9th October 2024

Response to anonymous reviewer comment RC2

Authors	Katharina Horn, Stenka Vulova, Hanyu Li, Birgit Kleinschmit
Title	Modelling Forest Fire Susceptibility in Brandenburg under Current and Future Scenarios
Manuscript type	Special Issue: Current and future water-related risks in the Berlin–Brandenburg region
Journal	Natural Hazards and Earth System Sciences (NHESS)
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Reviewer comments are marked with "RC1" and answers from the authors are marked with "A" in cursive. When applicable, we provided quotations of the modified sections from the manuscript to further illustrate the response. The modified sections that are quoted here are marked in ***bold****.*

We would like to warmly thank the reviewer for the extensive and qualitative feedback. We hope that the integration of the reviewer's feedback has improved the quality of the manuscript.

Reviewer Comment #2

RC2: The manuscript "Modelling Current and Future Forest Fire Susceptibility in north-east Germany" by Horn et al. presents an interesting approach by utilizing a variety of predictor variables to model forest fire susceptibility in Brandenburg. The study is well-written and employs state-of-the-art methods and datasets. However, significant methodological flaws heavily influence the results, raising concerns about the validity of the study's conclusions.

A: We thank the author for the valuable feedback and the appreciation of our work. We respect the criticisms regarding the methodology and the datasets. In the following, we will further elaborate on how we addressed these criticisms to improve the manuscript.

RC2: Firstly, the study aggregates meteorological variables at a monthly level and further combines them into three-month periods. This coarse temporal resolution is problematic, particularly when attempting to account for the effects of prolonged droughts. The current approach diminishes the impact of very dry periods that end or begin with heavy rainfall. A more appropriate method would be to use a daily or weekly measure that accumulates over time, such as a drought index or a fire weather index. The authors' claim that higher-resolution data is unavailable is outdated, as daily datasets with reasonable resolution, including wind, humidity, and other relevant variables, are available from sources like the Copernicus Climate Change Service.

A: We thank the reviewer for the valuable feedback and for pointing out additional data sources. It is true that a finer temporal resolution (e.g. daily, weekly) can better account for certain extreme weather events such as extreme rainfall events or heat waves. However, in the following text, we would like to provide further explanation as to why we decided on a three-month aggregation of the meteorological data.

First of all, in order to model and compare forest fire susceptibility under current and future scenarios, the same temporal and spatial resolution of the meteorological data was required to ensure comparability of the results. For our future selected scenarios (2081-2100 under SSP 3.70 and SSP 5.85), meteorological data was only available at a multi-annual monthly scale. Using different temporal resolutions for current and future scenarios (e.g. daily/weekly for the current scenarios and monthly for the future scenarios) would have decreased the comparability of the results. Consequently, in order to align with this temporal resolution, we processed monthly air temperature and precipitation data for both current and future scenarios. The Copernicus Climate Change Service mentioned by the reviewer does provide some very valuable and interesting data sets, such as "Climate extreme indices and heat stress indicators derived from CMIP6 global climate projections" or "Temperature statistics for Europe derived from climate projections". However, the spatial resolution of the data sets is too coarse to account for spatial variances on a regional scale such as in Brandenburg.

Second of all, for the scope of this research, we wanted to consider the effect of meteorological droughts on forest fire susceptibility in Brandenburg. To capture this, we decided on a three-month aggregation of the meteorological data. Several authors have used a three-month aggregation of SPEI to identify meteorological droughts: Zhou et al. (2023) have pointed out that a 3-month time lag is best to identify meteorological drought events. In their study, they compute the SPEI, which is a commonly used index to monitor meteorological droughts. Similarly, Petrovic et al. (2022) used a 3-month SPEI to examine droughts in Germany. Other authors have done the same for different regions across the globe (Wen et al. 2020, Guo et al. 2018).

Furthermore, a monthly aggregation of meteorological data has been applied by different authors working on forest fires to understand meteorological trends (Busico et al., 2019; He et al. 2022; Wang et al. 2021). He et al. (2022) further suggested using monthly or quarterly meteorological data to investigate fire emergence, which was another reason for the aggregation of air temperature and precipitation data to three months. Therefore, we consider a three-month aggregation of the meteorological data an adequate approach to investigate the relation between air temperature and precipitation patterns and forest fire susceptibility in Brandenburg. In particular, capturing long-term trends prior to the emergence of a forest fire was key to this investigation, which was ensured by using a three-month aggregation of the climatic data.

