Reply to Reviewer 1

> *This study analyzes the response of periods with relatively low NDVI to various climate variables in Europe, with a particular focus on forested areas. The authors use high spatial resolution data with long temporal coverage, complemented by ERA5-land data as climate inputs. Although the data used in this study has potential for this type of analysis, it appears that the research contributes minimally to the current understanding of climate impacts on forest health. Furthermore, the study is affected by significant uncertainties due to data aggregation and the statistical methods applied. Overall, the results are not informative, and the discussion section is lacking. I would not recommend accepting this article in its current format. To be considered for publication, it would need substantial revisions. Below, I provide some of the reasons for my decision.*

We thank reviewer #1 their time and their helpful comments, which supported the revision of the manuscript. We replied to the comments below and modified our manuscript accordingly.

> *Line 16: Forests consume large amounts of water, so I would not classify water storage and regulation as a service typically associated with forested lands. See, for instance, the review by Filoso et al. (2017).*

Thank you very much for your input. We agree that water storage can certainly be discussed (depending on the climate and the forest type/age), but we would rather keep "regulation", because it is well known that forests, compared to an absence of forest, slow down the landing of rain drops on the soil and facilitate water absorption instead of having flowing water on the soil surface. See for example https://efi.int/forestquestions/q7_en

In their review, Filoso et al. (2017) specify that forest restoration can decrease the amount of water directly accessible for humans, compared to other types of land use. Following your remark, we deleted the term "water storage" in the new version of the manuscript. We added more references to the list of ecosystem services, including references cited in Filoso et al. (2017).

"It is now well understood that forests offer essential ecosystem services such as soil conservation and fertility, water regulation and purification, protection against landslides and avalanches, air cleaning, wood production, habitat for specialized biodiversity, without forgetting their aesthetic, spiritual, and recreational value (Postel and Thompson Jr., 2005; Millennium Ecosystem Assessment, 2005; Neary et al., 2009; Jenkins and Schaap, 2018; EFI, 2025)."

> *Line 17: Additionally, biodiversity in homogeneous forest landscapes is generally much lower than in heterogeneous, fragmented landscapes.*

Thank you for your remark. We agree that the importance of biodiversity depends on various factors, including the level of heterogeneity but also many others, like forest types and management. If young, intensively exploited forests are quite poor, old-growth forests can be very rich. Moreover, the statement can depend on the considered taxonomic group: forests are often quite poor in plant species, but can be very rich in insects, birds and fungi species, even exploited forests if the tree composition is close to the natural conditions. We have now improved the sentence accordingly, by adding “specialized biodiversity” and added more references to back up the statements (“Thompson et al., 2011; Brockerhoff et al., 2017”).

> *Line 19: While an increase in forest activity is observed over large regions, how can this trend be explained? I think this assessment should be more balanced.*

Thank you very much for your input. We have reformulated and restructured the sentence to avoid any overstatement.

“These essential ecosystem services are at risk because of climate change, which causes increased detrimental conditions for forests, such as insect outbreaks (Pureswaran et al., 2018) and increased drought frequency (Senf et al., 2020; Adams et al., 2017; IPCC, 2021).”

> *Lines 44-45: A critical issue to address is the skill of the forecasting model. While the theoretical framework might be compelling, if the model does not demonstrate operationally reasonable accuracy, the study's value is limited.*

Thank you for your comment. We are not sure which forecasting model the review refers to (our prediction model for forest damage, or the ECMWF forecast for hydro-meteorological variables). We formulate an answer for each forecasting model.

The line numbers 44-45 in the pre-print refer to the ECMWF forecast model for hydro-meteorological variables. We do not use these forecasts in our analysis, but rather indicate that, once we know which variables are important and can predict low greenness events in a given region, then we can specifically monitor these variables in the model output from ECMWF forecasts. The skill assessment of various ECMWF forecast variables falls outside the scope of our study, as we do not use these varaibles. Relevant literature on this topic is available here:

Zampieri, M., Manzato, A., & Molteni, F. (2018). Skillful subseasonal forecasts of aggregated temperature over Europe. Meteorological Applications, 25(3), 353–360. https://doi.org/10.1002/met.2169
ECMWF Charts. (n.d.). 2m dewpoint temperature forecasts. Retrieved from https://charts.ecmwf.int/products/medium-2t-dp
Vannitsem, S., et al. (2023). Improving subseasonal forecast of precipitation in Europe by using a stochastic post-processing method. Quarterly Journal of the Royal Meteorological Society, 149(753), 3554–3575. https://doi.org/10.1002/qj.4733
Nicolai-Shaw, N., Zappa, G., Seneviratne, S. I., & Orth, R. (2025). Assessment of seasonal soil moisture forecasts over the Central Mediterranean region. Hydrology and Earth System Sciences, 29, 925–943. https://doi.org/10.5194/hess-29-925-2025
Recalde-Coronel, G. C., Zubieta, R., & Lavado-Casimiro, W. (2024). Contributions of initial conditions and meteorological forecast to subseasonal-to-seasonal hydrological forecast skill in Western Tropical South America. Journal of Hydrometeorology, 25(5), 1234–1250. https://doi.org/10.1175/JHM-D-23-0064.1

