Dear Editor,

Thank you very much for the opportunity to strengthen our manuscript. The authors wish to thank the anonymous referees for their constructive comments and suggestions, which have substantially improved our manuscript. We have considered the recommendations carefully and revised the manuscript accordingly. We made significant changes to the manuscript, particularly to further clarify the methods section, adding additional information on the variables used for each classification step, validation process and more details on the reference data.

Please, find a detailed response to the comments below. Original comments are in black and our response is in blue. Line numbers correspond to the track-changes file.

Yours sincerely,

Alba Viana-Soto.

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Response to Reviewer #1

The authors wish to thank the anonymous referee #1 for his/her constructive comments and suggestions, which have substantially improved our manuscript. We have considered the recommendations carefully and revised the manuscript accordingly. We made significant changes to the manuscript, particularly in the methods section, adding additional information on the variables used for each classification step and more details on the reference data.

Review for manuscript entitled: "The European Forest Disturbance Atlas: a forest disturbance monitoring system using the Landsat archive' submitted to the journal Earth System Science Data (Manuscript ID: essd-2024-361).

Overall:

In the manuscript the authors report the creation of an impressive dataset with multiple forest disturbances in Europe using multi-temporal Landsat data. The authors discuss an important topic that should be of interest to the readers of ESSD and establish large data set that includes a way to detect multiple disturbances within a single timeseries. I think the paper is well-written, but the methods description could be improved. Variable importance/selection is not discussed, and the reader is referred to other published work to assess the validity of the evaluation datasets. I commend the authors on producing such large dataset, that is consistently processed, well evaluated (at least I assume), and made openly available.

Thank you for the thoughtful feedback on our manuscript. In response to the comments, we have made improvements to the manuscript, particularly regarding the methods description. Specifically, we have added further details on the variables used and we now report variable importances from the models to classify forest land use, forest disturbances and agent (see Appendix A). Additionally, we elaborated on the reference datasets to better establish their reliability and ensure transparency for the readers.

Major comments:

L125 onwards: the Explanation of the reference data collection is somewhat inadequate. I assume that interpreters used higher resolution data to interpret disturbance occurrence within Landsat pixels. If not, I think it would be very hard (except maybe for clear cuts) to detect and attribute a disturbance. The reader is referred to a couple of other papers, but since this is a critical step, I recommend the authors to discuss this step in more detail.

We agree that reference data collection is an important step, and we have expanded the explanation of how the interpreters collected the data. Specifically, the interpreters used a combination of Landsat images, the spectral time series and Google Earth high-resolution imagery, to determine whether spectral changes corresponded to forest canopy disturbances or were caused by other factors such as clouds, phenological variation or illumination conditions.

Further, we used two distinct reference datasets for 1) annual disturbance detection (pixel-based) and 2) disturbance agent attribution (patch-based). For the latter, the initial creators of the reference database (Senf and Seidl 2021b, Seidl and Senf 2024) used the disturbance maps to extract patches (i.e. a disturbance pixel of the same year sharing an edge or node) and attributed the agent of this patch by visual inspection and with the help of additional auxiliary data. For further clarification, we edited the workflow to differentiate those two steps, i.e. a pixel-based classification of annual disturbance maps, which following served as input to the agent attribution (see Figure 1 and Lines 84-89).

In the protocol for collecting annual information on forest disturbance occurrences at the pixel level, interpreters relied on Landsat imagery in combination with pixel-based time series and high-resolution imagery (Figure 3) to determine whether a disturbance event occurred for a specific pixel and year. This dataset focuses solely on distinguishing disturbed and undisturbed pixels within forested areas, and it is based on an existing dataset described in full detail in Senf et al. 2018 and Senf et al. 2021. We nevertheless summarize the salient details in our manuscript:

> Lines 138-141: *"For each pixel, trained interpreters segmented the spectral time series into linear segments of stable, disturbance and recovery (Figure 3) using an established interpretation tool (Cohen et al., 2010). Using Landsat images and high-resolution imagery available in Google Earth, the interpreters can determine whether spectral changes correspond to forest canopy changes or whether spectral changes were caused by other artifacts, such as clouds, illumination conditions or phenological variations."*

The disturbance agent attribution process uses a separate reference dataset. This dataset is created by combining visual interpretation of the disturbance maps, Landsat data and high-resolution imagery from Google Earth with different databases on storms, insect and fire related disturbances. The dataset is based on Senf and Seidl (2021b) and Seidl and Senf

(2024) and we adapted it to our workflow. We acknowledge the importance of this step and extended the information on the reference data of disturbance agent.

> Lines 257-262: *"This dataset was created by combining visual interpretation of an existing disturbances map (Senf and Seidl 2021a), Landsat data and high-resolution imagery with different databases on storms (FORWIND, Forzieri et al., 2020), insect outbreaks (DEFID2, Forzieri et al., 2023) and fire related disturbances (EFFIS, https://forest-fire.emergency.copernicus.eu/). Additionally, papers documenting bark beetle outbreaks in Europe were used to support the interpretation of bark beetle patches (Hlásny et al., 2021)."*

Methods: The methodology seems pretty solid, but there is no discussion of variable selection, variable importance, or reduction of auto-correlated variables. I agree that random forest is somewhat robust against overfitting (although opinions vary on this), the authors should at a minimum discuss the variable importance and detail a bit more what variables where chosen and why no model reduction was performed.

We added a new figure (Figure A6) showing the variable importance returned from the Random Forest models. This figure provides detailed information of variable importance for each classification: forest land use, disturbance classification and agent attribution. While we acknowledge that there is interest in the importance of specific variables, the paper is already quite extensive, and a detailed analysis of variable importance is beyond its scope. This addition aims to give readers a clearer understanding of the predictors' contributions without expanding the main text further and complements the information on feature space of variables displayed in Figures A4 and A5.

Further, Random Forest is robust to correlated variables because it randomizes feature selection during tree construction, ensuring that no single variable dominates the model. While we understand that removing correlated variables might contribute to simplicity of the models, we prioritized preserving all the information in the dataset to maximize predictive performance.

> See: *Figure A6. Variable importance (as returned by the random forest algorithm) for a) forest land use classification, b) disturbance-no disturbance classification, and c) disturbance agent attribution model. Higher values indicate higher importance for discrimination.*

Note: In reviewing the final maps (which is an impressive dataset!) I found in some parts of Europe (in particular northern Europe/Scandinavia) >50% of the forest was disturbed and I wonder if this is realistic or whether the model is oversensitive/has many commission errors. Not sure how to test this as the accuracy metrics seem pretty balances. I just wonder if this is realistic… See also Sweden, Fig 5.