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In order to address this decision more clearly in the manuscript, we modified the following paragraph in section 2.3.2 a) Meteorology (ll. 119 ff.):

"Following the suggestions by He et al. (2022), we used monthly climate data between 2013 and 2022, which was aggregated to three months to incorporate precipitation and air temperature prior to the occurrence of a forest fire. ***Several forest fire related studies have used a monthly aggregation of meteorological data sets to model forest fires (Busico et al., 2019; Wang et al., 2021; He et al., 2022). He et al. (2022) further argue that future studies should consider a monthly or quarterly aggregation of meteorological data when investigating forest fires. Especially in order to identify conditions of meteorological droughts prior to the emergence of a forest fire, we followed the methodology of other authors that used a three-month aggregation of the broadly used SPEI drought index to identify meteorological droughts (Zhou et al., 2023; Wen et al., 2020; Guo et al., 2018).****"*

References:

Guo, H., Bao, A., Liu, T., Jiapaer, G., Ndayisaba, F., Jiang, L., Kurban, A., & De Maeyer, P. (2018). Spatial and temporal characteristics of droughts in Central Asia during 1966–2015. Science of The Total Environment, 624, 1523–1538. https://doi.org/10.1016/j.scitotenv.2017.12.120

Wen, X., Tu, Y., Tan, Q., Li, W., Fang, G., Ding, Z., & Wang, Z. (2020). Construction of 3D drought structures of meteorological drought events and their spatio-temporal evolution characteristics. Journal of Hydrology, 590, 125539. https://doi.org/10.1016/j.jhydrol.2020.125539

Zhou, Z., Zhang, L., Chen, J., She, D., Wang, G., Zhang, Q., Xia, J., & Zhang, Y. (2023). Projecting Global Drought Risk Under Various SSP-RCP Scenarios. Earth's Future, 11(5), e2022EF003420. https://doi.org/10.1029/2022EF003420

RC2: A further indication that there are underlying issues with the model is the minimal influence of climate on fire susceptibility in the random forest model. While I agree that urban characteristics are an important factor in Brandenburg, many of the large fires in recent years have occurred during heatwaves and dry periods. Further investigation into the model's mechanisms, such as incorporating partial dependency plots and examining the validation set for typical false positives and negatives, could help identify where the model needs improvement.

A: We thank the reviewer for the critical feedback on the model validation. We agree with the reviewer that the previous model evaluation was incomplete. To further investigate the model's mechanisms, we:

1. *computed partial dependence plots for a) air temperature and precipitation and b) the three most important predictors (distance to urban settlements, percentage of broadleaf forest, and distance to railways) to show the relationship between these parameters and forest fire susceptibility.*
2. *Furthermore, we computed and analysed the false positive rate (FPR) and false negative rate (FNR) for all models and compared the rates to the meteorological data.*

1. *Partial dependence plots*

We added the following partial dependence plots and their descriptions to the Supplement.

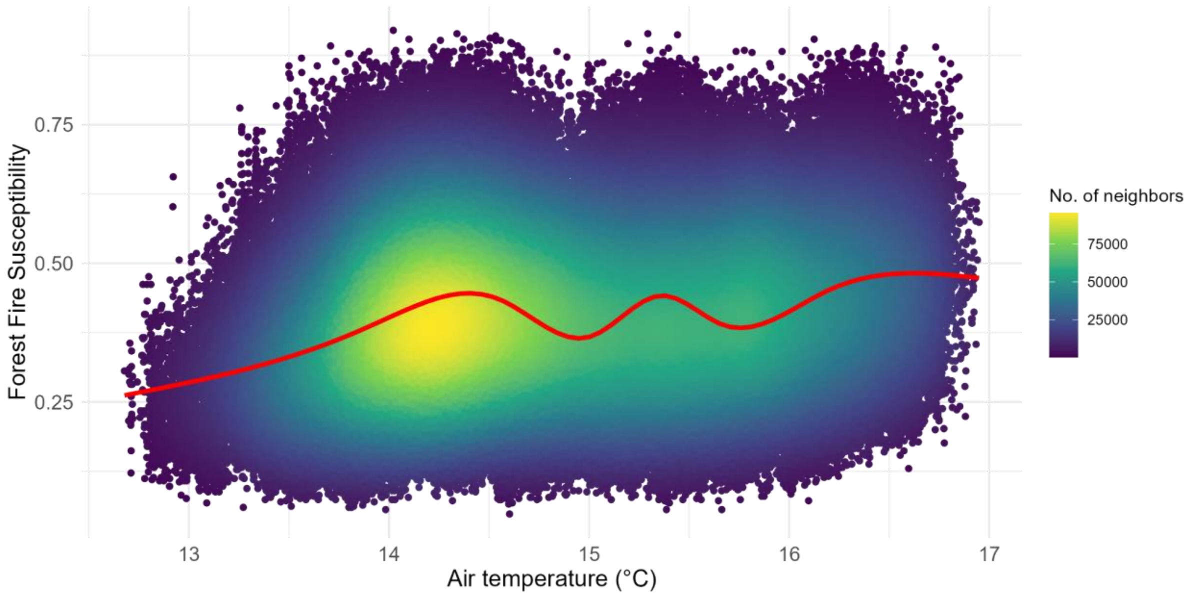


Figure S 7. Partial dependence plot for air temperature and forest fire susceptibility. To compute this plot, a random subset of 100,000 pixels from each of the four FFS predictions (2016, 2022, 2081-2100 under SSP 3.70 and SSP 5.85) was combined (400,000 data points in total). Data for June 2016 and June 2022: DWD Climate Data Center (CDC): Grids of monthly averaged daily air temperature (2m) over Germany, version v1.0. Data for June 2081-2100: Multi-annual monthly air temperature of GCM MPI-ESM1-2-HR (SSP 3.70 and SSP 5.85) from CMIP6 multi-model ensemble derived from WorldClim (2023).