Regarding this point, we added the following paragraph in the discussion section:

“Our analysis identifies key variables for predicting low greenness events. These variables can be specifically monitored using model outputs from ECMWF forecasts. While evaluating the predictive skill of various ECMWF forecast variables lies beyond the scope of this study —since these datasets were not used— relevant literature on this topic is available (Zampieri et al., 2018; ECMWF, 2025; Vannitsem et al., 2023; Nicolai-Shaw et al., 2025; Recalde-Coronel et al., 2024)”

If the reviewer refers to the random forest model used to predict forest browning, we provide accuracy measures using the AUC and CSI metrics (section 3.2 Performance). The goal of this study is to share a prediction method, its assessment, and to determine whether using solely hydrometeorological conditions is effective. We apply this method to actual remote sensing NDVI observations, with accuracy measures computed using testing data from years not included in the model fitting. Considering your remark, we added the following paragraph in the discussion section:

"For smaller-scale operational forecasts, such as those for small-scale forest management, we recommend following our method but training the model on higher spatial resolution data, such as station observations of hydro-meteorological data and forest field measurement, if available for long periods. Additionally, we suggest using our verification method, with both CSI and AUC, to measure accuracy."

Lines 59-61: Recent studies suggest that using vegetation indices may not be the best approach for assessing tree health and climate impacts compared to studying secondary forest growth (Gazol et al., 2018; Hoek van Dijke et al., 2023). This should be considered if the primary aim is to evaluate the effects of climate variability on forest conditions. Moreover, it is widely known that NDVI tends to saturate at high Leaf Area Index (LAI) values (Carlson & Ripley, 1997). Why not use kNDVI, which addresses many of these issues (Camps-Valls et al., 2021)?

Thank you for your comment and suggesting these studies.

Both Gazol et al. (2018) and Hoek van Dijke et al. (2023) compare point data (tree rings or observations from flux towers) with NDVI satellite imagery with a medium spatial resolution. Following your comment, we added a paragraph in the discussion section:

"Compared to pointwise measurements, NDVI has two main limitations: (1) it tends to underestimate drought impacts (Hoek van Dijke et al., 2023), and (2) it lacks sensitivity to underlying structural or physiological forest damage (Gazol et al., 2018). To address limitation (1), we use a binary definition of forest damage, focusing on the relative extremeness of low greenness events rather than their absolute magnitude. Regarding point (2), our aim is to conduct a continental-scale analysis, thanks to the broad spatial coverage of the AVHRR NDVI dataset. For smaller-scale operational forecasts, such as those for small-scale forest management, we recommend following our method but training the model on higher spatial resolution data, such as station observations of hydro-meteorological data and forest field measurement, if available for long periods."

Thank you for suggesting kNDVI. We selected NDVI for its computational efficiency for our large dataset and to be able to compare our dataset with existing products from NOAA or NASA (MODIS VI products, Global Inventory Modeling and Mapping Studies (GIMMS) NDVI3g (Pinzon and Tucker, 2014) and the LTDR4 NDVI (Pedelty et al., 2007)). In addition, kNDVI requires the careful selection of parameters and kernel for the present use case (Qiang Wang et al., 2023). For example, Wang et al. (2022) uses the default settings presented in Camps-Valls et al. (2021) and observed no notable difference in performance between NDVI and kNDVI.

Following your comment, we added the following paragraph in the discussion section: "NDVI tends to saturate at high leaf area index (LAI) values, particularly in dense broad-leaved forests (Aklilu Tesfaye and Gessesse Awoke, 2021). Our compositing strategy, using the median value of the NDVI for 10 days, slightly mitigates this effect. An alternative is the kernel-based NDVI (kNDVI), which can address some limitations of the NDVI (Wang et al., 2023). However, using the kNDVI requires careful adjustment of parameters and kernel selection based on the specific use case. For example, Wang et al. (2022) found no significant improvement between using the NDVI versus the kNDVI, likely due to the default kernel values not being universally applicable. Additionally, the computational cost of applying the kNDVI to large datasets, such as 40 years of AVHRR data, can be prohibitive due to the need to fit parameters for each pixel, e.g. if sigma differs from the default value."