Thank you for your comment and appreciation of the dataset. The disturbance maps in northern Europe, particularly in Scandinavia, are quite realistic compared to official statistics, although we do acknowledge commission errors contribute to some overestimation in certain areas. In Table 6 we showed that commission errors are higher in northern Europe (23.3 %) in comparison to central (13.7 %) and southern Europe (16.9%) and further discussed the sources in Lines 479-482 (e.g. remaining clouds, difficult illumination conditions, short summer season).

Particularly Sweden and Finland are highly forested countries and dominated by productive forests characterized by intensive clearcut forestry practices. The observation of >50% forest disturbed is not too unrealistic. First, assuming a relatively constant harvest rate of 1% per year (i.e. a rotation period of 100 years), approximately 40% of the forest area will be affected by harvest alone. The Nordic countries are well known for their intensive timber industries and rates of >1% year have been reported in the literature (Senf et al., 2021c; Turubanova et al., 2023). Adding natural disturbances on top, 40-50 or even >50% of disturbed area is not unrealistic but rather expected. Second, our results also align well with reported statistics: For example, Sweden has approximately 69% forest cover, amounting to roughly 28.4 million hectares (NFI statistics). Of this, around 23.5 million hectares are productive forest land, equivalent to 58% of the land area, with thinning and harvest activities contributing significantly to observed disturbances. According to FAO (2022), roundwood production (i.e. volume of wood harvested for commercial use) is around 64.5 million m^3 per year on average (ranging from 54 to 77 million m^3 from 1985 to 2022). Rates of >1% year cumulatively over a 40-year period, can result in ~40% of the growing stock disturbed, which could get close to 50% of forest areas, given the relatively low biomass density in northern regions. On top of that, windstorms (e.g. storm Gudrun in 2005) and more recent bark beetle outbreaks have also contributed to the high numbers of disturbances. Same applies to Finland (73% forest land cover, 22.8 million ha of forest), reporting a roundwood production is around 51 million m^3 per year on average (ranging from 41 to 67 million m^3 from 1985 to 2022) (FAO 2022). Finally, also other products (e.g. Hansen et al., 2013; Turubanova et al., 2023) show very high disturbance rates in Fenno-Scandinavia, underpinning our results.

FAO (2022). Forest Products 2022. https://doi.org/10.4060/cc3475m

Forest Europe. *State of Europe's Forests 2020* (Ministerial Conference on the Protection of Forests in Europe, 2020).

Senf, C., Sebald, J., and Seidl, R.: Increasing canopy mortality affects the future demographic structure of Europe's forests, One Earth, 4, 749–755, https://doi.org/10.1016/j.oneear.2021.04.008, 2021.

Turubanova, S., Potapov, P., Hansen, M. C., Li, X., Tyukavina, A., Pickens, A. H., … and Stolle, F.: Tree canopy extent and height change in Europe, 2001–2021, quantified using Landsat data archive, Remote Sens. Environ., 298, 113797, https://doi.org/10.1016/j.rse.2023.113797, 2023.

Minor comments:

L15: Could add "overlapping" to "…accounting for multiple *overlapping* disturbance events". To be a bit more clear.

We changed to multiple *overlapping* disturbance events.

L24: Change to: "…spanning from timber production and carbon storage (Lindner et al., 2010), to water purification and regulation (Orsi et al., 2020), to recreation and spiritual value (Saarikoski et al., 2015)."

Changed.

L67: “Shortly after, Senf and Seidl (2021a) created the first pan-European characterization of forest disturbance by combining a trajectory-segmentation algorithm (LandTrendr; Kennedy et al., 2010) with a random forest classification approach.” ◊ this might need a bit more info since about you categorized LandTrendr into “(1) trajectory segmentation approaches”. What was the RF classification used for? Maybe also explain why this method cannot detect multiple disturbances per timeseries.

We added some more information to clarify the methods used in Senf and Seidl (2021a) and why they did not include multiple disturbances per time series:

> Lines 67-71: *“Shortly after, Senf and Seidl (2021a) created the first pan-European characterization of forest disturbance by combining a trajectory-segmentation algorithm (LandTrendr; Kennedy et al., 2010) with a random forest classification approach to filter out false positives from the LandTrendr segmentation (Cohen et al., 2018). While delivering spatially consistent data across Europe, this approach was constrained to the greatest change event per pixel and thus cannot include multiple disturbances per pixel.”*

As a trajectory segmentation approach, LandTrendr processes time-series by identifying and segmenting periods of relatively stable conditions, followed by abrupt changes, which correspond to potential disturbance events. In its simple implementation, LandTrendr tends to detect several changes per time series, making it difficult to distinguish between true disturbances and artifacts (see Cohen et al. 2018). Therefore, Senf and Seidl (2021a) applied a Random Forest model to filter out false positives in LandTrendr outputs using the metrics of spectral change magnitude and duration from each segment to classify each pixel into either no-forest, undisturbed forest or disturbed forest. By following this process, the method inherently constrains the number of disturbances per pixel to one, as it relies on the greatest change segment. Similar limitations exist with approaches used in Canada, where random forest also was used to filter out commission errors from the time series segmentation. In our analysis, we completely abandon segmentation approaches, overcoming their limitations. This was done, because (i) modern processing routines (as used in our study) lead to largely noise-free image time series with little need for smoothing, (ii) time series segmentation relies on only one spectral index and not the full set of indices and bands available, (iii) allows for mapping complex disturbance sequences and several disturbances per pixel. Further, we did not aim at developing an algorithm that automatically detects disturbances (as with LandTrendr), but we had an exhaustive reference database available, allowing us to use direct classification (which was found to be superior to threshold/breakpoint based methods, see Cohen et al. 2017 and 2018).

Cohen, W., Healey, S., Yang, Z., Stehman, S., Brewer, C., Brooks, E., Gorelick, N., Huang, C., Hughes, M., Kennedy, R., Loveland, T., Moisen, G., Schroeder, T., Vogelmann, J., Woodcock, C., Yang, L., and Zhu, Z.: How Similar Are Forest Disturbance Maps Derived from Different Landsat Time Series Algorithms?, Forests, 8, 98, https://doi.org/10.3390/f8040098, 2017.

Cohen, W. B., Yang, Z., Healey, S. P., Kennedy, R. E., and Gorelick, N.: A LandTrendr multispectral ensemble for forest disturbance detection, Remote Sens. Environ., 205, 131–140, https://doi.org/10.1016/j.rse.2017.11.015, 2018.

