2016, data availability for insect disturbance reports covered 98% of forested areas in North and Central America and 86% in Europe, but only 45% in Asia (Food and Agriculture Organization, 2020)."*

*L58: The phrase “more recently, the Sentinel fleet” should specify the approximate launch period to better clarify the temporal contrast with MODIS and Landsat.

Thank you for pointing this out. We agree with the reviewer that the original sentence was not sufficiently clear and assumed too much prior knowledge. To improve the clarity of the manuscript, we have rewritten the sentence, which now reads:

> *“Remote sensing provides a spatially and temporally consistent and cost-effective solution for tracking forest conditions across large areas and extended periods. This is enabled by long-running satellite missions and sensors, including MODIS (operational since 1999; Justice et al., 1998), the Landsat program (initiated with Landsat 1 in 1972 and most recently continued with Landsat 8 launched in 2013; Markham and Helder, 2012; Hansen and Loveland, 2012), and, more recently, the Sentinel satellite fleet operated by ESA, with multiple satellite missions launched between 2014 and 2025 (ESA, n.d.) [10]”*

*The study area description in Section 2.1 lacks quantitative climate data (e.g., precipitation, temperature) essential for contextualizing disturbances. Please add a brief summary.

Thank you for this suggestion. We agree that quantitative climate information is important for contextualizing forest disturbances. We have therefore added a brief summary of temperature and precipitation patterns in Section 2.1 at L147 to better characterize the climatic conditions of the study area.

> “*The study region spans a broad climatic gradient typical of the southeastern United States. Mean annual temperatures generally range from approximately 12–14 °C in the northern and higher-elevation areas to 20–22 °C in the southern coastal and lowland regions. Annual precipitation is relatively high across the region, typically ranging from about 1,100 to 1,600 mm, with higher rainfall in coastal zones and the Appalachian Highlands. The region is characterized by humid subtropical conditions in the south and east, transitioning to more temperate climates at higher elevations and latitudes. In addition, large portions of the study area lie within the North Atlantic hurricane track, making the region frequently exposed to tropical storms and hurricanes that bring strong winds and heavy rainfall, particularly in coastal and lowland areas. These climatic gradients and extreme weather events strongly influence forest composition, productivity, and disturbance regimes, including insect outbreaks, storm damage, and drought-related stress.”*

*L153: The Tree Canopy Cover (TCC) dataset is mentioned for the first time without introduction. Consider briefly referencing it in the Introduction when discussing validation approaches.

We thank the reviewer for this suggestion. We have now briefly introduced the Tree Canopy Cover (TCC) dataset in the Introduction when discussing validation approaches. Specifically, in L121, we have added the following sentences (highlighted in bold) to the paragraph:

> "*As discussed above, IDS suffers from limitations inherent to aerial detection surveys, such as human error, inconsistent sampling, coverage gaps, and spatial inaccuracies (Forest Service U.S. Department of Agriculture, 2024; McConnell, 2000; Coleman et al., 2018; Eifler et al., 2024; FAO, 2020; Kautz et al., 2017).* ***To support validation and quality control, we additionally include the Tree Canopy Cover (TCC) dataset, which provides independent, high-resolution estimates of forest canopy cover.*** *By combining these datasets, we aim to leverage IDS's detailed mapping [...].*"

*L157: This sentence repeats IDS basics already covered in the Introduction.

We appreciate the reviewer's comment. While the basics of the IDS dataset are indeed introduced in the Introduction, we believe it is important to provide a full description of the dataset in the Data section as well, where we formally introduce all datasets used in this study. This ensures that readers have all the necessary details in the context of our analysis, without needing to refer back to the Introduction.

*L216: The text states that TCC data are available for 2015–2020, but Table 1 lists only 2017. Please clarify whether only 2017 data were used (and why), whether it is a time series, or describe the selection criteria to avoid confusion.

Thank you very much for spotting this. This was a carryover from previous drafts, and we have now updated Table 1 to correctly list the time range as 2015–2020.

*L235: PlanetScope is introduced here without prior mention in the Introduction or Table 1. Please clarify its specific role in the analysis (e.g., manual validation, comparison with S1DM/IDS) and explain why it was not included in Table 1 alongside the key datasets.

We thank the Reviewer for highlighting this inconsistency. We agree that it was an oversight not to list Planet alongside the other datasets in Table 1. We have therefore updated Table 1 to include Planet, adding a dedicated row for each dataset specifying its purpose in our study. Additionally, we have added a sentence to L235 to clarify PlanetScope's role, consistent with how we describe the other datasets in the previous subsection. The sentence now reads:

> "*Planet data was used in this study to manually validate the new dataset and statistically assess whether the methodology produced a significantly improved product compared to IDS.*"

We also state the inclusion of Planet satellite data in our introduction:

> "*Additionally, we use high-resolution Planet imagery with manual labeling to validate whether this combined approach leads to significantly improved disturbance detection.*"

The updated table now shows:

	IDS	S1CD	TCC	Planet
Information	Forest damage and mortality caused by various disturbance agents	Information on structural change on the Earth's surface based on Sentinel-1	Tree canopy cover for CONUS in 2017	High-resolution optical imagery capturing surface reflectance and vegetation dynamics
Data	Spatial data structured in points and polygons with associated attributes documenting forest health and disturbances.	Raster data in binary format (1s and 0s) indicating structural change status.	Raster data in GeoTIFF format representing tree canopy cover as a percentage.	Raster imagery in multiple spectral bands (e.g., RGB, NIR) at high spatial resolution
Spatial resolution	0.5 m^2 – 62,231 km^2 polygons	20 x 20 m raster	30 x 30 m raster	~3–5 m (depending on sensor)
Temporal availability	Yearly data since 1997	Yearly data from 2016 to 2021	2016-2020	Daily to weekly, depending on location and cloud cover
Purpose in Study	Provides agent-specific disturbance information for comparison and analysis	Detects structural changes in forest canopy to cross-validate IDS and quantify disturbances	Identifies forested areas and canopy cover to exclude non-forest disturbances	Serves as an independent optical validation source

Table 1: Key characteristics of the datasets used in this study: the Insect and Disease Survey (IDS), Sentinel-1 Change-Detection (S1CD), Tree Canopy Cover (TCC) and Planet. This table summarizes the data type, format, spatial resolution, temporal availability and purpose for each dataset, providing an overview of the input data used to assess forest disturbances and canopy changes across USDA Region 8.

*L411: Standardize result reporting (e.g., all as “% IDS events with S1DM match”) for consistency across disturbance types. Also clarify in the text whether percentages refer to totals across all years (matching absolute numbers in the caption: wind 478 IDS/469 S1DM, etc.).

We thank the reviewer for this helpful comment. Indeed, the text previously alternated between reporting percentages of corresponding and non-corresponding events, which could be confusing for the reader. We have updated the section, including Figure R2.1 requested in **RC2**, which highlights omission percentages more clearly.

Please refer to **RC2** for the changes.

*L427: The text refers to “Panel a” without specifying “Figure 5.” Please include the full figure number (e.g., “Figure 5, Panel a”) and correct similar minor inconsistencies throughout.

Thank you for pointing this out. Upon reviewing the manuscript, we found several instances in which figure references were inconsistently formatted. We have corrected the specific error in L427 and revised the rest of the manuscript to follow a consistent notation throughout, as you suggested (e.g., Figure 5, Panel a).

*L428: The figure interrupts the paragraph. Please follow standard formatting by placing figures at the beginning or end of relevant paragraphs or sections.

Thank you for pointing out the formatting issue. We have adjusted the figure placement to conform to standard formatting conventions, now positioning it at the end of the relevant paragraph.

*Figure 8: The legend shows a black star, but the plot uses an asterisk (*). Please standardize the symbols.

Thank you for noting the inconsistency between the legend and the plot. We have updated Figure 8 (see below) so that the legend and plot now use the same symbols, ensuring full consistency.

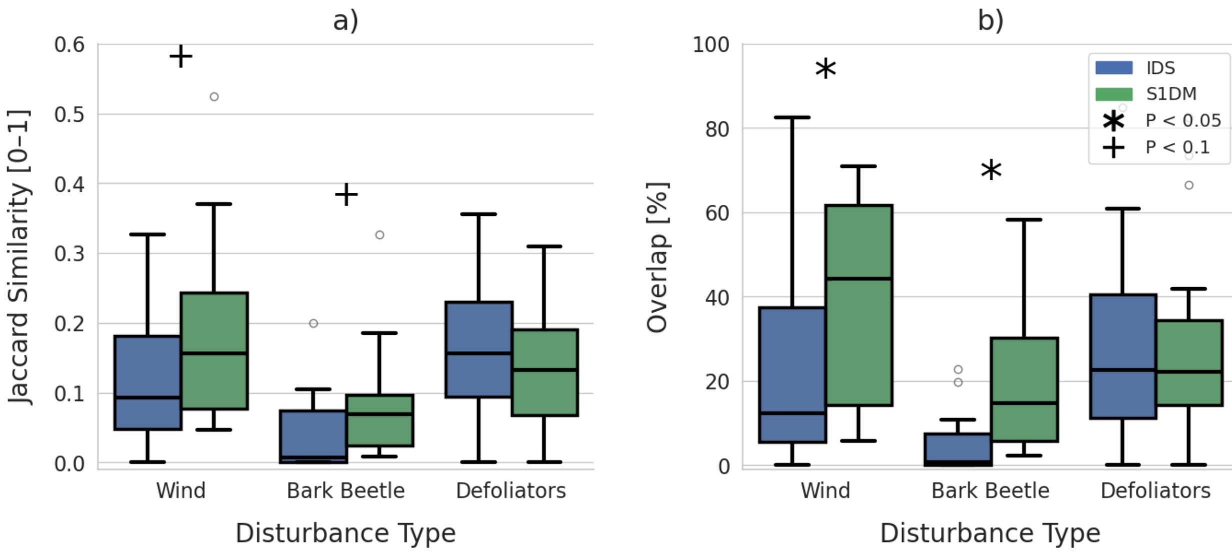

Figure 8: Comparison of agreement between IDS and S1DM disturbance maps with manually delineated reference polygons. Panel (a) shows the Jaccard similarity, and panel (b) shows area overlap (in percentage), both displayed as box plots. Statistical significance from a one-sided Wilcoxon rank test is indicated by a black star for p < 0.05 and a black cross for p < 0.1.

*Sections "5.1.1 (1) Location and delineation of disturbance patches" and "5.1.2 (2) Timing of disturbances:" Please correct subsection numbering errors (remove numbers in parentheses).

We thank the Reviewer for pointing this out. We have removed the numbers in parentheses and corrected the subsection numbering in Sections 5.1.1 and 5.1.2.

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