Lines 69-79: It is unclear whether the authors developed their own NDVI data using the original AVHRR raw images. If so, several issues must be considered, such as geometric correction, atmospheric correction, topographic correction, and data gap filling. These are not explained in the study, yet they are critical for evaluating the quality of the dataset. Developing a high-resolution LAC dataset for Europe since 1981 is a substantial task, and summarizing it in two brief paragraphs is insufficient.

Thank you for your comment and sorry that this was unclear. We used the processed data downloaded from the AVHRR Archive from the University of Bern. We cite Barben et al. (2024), as they describe the general procedure to derive the NDVI dataset (Section 2.2 and 2.4). We have now clarified the source and how these data were produced. In addition, more information about the AVHRR Archive from the University of Bern can be found in:

Hüsler, F.; Fontana, F.; Neuhaus, C.; Riffler, M.; Musial, J.; Wunderle, S. AVHRR Archive and Processing Facility at the University of Bern: A comprehensive 1-km satellite data set for climate change studies. EARSeL eProceedings 2011, 10, 83–101

Or in :

Weber, H. GCOS Switzerland Project: Fractional Snow Cover Time Series (1981–2021)—A Novel Dataset from Space to Support Climate Studies in Switzerland, Final Report; Technical Report; Federal Office of Meteorology and Climatology—MeteoSwiss: Zurich, Switzerland, 2022.

Both sources are cited in Barben et al.

Following your comment, we reformulated the data description as follows:

"We use the NDVI 10-day composites dataset generated from the Advanced Very High Resolution Radiometers (AVHRR) local area coverage data (Dupuis et al., 2024; Barben et al., 2024; Weber et al., 2021). This dataset is archived at the University of Bern, Switzerland. The AVHRR sensors are onboard the National Oceanic and Atmospheric Administration's (NOAA) satellites and the European operational satellite agency (EUMETSAT) MetOp satellites series (MetOp1, MetOp2 and MetOp3). The NDVI compositing is generated by retaining the 10-day median value of NDVI (Asam et al., 2023). Prior to that, the dataset was orthorectified, radiometrically calibrated, and filtered for clouds, and the NDVI values were spectrally corrected for the different versions of the AVHRR instrument as described in Barben et al. (2024). The advantage of the AVHRR dataset over Europe are the long period of data availability, from 1981 to 2022 (for our analysis), and the good trade-off between temporal resolution (10-day) and spatial resolution (0.01∘W× 0.01∘N, effective footprint of approximately 1 km2). We discarded NOAA-15 due to poor data quality and MetOp3 due to the absence of specific correction coefficients for the spectral response function (see Fig. A1 in the appendix for the time distribution of the satellites used). As several platforms (NOAA-6 to -18 and the MetOp-series) may be available for a given 10-day composite, we selected the maximum NDVI value among the MED (median value composite) NDVI values to obtain a single time series."

Line 92: The significance of the 80% value is unclear. Does this refer to 80% of European forests, individual forest types, or forest patches?

Thank you for your remark, we reformulated the sentence for more clarity:

"A 0.1° gridpoint (GP) is considered to experience a low-greenness event (or summer forest damage), if over 80% of its constituent 0.01° forest pixels show a negative anomaly of NDVI in at least 5 out of the 6 ten-day NDVI composites spanning July–August."

Lines 103-105: How are land cover changes accounted for? In some regions, deforestation (e.g., due to forest fires) or reforestation (due to land abandonment) has been particularly intense. This should be considered since NDVI anomalies could be linked to land cover changes.

Thank you for pointing this out. To test the effect of land cover change, we used all the masks available for the whole Europe over the studied period and discarded 0.01° pixels that experienced a forest change between 2006, 2012 and 2018. We then reprocessed the NDVI binary time series. We re-ran the RF model for all grid points and updated all our figures. 189 out of the 1248 initial grid points were discarded with this procedure. The take home message of the figures and the manuscript in general did not change, only minor differences in the specific number of grid points including certain variables as a top 10 predictor (Figure 4).

We adapted accordingly the method section according to the above mentioned changes::

"The forest coverage and forest type (broad-leaved, coniferous, mixed forests, see Fig.D1) are extracted from the CORINE (Coordination of Information on the Environment) Land Cover for the reference years 2006, 2012 and 2018 (EEA, 2020a, b, c). We discard 0.01° pixels that are not classified as forest, or that experience a forest change between 2006, 2012 and 2018 (i.e. a change in land cover or forest type)."