Figure 1: why does the validation stop -- connect an arrow to accuracy assessment?

We corrected the workflow accordingly.

L189-L191: How was this applied? Are all forested pixels smaller than 6 adjacent pixels in all configurations set to non-forest? Please clarify.

We applied a spatial filter using the queen-contiguity to convert to non-forest those groups of forest pixels smaller than 6 contiguous pixels in all directions (i.e. considering pixels that share either an edge or node within the 8-connected neighbours). This approach ensured that only larger forest patches, with sufficient connectivity, were retained, while smaller, isolated patches were classified as non-forest.

We clarified this in text (Line 194-196): *"According to the FAO definition, we also defined a minimum mapping unit (MMU) consisting of 6 Landsat pixels for the forest mask (0.54 ha), converting smaller patches to non-forest."*

L197-199: Please provide formulas for the different spectral indices. Could be added to Fig. A5, if you needed to keep appendices to a minimum. Note that there are different TC indices for different Landsat sensors and the DI is somewhat less known.

We added a table in the appendix (Table A1, Line 586) detailing the equations for the spectral indices and Tasseled components. Processing steps for creating the Landsat data cube already include sensor harmonization from TM-EM+ to OLI sensors following Roy et al. (2016). Therefore, we applied the coefficients proposed by Baig et al. (2014) for OLI sensors.

Roy, D. P., Kovalskyy, V., Zhang, H. K., Vermote, E. F., Yan, L., Kumar, S. S., and Egorov, A.: Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity, Remote Sens. Environ., 185, 57–70, https://doi.org/10.1016/j.rse.2015.12.024, 2016.

Baig, M. H. A., Zhang, L., Shuai, T., and Tong, Q.: Derivation of a tasselled cap transformation based on Landsat 8 at-satellite reflectance, Remote Sens. Lett., 5, 423–431, https://doi.org/10.1080/2150704X.2014.915434, 2014.

L211: So the minimum forest patch is 6 pixels and within that the minimum disturbed patch is 3 pixels, if I understand this correctly. You might want to restate the minimum forest patch size again here to remind the readers.

Yes, that is correct. We restated this in Line 214: "*First, annual maps were masked according to the forest land use mask (MMU=0.54 ha) and a minimum mapping unit of 3 Landsat pixels was assigned (0.27 ha), reducing the number of single false positive pixels (so-called salt-and-pepper effect typical for pixel-based classification)*".

L255-258: This needs more information -- "We thus used an approach developed in Senf and Seidl, 2021b and selected a random background sample from all disturbance patches. As harvest is assumed to be the major disturbance agent in Europe (Patacca et al., 2023; Seidl and Senf, 2024). This background sample will represent harvest conditions in contrast to the agent information available in the existing databases."

- What do you mean be "random background sample"?
- How did you ensure this is harvest, please add more details here?

Thanks for this comment, highlighting a sub-optimal description of our methods. We opted for this approach since there is no reliable and spatially explicit information on harvest, and it is very difficult to exclude an underlying natural disturbance (i.e. salvage logging). Due to those shortcomings, Senf and Seidl (2021b) proposed the concept of a random background sample to represent harvest. This approach rests on the assumption that the majority of disturbances in Europe are caused by harvests (estimates range between 80-90%; Senf and Seidl 2021b, Seidl and Senf 2024, Patacca et al. 2023, Ritter et al. *in review*). That is, by randomly selecting disturbance patches, there is a high chance those patches represent harvest. The model contrasts non-harvest patches (i.e. wind, bark beetle and fire) against patches dominated by harvest (background sample) and identifies the predictor combinations most associated with non-harvest disturbances. This approach is very similar to species distribution modelling, where species presence data is available, but species absence data is not (e.g. MaxEnt models). Similar to those models, we model the spatio-spectral "niche" of natural disturbances compared to a background sample that represents average spatio-spectral conditions dominated by harvest disturbances.

While this approach certainly has limitations, it is well suited to identify disturbances patches caused by natural disturbances. This becomes evident when inspecting the maps, where known large scale storm-events (e.g. Vivien/Wiebke in 1990, Lothar in 1999, Gudrun in 2005, Kyrill in 2007, Klaus in 2009, convective events in Slovakia, Slovenia and Poland in 2004, 2014 and 2017, Vaia in 2018, etc.), fire seasons (e.g. 1994/1995, 2003, 2007, 2012, 2017, 2022) and recent bark beetle outbreaks in Central Europe (since the 2018/2019 drought) are all well captured. Previous studies have also compared the classification approach to other datasets and existing databases (see Senf and Seidl 2021b and Seidl and Senf 2024) and found good agreement. In a yet unpublished study, we could also show the fire maps to match well with official fire statistics. Nevertheless, we acknowledge that more information is needed to fully understand our approach and we revised the description as following:

> We rephrased lines 267-274: *"We did not have dedicated information on harvest in the reference database, because there is no reliable spatially explicit information on harvest activities and interpreting harvest is difficult, because harvest can happen in reaction to natural disturbances (i.e. salvage logging). We thus used an approach developed in Senf and Seidl (2021b) and selected a random background sample from all disturbance patches to indicate the absence of fire, windthrow or bark beetle outbreaks in the model. As harvest is assumed to be the major disturbance agent in Europe (Patacca et al., 2023; Seidl and Senf, 2024), this background sample will represent harvest conditions in contrast to the agent information available in the existing databases. In essence, this approach is similar to presence-only species distribution models, where absence data is also rare (Valavi et al., 2022)."*

Patacca, M., Lindner, M., Lucas-Borja, M. E., Cordonnier, T., Fidej, G., Gardiner, B., … and Schelhaas, M.: Significant increase in natural disturbance impacts on European forests since 1950, Glob. Change Biol., 29, 1359–1376, https://doi.org/10.1111/gcb.16531, 2023.

Senf, C. and Seidl, R.: Storm and fire disturbances in Europe: Distribution and trends, Glob. Change Biol., 27, 3605–3619, https://doi.org/10.1111/gcb.15679, 2021b.

Seidl, R. and Senf, C.: Changes in planned and unplanned canopy openings are linked in Europe's forests, Nat. Commun., 15, 4741, https://doi.org/10.1038/s41467-024-49116-0, 2024.

Valavi, R., Guillera-Arroita, G., Lahoz-Monfort, J. J., and Elith, J.: Predictive performance of presence-only species distribution models: a benchmark study with reproducible code, Ecol. Monogr., 92, e01486, https://doi.org/10.1002/ecm.1486, 2022.

