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.

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.

***

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).

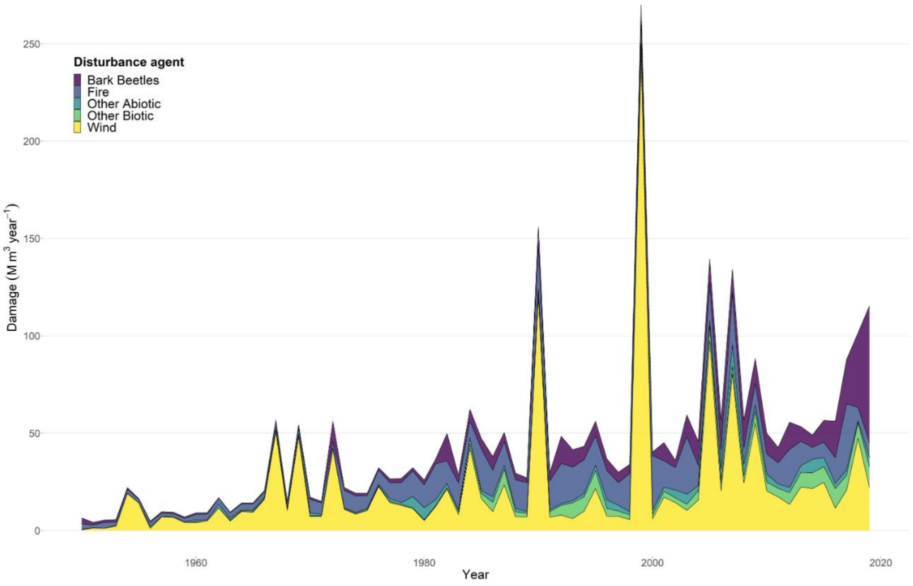
As shown in the database, the volume affected by bark beetle was always smaller than the volume affected by wind and fire disturbances. The largest disturbance events recorded in the recent history in Europe were large-scale wind events that affected several magnitudes more timber than any previous bark 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