Line 113: This appears to be an error. AVHRR NDVI data typically has a spatial resolution of 1.1 km at the nadir.

Indeed this line is incorrect, we removed l.111-115.

Line 127: Have the normality assumptions for these variables been checked? I suspect that at least precipitation does not follow a normal distribution, and alternative probability distributions should be used to normalize z-scores.

Thank you for this valuable comment. We did not test the monthly and seasonal means of hydro-meteorological variables for normality. We acknowledge that precipitation, in particular, is typically non-normally distributed at daily scales. However, aggregation to monthly and seasonal scales tends to produce distributions that are closer to normal, consistent with expectations from the Central Limit Theorem.

Our objective in standardizing the predictors (i.e., removing the mean and dividing by the standard deviation) is not to enforce strict normality but to facilitate comparability across predictors. Although some asymmetry may remain—for example, a difference between the mean and median—this does not materially affect our interpretation. Importantly, we do not treat the zero-anomaly point as a sharp threshold in the analysis. Instead, we interpret the partial dependence plots qualitatively, focusing on general trends rather than precise values.

Given the exploratory nature of the interpretation and the robustness of the approach at the aggregated scale, we believe that using the mean and standard deviation to compute anomalies is sufficient for our purposes. Nonetheless, we agree this is a valuable point and have added a short clarification in the discussion section: "To ensure comparability across predictors, we standardized all hydro-meteorological variables by removing the mean and dividing by the standard deviation. While we acknowledge that some variables (e.g., precipitation) are typically not normally distributed, particularly at daily scales, aggregation to monthly and seasonal means reduces skewness and tends to produce distributions closer to normal, in line with the Central Limit Theorem. Our goal was not to enforce normality but to center and scale variables consistently for model interpretation".

> *Lines 130-131: Cumulative conditions typically have negative consequences for vegetation (Bachmair et al., 2018), so the compartmentalization of the climate data could be problematic.*

Thank you for your comment. We acknowledge that temporal clustering of adverse conditions can result in a compounding effect, leading to a greater impact than the sum of individual events. However, this aspect is beyond the scope of our study, which aims to provide an overview of detrimental conditions. We chose to analyze anomalies separately to determine if distinct periods have similar or opposing effects. We agree that a follow-up study could explore the impact of temporally compounding adverse conditions, potentially revealing a worsened (or reduced) impact compared to individual events. The following sentence is present as future perspectives in the discussion section: "We established a statistical link between the preceding seasonal conditions and forest damage during the following year, hinting towards a source of inter-annual predictability for European forests. Indeed, forests impacted by extreme summer conditions are more vulnerable to adverse conditions the following year Brun et al. (2020); Frei et al. (2022). Consecutive years with adverse conditions may reduce tree resilience, reflecting a "memory effect" (Anderegg et al., 2015; Hermann et al., 2023). A causality analysis (Peters et al., 2017) could explore the role of previous summers' forest state or insect infestations as predictors, although this framework is beyond the scope of our study."

> *Line 189: The spatial resolution of the data seems too coarse. This contradicts the 0.1º spatial resolution indicated earlier. Additionally, several forested areas are missing from the analysis, such as large parts of the Mediterranean Iberian Peninsula, Norway, and the Irish and British Isles. This discrepancy contrasts with the maps in Figure B1, which record forest coverage over larger regions, but also show differences in coverage across years that are not explained. It is unclear why forest areas at 0.1º resolution in Figure B1 are not analyzed at this resolution but instead aggregated at 0.5º, which introduces uncertainties by mixing different land cover types. If climate and NDVI data are available at the same spatial resolution, there seems to be no reason for such aggregation, which reduces the coverage and introduces errors.*

Thank you for your remark. The spatial resolution of the data used as input data for the Random Forest is indeed 0.5°. This is due to the stacking procedure applied to the 0.1° data, as explained in section "2.4 Aggregating data for longer time series", and figure C1 in the appendix. With the resolution of 0.1°m 41 years of NDVI implies 41 datapoints for the random forest, which is not enough for a robust statistical fitting of the model. Therefore, we stacked together timeseries of 0.1°gridpoints located in the same 0.5° gridbox, as shown in fig. C1.