L267: I do not agree here: there are many bark beetle outbreaks (and other biotic disturbances) throughout Europe prior to 2017. For instance, a large outbreak in the 1990s and early 2000s on the German and Czech border. See Kautz at al. (2017) and this paper: https://annforsci.biomedcentral.com/articles/10.1007/s13595-013-0279-7 and the many references therein. In my opinion its ok to combine the 2 classes but I would stay away from stating the bark beetle disturbance was minor without much evidence. For example: Fire and Bark beetles are of the same magnitude from 1980 to 2015 (Patacca et al, 2023, Fig. 5).

Kautz, M., Meddens, A.J., Hall, R.J. and Arneth, A., 2017. Biotic disturbances in Northern Hemisphere forests–a synthesis of recent data, uncertainties and implications for forest monitoring and modelling. *Global Ecology and Biogeography*, *26*(5), pp.533-552.

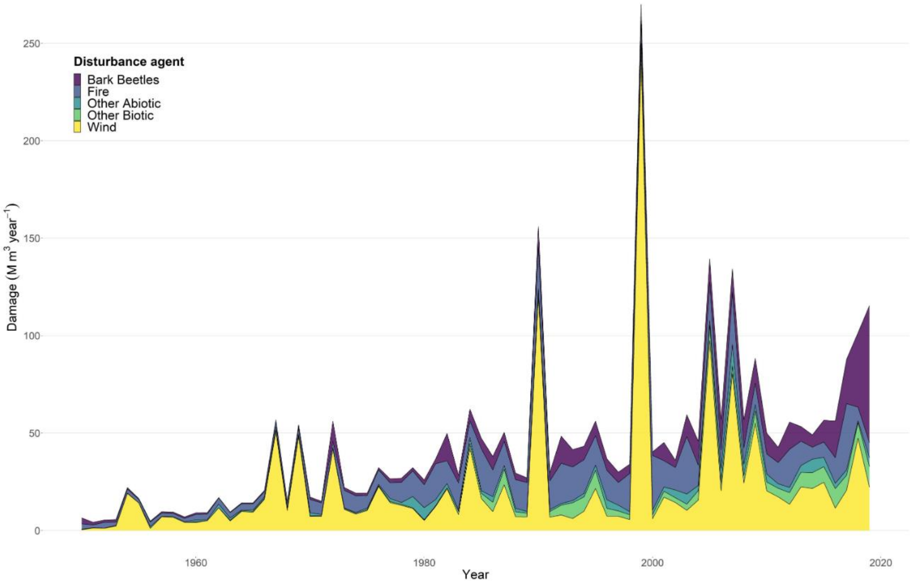
Thanks for this comment, but we politely disagree with the statement. While we agree bark beetle has been a disturbance agent of importance in Europe, it has affected several magnitudes less timber than wind and fire disturbances before the large-scale outbreaks in 2018/2019. The relative minor importance of bark beetle compared to wind and fire disturbances has been well documented in the literature, with the most recent (and probably most reliable) database being the latest update of the European natural disturbance information system by Patacca et al. (2023) (see Figure below and cited by the reviewer).

As shown in the database, the volume affected by bark beetle was always smaller than the volume affected by wind and fire disturbances. The largest disturbance events recorded in the recent history in Europe were large-scale wind events that affected several magnitudes more timber than any previous bark beetle outbreak. Moreover, while the difference in volume between fire and bark beetle is less strong than for wind (even though fire has affected still a substantially larger volume), fires mostly burn in less productive areas (Mediterranean forests) and a comparable or even higher volume will mean a much larger area than similar volumes in more productive areas susceptible to bark beetle attacks.

Finally, the reviewer refers to the large-scale bark beetle outbreaks on the German/Czech border in the 90s (and 00s), more specifically in the Bavarian Forest and Sumava national parks (often referred to as the Bohemian ecosystem). While this outbreak is the prototype of a bark beetle outbreak in Central Europe (and it has been researched for decades), it is a special case and not representative of the overall situation in Europe. First, and foremost, the area affected by bark beetle in the Bohemian ecosystems is nowhere close to areas affected by windstorms. Overall, it is roughly an area of 30-40,000 hectare that was affected, which is about one tenth of the area affected by one individual storm event (e.g. Gudrun, a relatively "small" storm that affected ~300,000 ha in 2005 in Sweden). Second, the outbreak was severe and large because it was unmanaged forest (the Bavarian Forest is a IUCN2 National Park and interventions are thus forbidden). There are no similar outbreaks documented anywhere else in Europe, mostly because eruptions of bark beetle are heavily managed by salvage and sanitation logging. The Bavarian Forest outbreaks was thus unique in its setting and severity. That said, things have changed after 2018, where bark beetle became more important, with large-scale outbreaks across Central Europe. We revised our text to better reflect on the importance of bark beetle disturbances:

We rephrased (Lines 280-286):

> *"Since less historic information was available on bark beetle disturbances that could have improved model skill, we decided to group wind and bark beetle disturbances into one category. Ecologically, both disturbance agents form a disturbance complex with wind disturbances often triggering bark beetle disturbances and vice versa (Seidl and Rammer, 2017). That said, as bark beetle has been a less important natural disturbance agent compared to wind and fire disturbances prior to the recent Central European drought event (Patacca et al., 2023), disturbances in the wind/bark beetle category prior to 2017 can be considered as mostly wind dominated, while disturbances in the same class can be considered bark beetle dominated after 2017."*



Patacca et al. (2023): Total reported damage caused by natural disturbances in Europe between 1950 and 2019.

Figure 10. There are very large discrepancies in 2018 across the different data sets, is there a way to improve this? In L449 this is attributed to dry years, but I assume there are many more "dry" years in the time series. Could you relate (correlate?) drought years to this overestimation?

We here referred to the extreme drought event in 2018 affecting Fenno-Scandinavia and Central Europe (Knutzen et al., 2025). The event was an extreme anomaly, and according to Hari et al. (2020) the consecutive droughts in 2018 and 2019 were unprecedented in the last 250 years in Europe. As such drought events are rare events (i.e. occurring only once in our dataset), we do not expect a clear linear relationship between dryness and overestimation. We rephrased the lines to convey the uniqueness of the event more clearly.

> Lines 453-454: *"Both years were particularly dry in Fenno-Scandinavia and Central Europe (Knutzen et al., 2025), leading to strong spectral differences…"*

Knutzen, F., Averbeck, P., Barrasso, C., Bouwer, L. M., Gardiner, B., Grünzweig, J. M., ... & Gliksman, D. (2025). Impacts on and damage to European forests from the 2018–2022 heat and drought events. Natural Hazards and Earth System Sciences, 25(1), 77-117.

Hari, V., Rakovec, O., Markonis, Y., Hanel, M., & Kumar, R. (2020). Increased future occurrences of the exceptional 2018–2019 Central European drought under global warming. Scientific reports, 10(1), 12207.

Note some minor spelling comments/edits in the attached pdf.

We reviewed the comments pointed out in the file:

Line 15: we changed to *multiple overlapping* disturbance events

Line 17: we prefer to keep it as validation, since it actually refers to the temporal validation results.

Lines 24-25: corrected

Line 88: replaced "finally" with "fifth"

Line 256: corrected

Line 457: corrected

Response to Reviewer #2

The authors wish to thank the anonymous referee #2 for his/her constructive comments and suggestions, which have substantially improved our manuscript. We have considered the recommendations carefully and revised the manuscript accordingly. We made significant changes to the manuscript to further clarify the methods and validation process.

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General comments

It is certainly a great paper, describing a huge processing effort to identify long-term changes in forested areas in Europe. The generated dataset will certainly be very useful to monitor changes throughout the European territory and identify the main drivers which should lead to better conservation of European forest patrimony.

I have a few general remarks and a longer list of specific comments that may help the authors to improve the current version of the manuscript, but my general impression is very positive.

First, it is not clear why the authors selected pixel instead of plots as reference data for calibrating and validating the outputs. Single pixels are difficult to characterize and may be affected by geolocation errors, particularly when detecting changes. In this regard it is not clear why the authors start commenting at length about this pixel reference database, but then make several analyses at patch level when they do agent attribution. It seems inconsistency here, which would be convenient to clarify. It would be convenient to clarify the text now included in sections 2.2 and 2.6 and explain why two different approaches were necessary to classify and to assign agents.

We thank the reviewer for their comment, which pointed out a sub-optimal description of our methods. We used two distinct reference datasets for 1) annual disturbance mapping, and 2) disturbance agent attribution. To date, there is no reference dataset that fulfils all the requirements to calibrate and validate disturbance models per agents in a single step (i.e. a systematically collected, spatially explicit and covering all of Europe and all years since 1984). We therefore relied on two separate existing datasets to first calibrate and validate a pixel-based disturbance model and following calibrate a patch-based attribution model. Separating disturbance detection and attribution into two steps is quite common and has been done also in other studies (Kennedy et al., 2015; Sebald et al., 2021; Senf et al., 2017; Shimizu et al., 2019; Stahl et al., 2023).

The first step focuses on annually mapping disturbed and undisturbed pixels within forested areas relying on spectral changes from a given year (t_0) and the previous year (t_{-1}) at the pixel level. We did this mapping-step at the pixel level, because the reference database used for model training exists at the pixel level and it would have been impossible to translate this pixel-based reference database into a patch-based database (we would need high-resolution imagery back to 1984 for doing this). While we acknowledge that single-pixel reference data may introduce potential geolocation uncertainties, we minimized these issues by employing robust preprocessing methods (i.e. spatial co-registration) and given the large number of samples (n = 20,084), it can safely be assumed that uncertainties in matching pixels to reference points will not affect the overall training success and validation precision.

The second step (agent attribution) was done at the patch level, because several patch-based predictors were derived from the maps (i.e. patch size and form). For doing this, patches need to be identified, for which a pixel-based classification is needed in the first place. Thus, doing both classification steps in one model would be impossible. Using patch-based predictors for agent attribution has been done in many previous studies (Oeser et al., 2017; Sebald et al., 2021; Senf and Seidl, 2021b; Stahl et al., 2023) and builds upon ecological understanding on the distinct spatiotemporal dynamics of natural disturbances. To better explain the two processing steps (disturbance mapping at the pixel level and agent attribution at the patch level), we expanded the information on how each reference dataset was created and more prominently highlight the difference between the two classification steps:

> Lines 84-89: "*The overall workflow behind the EFDA contains six processing steps summarized in Figure 1 and described in full detail in the following sub-sections: First, building a consistent Landsat data cube for Europe. Second, compiling a reference dataset on forest land use and forest disturbances. Third, creating a consistent forest land use mask. Fourth, developing a classification-based approach to detect disturbances annually at the pixel level. Following this, validating the forest land use mask and disturbances maps based on an independent reference sample. Fifth, identifying disturbance patches and the likeliest agent of disturbance at the patch level. Lastly, creating a set of summary layers on forest disturbances and forest disturbance agents.*"

Lines 240-249: "*To identify the most likely agent of disturbances, we adapted an existing attribution algorithm (Sebald et al., 2021; Seidl and Senf, 2024; Senf and Seidl, 2021b) for the annual disturbance maps. The algorithm first detects disturbance patches by grouping pixels disturbed in the same year that are connected by an edge or corner using queen-contiguity. That is, the analysis is performed at the patch-level and not at the pixel level anymore, allowing us to derive patch-level predictors important for disturbance agent attribution (Oeser et al., 2017; Sebald et al., 2021; Stahl et al., 2023). To correct for timing errors in the disturbance map (e.g., a fire mapped over two years might appear as two separate fires), patches from consecutive years that share an edge are merged, with the disturbance year assigned based on a majority vote (see Senf and Seidl 2021b for details). For each patch, we generated a set of 18 predictors, including its size, shape, spectral characteristics, and surrounding landscape (see Table 2 for details and Figure A6 for further details on variable importance, as well as Seidl and Senf, 2024; Senf and Seidl, 2021b).*"

References:

Kennedy, R. E., Yang, Z., Braaten, J., Copass, C., Antonova, N., Jordan, C., and Nelson, P.: Attribution of disturbance change agent from Landsat time-series in support of habitat monitoring in the Puget Sound region, USA, Remote Sensing of Environment, 166, 271–285, https://doi.org/10.1016/j.rse.2015.05.005, 2015.

Oeser, J., Pflugmacher, D., Senf, C., Heurich, M., and Hostert, P.: Using Intra-Annual Landsat Time Series for Attributing Forest Disturbance Agents in Central Europe, Forests, 8, 251, https://doi.org/10.3390/f8070251, 2017.

Sebald, J., Senf, C., and Seidl, R.: Human or natural? Landscape context improves the attribution of forest disturbances mapped from Landsat in Central Europe, Remote Sensing of Environment, 262, 112502, https://doi.org/10.1016/j.rse.2021.112502, 2021.

Seidl, R. and Senf, C.: Changes in planned and unplanned canopy openings are linked in Europe's forests, Nat. Commun., 15, 4741, https://doi.org/10.1038/s41467-024-49116-0, 2024.