To increase the visibility of the section “Aggregating data for longer time series”, we mention it at the end of section 2.2:

“Note that the length of the binary damage time series is maximum 41 data points for each grid point, which is not sufficient to establish a robust statistical link with hydro-meteorological predictors. Therefore, we concatenate time series from neighboring grid points to obtain longer time series (see section 2.4)”

> *Line 215: Regarding the analysis, I wonder if overfitting might be an issue with the model outputs. For example, in the Jura forest in France, the explanatory climate variables are highly correlated—soil moisture is linked to precipitation, the primary infilling factor, but also to temperature, which affects atmospheric evaporative demand and land evapotranspiration. How can it be explained that soil moisture from the previous summer is the most important factor? It would seem that current soil moisture is more relevant than that from one year ago, which may indicate a statistical artifact from the analysis method used.*

Thank you for your comment. We acknowledge that multicollinearity among predictors (e.g., between precipitation, soil moisture, and temperature) is a concern. To reduce the risk of overfitting, we limited the number of variables considered at each tree split in the random forest (set to 3), which helps mitigate the influence of correlated variables dominating the model. Following your remark, we added the following sentence in section 3.1: “Moreover, using a low number of predictors per tree helps reduce the dominance of correlated variables in the model (Strobl et al., 2008; Gregorutti et al., 2013).”

We also compared the random forest's performance with a LASSO regression model, which explicitly addresses multicollinearity. The random forest showed superior performance on independent test data, giving us additional confidence in its robustness (section 4.1).

We would like to emphasize that the ranking of the top 10 predictors should not be interpreted too rigidly — the differences in mean decrease accuracy are relatively small, and several variables may carry similar levels of explanatory power. While some predictors are indeed correlated, those with stronger and more consistent explanatory value tend to emerge with higher mean decrease accuracy scores across the ensemble of trees. We clarified this point in section 4.2.1 with the following sentence: “The ranking of the top 10 predictors should not be interpreted too rigidly, as the differences in mean decrease accuracy are relatively small and several variables may carry similar levels of explanatory power.”

Please note, that we changed Fig.3 (A) (formerly figure 2) for a the representative grid point with a higher critical success index (CSI).

> *Section 4.2.2: This section is overly cryptic and excessively summarized. For instance, it is impossible to spatially assess the role of the different variables on NDVI. The summaries provided in Figure 3 are not informative. It is unclear which regions are more or less affected by the variables, nor is the overall efficiency of the predicted model clear. Similarly, Figure 4 is not informative, and it is difficult to extract any meaningful patterns from it.*

Thank you for your comment, that helped us to improving the graphical representation of our model's output. In addition to figure 3, we have now added a figure to represent the spatial distribution of the relative importance of some predictor types across Europe. Fig.E1 was added to show, for each gridpoint, the number of predictors, out of the top 10 predictors, that are temperature predictors or soil moisture predictors (any period) or predictors from the preceding year (any variable). We added the following text in the result section:

"We do not identify any specific regions where temperature (in any month or season) or soil moisture (in any month, season, or depth) consistently dominate as the most influential predictors; their importance appears relatively evenly distributed across Europe (FigE1, left and middle panels). Variables from the preceding year are among the top 10 predictors at most grid points, with a moderately greater importance observed at higher latitudes (Fig E1, right panel)."

In addition to the new maps (Fig E1), we modified the text in section 4.2.2. "Results over Europe", to improve the readability.

> *Finally, the discussion section is very weak and lacks depth. Any scientific study must include a discussion that compares its findings with previous research to highlight contributions, gaps, and limitations. This is notably absent from the current manuscript.*

Thank you for your remark.

We extended the discussion on the "identified adverse conditions", adding the following points:

"Temperature and moisture conditions in spring, summer, and autumn of the preceding year play a smaller role. Moreover, increasing temperatures have a direct impact on vapor pressure deficit (VPD), which increased consistently with temperature over these last decades in many regions (Hermann et al., 2024; Schoenbeck et al., 2022). With higher VPD, plant transpiration increases, and once soil is dry, plants have to close their stomates (Grossiord et al., 2020). This induces a risk of carbon starvation and hydraulic failure."

"Low precipitations and extremely warm conditions result in insufficient water availability for tree growth during the whole summer and an increased risk of death (see e.g. Gharun et al., 2024)."

"In stressful conditions, conifers fitness decreases, directly impacting resin production and thus the capacity to control insect infestation (Netherer et al., 2024)."

"Two processes can explain this trend. On the one hand, with dry conditions in spring or summer, if normal rainfall is not encountered during the next months, the following growth season starts with smaller water storage in the soil, which increases the risk of drought on trees. On the other hand, forests impacted by extreme summer conditions are more sensitive to adverse conditions the following year (Brun et al.,2020; Frei et al., 2022)."

We added a paragraph discussing the saturation of NDVI and the use of kNDVI, in the subsection "Dataset limitations" (see above).

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