Senf, C., Seidl, R., and Hostert, P.: Remote sensing of forest insect disturbances: Current state and future directions, International Journal of Applied Earth Observation and Geoinformation, 60, 49–60, https://doi.org/10.1016/j.jag.2017.04.004, 2017.

Shimizu, K., Ota, T., Mizoue, N., and Yoshida, S.: A comprehensive evaluation of disturbance agent classification approaches: Strengths of ensemble classification, multiple indices, spatio-temporal variables, and direct prediction, ISPRS Journal of Photogrammetry and Remote Sensing, 158, 99–112, https://doi.org/10.1016/j.isprsjprs.2019.10.004, 2019.

Stahl, A. T., Andrus, R., Hicke, J. A., Hudak, A. T., Bright, B. C., and Meddens, A. J. H.: Automated attribution of forest disturbance types from remote sensing data: A synthesis, Remote Sensing of Environment, 285, 113416, https://doi.org/10.1016/j.rse.2022.113416, 2023.

Second, it is not clear whether the authors used multitemporal changes in the detection of disturbances or classified single years without any consideration of previous years. There is a comment in lines 214-215 that indicates that double disturbances were removed in post-processing, but it would have been simpler to classify with both current year and previous year indices, so the change would have been included explicitly in the classification, thus removing double detections.

To identify disturbed and undisturbed pixels annually, we indeed use the spectral information from the previous year (t-1) and the target year (t0) (see section 2.4. lines 200-203). We thus do multi-temporal classification. The case presented in Figure 4 is an example of the illogical sequences that may appear when relying on year-to-year changes. In the example shown (sequence of Disturbed-Undisturbed-Disturbed), the second falsely classified disturbance is difficult to prevent even when considering additional previous years, because there is a negative change not only with respect to the previous year, but also with the year t-3 and backwards. Further, including years back in time would have restricted the time series starting point to early 1990s.

My third comment refers to the confusion that appears in some paragraphs of the paper between validation and uncertainty characterization. They are not the same, the former meaning the level of agreement with the reference data, and the latter the probability of being sure that the classification was properly done. This is clear when authors use the probability of the RF classifier, but they do not mention uncertainties derived from the pre-processing or the compositing periods or even the lack of observed areas. In addition, in lines 404-05 it is indicated that the authors aimed to provide a full characterization of uncertainty, but they talk about validation results.

We thank the reviewer for this comment, and we agree that we wrongly wrote that we provide a full quantification of uncertainty, which – in fact – we do not. We provided a detailed assessment of classification errors and a comparison of our data products to existing products. We further provide classification probabilities derived from the Random Forest model, but we do not use those probabilities in later analyses. They are just provided as a decision support for user and can be used to apply more/less strict thresholds for disturbance classification (e.g. to reduce commission errors) (see Figure B1 appendix). Therefore, we revised the manuscript to strictly refer to validation and not uncertainty quantification throughout the manuscript.

Finally, the spatial validation is well explained but nothing is very little is said about the temporal reporting accuracy, that is how longer after the actual disturbance your product detects it. Include this on your validation approach with a proper consideration to the impacts of your annual compositing method.

We assessed temporal accuracy in lines 358 to 367 showing annual commission/omission errors (see Figure 8) and detailed confusion matrices of disturbance detection assessment per period can be found in Table B2 of the Appendix. We further showed in Figure 9 the validation of the disturbance year by comparing the estimated disturbance year versus manually interpreted year, with a mean absolute error of 1.91 years, meaning that we detect disturbances within the next 2 years after and many fall into the same year. This is already an improvement compared to previous assessments which reported more than 3 years (Senf and Seidl, 2021a). We are unsure what additional analyses is proposed by the reviewer.

Beyond the results section, we further discuss sources of errors in the discussion section, and specifically how our compositing approach contributes to the delayed detection of disturbances.

Lines 461-462: *"Further, image availability and observation gaps (e.g. ETM+ SCL-off problems) can also contribute to missing disturbed areas in large disturbance patches".*

Lines 482-485: *"We further found that omission errors were caused by a delayed detection of disturbances (i.e. disturbances detected one year after the reference). The detection of disturbances with a delay of one year is a common problem when working with annual summer composites, where disturbances can occur in the same year but after the compositing date (i.e. a pixel is selected from August, but the disturbance occurs in November and will thus only be detected the next summer)."*

Specific comments

Lines 114-15. Please further clarify the methods used for the annual compositing. The reader should not need to read another paper to understand yours.

Thanks for the suggestion. We reviewed the description and added more information on the compositing process.

Lines 115-121: "*For creating the best available pixel composites, we selected for each pixel the best observations based on a parametric weighting scheme established in previous research (Griffiths et al. 2013). Observations were ranked per pixel according to distance to clouds and cloud shadows, haze opacity and proximity to a predefined target date (1st of August; Figure A1- Appendix). Each of these factors is assigned a specific weight in the scoring algorithm and only high-quality pixels are considered, i.e. observations with very low cloud or haze score are discarded. The observation with the highest cumulative score is then selected as the best pixel for each location, ensuring both spectral and temporal consistency in the composites."*

Lines 118-19. Gap-filling with a previous year is quite controversial. In my opinion, it would have been more convenient to fill the date with a pre-summer image or just keep the unobserved data as unobserved and more the analysis to the following year.

Thanks for this comment. Indeed, gap-filling can introduce problems. That said, in most cases the trajectory is stable over time and filling the missing observation with the previous year will not change the outcome (i.e. a stable forest pixel). The worst case is that a disturbance happens exactly in the year of a missing observation. In this case, the disturbance will be detected one year later (as the stable forested conditions from the year before will be superimposed). This drawback is, however, minor compared to having many missing observations in the final map, because the bitemporal classification does not work with missing observations. Using a pre-summer observation is also challenging, as in many regions there will still be snow before summer, introducing large spectral changes and thus a high risk of false positives. Hence, our filling only "delays" the analysis into the next year, as proposed by the reviewer. Consequently, we did not change our approach.

Line 189: Not clear to me why you used a single forest mask for the whole period. What happens with areas that converted from crop to forest or from forest to urban during your time period? You indicate in line 191 that "All non-forest land use pixels were excluded from following analyses", non-forested when, anytime in between 1983-2023. How about areas of new urbanization in that period?

Thank you for this comment. First and foremost, it is important to understand that we aimed at creating a land use mask instead of a land cover mask. For forest areas, land cover can be dynamic, while land use remains static. A harvested area is still considered a forest, even though temporary unstocked. Using a forest land cover map (i.e. existing maps) would have masked out those temporally unstocked areas, leading to the exclusion of many disturbed areas. Further, creating a reliable land use mask allowed us to mask out all unrelated land uses (e.g. permanent agricultural areas, urban areas, waters, etc.), even though they might have trees as land cover (e.g. in urban areas).

We approach the problem of land use mapping by applying a multitemporal classification to map forest and non-forest land uses, leveraging the full time series of reference data (1985–2018) as input to the Random Forest model (see lines 190 onwards: "*we trained a random forest model with a stack of all annual best available pixel composites as input (i.e. 34 years with 6 spectral layers and 6 spectral indices, resulting in 408 features, see Table A1 and Figure A4*)". This method allowed us to classify each pixel into its predominant land use over the entire time frame, rather than being limited to a specific subset of years or a single year. This approach was first and foremost used to exclude areas that have been non-forest land use over the full temporal period. This approach also ensures that young forests of lower tree cover, areas of reforestation and temporally unstocked areas (e.g. forestry roads) will be included. We consider this multitemporal classification an effective solution compared to the use of a static forest mask, which would mask out recently disturbed areas that are temporarily unstocked.

We acknowledge, however, that this approach does not account for all types of land use changes, such as urbanization or afforestation events. Yet, forest disturbances related to land use conversions in Europe account for only 2.6% of all disturbances (Senf and Seidl, 2021b), and those will not cause any problems as the majority are related to infrastructure development (e.g. highways, parking lots, industrial areas) and show little spectral changes after disturbance (i.e. forest to non-forest land cover change). Problems would arise if a forest turned into cropland with year-to-year spectral changes after disturbance that would be falsely detected as disturbance. Forest to agricultural conversion is – however – rare in Europe. Afforestation areas will also be included in our mask, but those afforestation patches will likely not cause any false positives, because spectral properties are very different to disturbances (in fact, the opposite behaviour). Thus, while there will be uncertainty from the multi-temporal land use mask, it ensures the inclusion of all forests and does not mask out temporally unstocked and recently disturbed areas.

A year-specific land cover and thus dynamic land use map would be an important next step in understanding land cover dynamics across Europe. However, creating such a dataset is beyond the scope of this study.

Line 198, you include here the use of NDVI and Disturbance index but none of the two are quoted in table 2. Please clarify why?

We used a different set of predictors for the annual disturbance mapping and for the agent attribution. To provide clarity, we included a figure in the appendix (Table A1) detailing the indices used as inputs for the forest land use and forest disturbance classifications (see also Lines 190–194 and Lines 202–205 and Figures A4 - A5 for feature-space information on the predictors). Table 2 summarises the variables used only in the disturbance agent attribution model. For the agent attribution, we used the NBR and Tasseled Cap components because they showed higher predictive importance for the forest disturbance detection (see Figure A6).

Line 239-240: Not sure why do you consider that a burned area cannot occur in two consecutive years in a neighbour region. In Europe is less frequent but in other ecosystems is quite common.

We agree that fires can occur in two consecutive years but is very rare Europe – as pointed out by the reviewer. As we focus on Europe in our study, we consider our wording appropriate. The reason we merged patches from consecutive years is that temporal errors in our disturbance map can cut large disturbance events into two pieces. This happened most often with large fires that burnt over the summer and thus over the temporal cut-off for the compositing algorithm. The problem became most obvious with SLC-off strips, showing gaps in the fire pattern that are filled in the following year (see Figure 11a). We thus consider the potential error introduced by this processing step as minor to the benefits. We note that a similar technique is also used by Acil et al. (2024) and Hermosilla et al. (2015).

Acil, N., Sadler, J. P., Senf, C., Suvanto, S., and Pugh, T. A. M.: Landscape patterns in stand-replacing disturbances across the world's forests, Nat Sustain, 8, 86–98, https://doi.org/10.1038/s41893-024-01450-3, 2024.

Hermosilla, T., Wulder, M. A., White, J. C., Coops, N. C., and Hobart, G. W.: Regional detection, characterization, and attribution of annual forest change from 1984 to 2012 using Landsat-derived time-series metrics, Remote Sensing of Environment, 170, 121–132, https://doi.org/10.1016/j.rse.2015.09.004, 2015.

Line 241: How patches were created? What is the impact of your compositing period to create those patches?

We created individual disturbance patches using queen-contiguity (i.e. considering the 8-connected neighbours), combining all pixels disturbed in the same year sharing either an edge or node. We clarified that now in Lines 244-249: *"The algorithm first detects disturbance patches by grouping pixels disturbed in the same year that are connected by an edge or corner using queen-contiguity (…) To correct for timing errors in the disturbance map (e.g., a fire mapped over two years might appear as two separate fires), patches from consecutive years that share an edge are merged, with the disturbance year assigned based on a majority vote".*

The compositing period can impact the formation of patches (see comment before), and we discuss this in detail in the discussion (see Figure 11). Lines 479-482*: "We further found that omission errors were caused by a delayed detection of disturbances (i.e. disturbances detected one year after the reference). The detection of disturbances with a delay of one year is a common problem when working with annual summer composites, where disturbances can* *occur in the same year but after the compositing date (i.e. a pixel is selected from August, but the disturbance occurs in November and will thus only be detected the next summer).”*

Additionally, we show here an example of a fire in Portugal that was mapped over two years due to the composite dates (DOY before and after the fire event occurred):

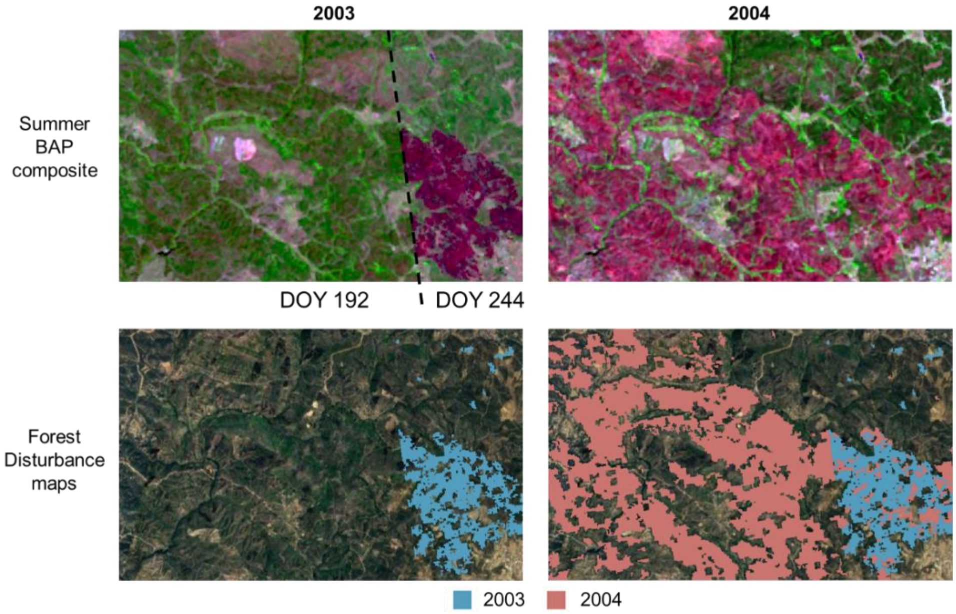

Figure 5. It is not clear what the colours mean, as three different colour legends are included above.

We edited the figure for better clarity and placed the legends below each corresponding layer for the 3 examples.

Figure 7. Include country abbreviations (perhaps in Table 1)

We included country abbreviations in Table 1.

Line 350. Indicate why accuracy is reduced before 2000. I assume it will be a question of image availability, but this should have been considered when computing the uncertainty, and therefore the estimations done with broader confidence intervals.

Accuracies are lower before 2000 due to higher commission errors related to image noise (i.e. remaining clouds, difficult illumination conditions) and omission errors are also slightly higher for that period, likely due to lower image availability (though this is hard to test). We included the following details in the results:

Lines 358-362: *“The high commission error prior to 2000 was driven by the very early years of our time series (<1990), where commission error was on average 22.5% (compared to 16.4% between 1990 and 1999), likely due to higher noise in the underlying data. Omission errors showed a less clear pattern, with also higher omission rates in the 80s (23.3%), likely due to lower image availability, but less pronounced differences before/after the year 2000 (22.5% and 20.5%, respectively).”*

How the image availability should be reflected in the confidence intervals is unclear to us. It is important to note that our study does not involve any kind of area estimation (the numbers shown in Figure 6 are raw pixel counts). There are thus no confidence intervals given for the disturbance area estimates.

Line 394. Include a comment of the disturbance return times in the paper, as you indicate is a novelty of your product.

We included a comment on the disturbance return times in lines 406-409. "*We found, for example, return times of 15-20 years in recurrent fires in the Mediterranean or in short rotation plantations across Europe (e.g. Hungary, Sweden, Netherlands), and further temporal interactions between harvest and wind disturbances in the Gascony area in France (i.e. wind disturbance following a harvest event).*"

Line 426. You are right that is difficult to compare you map with static land cover. Maybe you can make a comparison with the LC CCI product, which provides annual changes, even though at coarser resolution product than yours.

Although a comparison of our forest land use map would be interesting (we compared already with country forest cover form Forest Europe 2020), we decided to focus on comparing our product to maps that specifically map forest disturbances/changes, and that provide information at the same spatial resolution as our product.

Further, several studies have highlighted limitations in using the CCI-LC product for annual land cover changes analysis. For instance, Li et al (2018) used the annual ESA CCI land cover maps (1992–2015) for gross and net land cover changes in the main plant functional types and noted discrepancies when compared with other datasets, suggesting caution in their application for detailed land cover change analyses, particularly due to its spatial resolution limitations (1km).

Li, W., MacBean, N., Ciais, P., Defourny, P., Lamarche, C., Bontemps, S., ... & Peng, S. (2018). Gross and net land cover changes in the main plant functional types derived from the annual ESA CCI land cover maps (1992–2015). Earth System Science Data, 10(1), 219-234.

Figure 11 shows most likely ETM derived strips in the fire area of central Portugal. This was not commented in the paper and it should, as it creates an evident noise in the output. Please include the map location of the three sites.

Figure 11(a) shows fire events in Portugal that were recorded across two different years in EFDA. The pattern observed in the year 2003 due to ETM+ data corresponds to true disturbed pixels, with the disturbance patch being fully completed in the subsequent year 2004. We acknowledge this as a valid observation; however, it is important to note that this is distinct from ETM+ artifacts, which can introduce false disturbances. This example nicely shows the problem of using annual composites for disturbance mapping (see also discussion above) and is a great example of why we group consecutive and neighbouring disturbance events together before doing the patch-based agent attribution.

We edited Figure 11 to include the map location of the three sites for better clarity and commented on the ETM derived strips in Lines 461-462: *"Further, image availability and* *observation gaps (e.g. ETM+ SCL-off problems) can also contribute to missing disturbed areas in large disturbance patches."*

Line 461. You indicate the potential problems to detect grading changes. Have you explore the use of spectral unmixing approaches?

Spectral unmixing is indeed a valuable technique used to disentangle changes in vegetation cover types within a pixel. It could certainly be a promising approach for detecting more subtle disturbances, particularly those that do not produce a clear opening of the canopy (e.g. gradual defoliation). Testing spectral unmixing is, however, beyond the scope of this study. We like to note, though, that we aim at exploring spectral unmixing in a follow-up project.

Line 485. You indicate potential problems with several years with poor image availability. Have you tried to use MODIS 250m resolution reflectances for those years? A few methods that compare Landsat-MODIS to merge reflectances are available in the dedicated literature.

Incorporating MODIS reflectance for years with limited image availability could be an interesting avenue to explore. However, most of the gaps in our time series occur in the years before the 2000s, for which MODIS is not available (see Figure A2 showing the annual percentage of no-data pixels for best available pixel composites). Further, this approach would introduce additional limitations. For instance, MODIS lacks SWIR bands at a 250m resolution (only available at 500m - 1km), which are crucial for detecting forest disturbances due to its high sensitivity to forest structure and vegetation water content (see importance of NBR and TCW in Figure A6). Moreover, merging datasets with differing spatial resolutions would introduce further uncertainties to the disturbance detection, especially in Europe where disturbances are small, and forests are highly fragmented.

Line 505. I agree on the need of having publicly access validation databases. May be you can refer to the BARD, which is a global (not just European, but with European sites) validation database of burned perimeters (Franquesa et al. 2020). References:
Franquesa, M., Vanderhoof, M.K., Stavrakoudis, D., Gitas, I.Z., Roteta, E., Padilla, M., & Chuvieco, E. (2020). Development of a standard database of reference sites for validating global burned area products. *Earth Syst. Sci. Data 12*, 3229-3246.

Indeed. We incorporated examples of public databases in Lines 520-522: "*Further research should thus increasingly focus on generating reference data that can be used for remote sensing applications (e.g. Franquesa et al., 2020; Senf, 2019), and we urge authors to make their reference data openly available, ultimately leading to a better understanding of forest change across Europe.*"