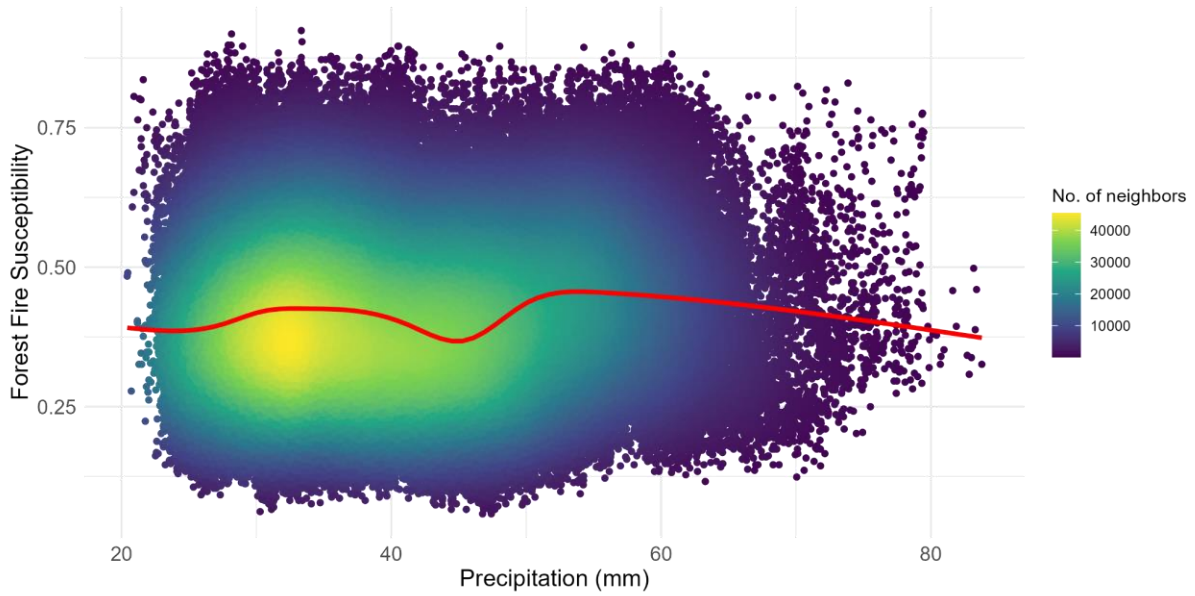
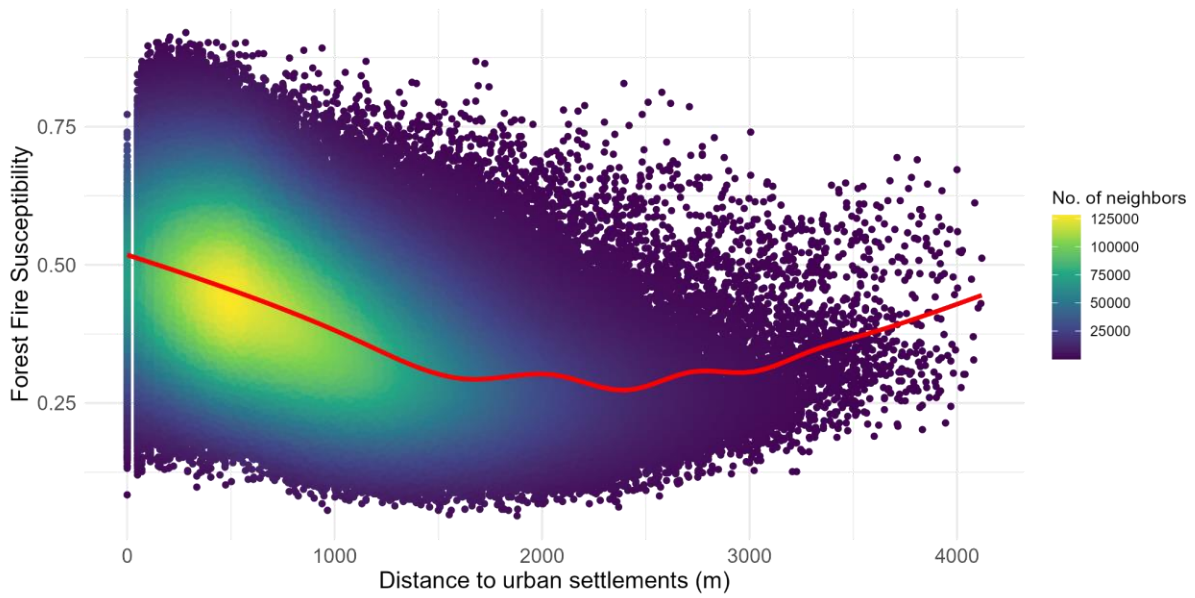
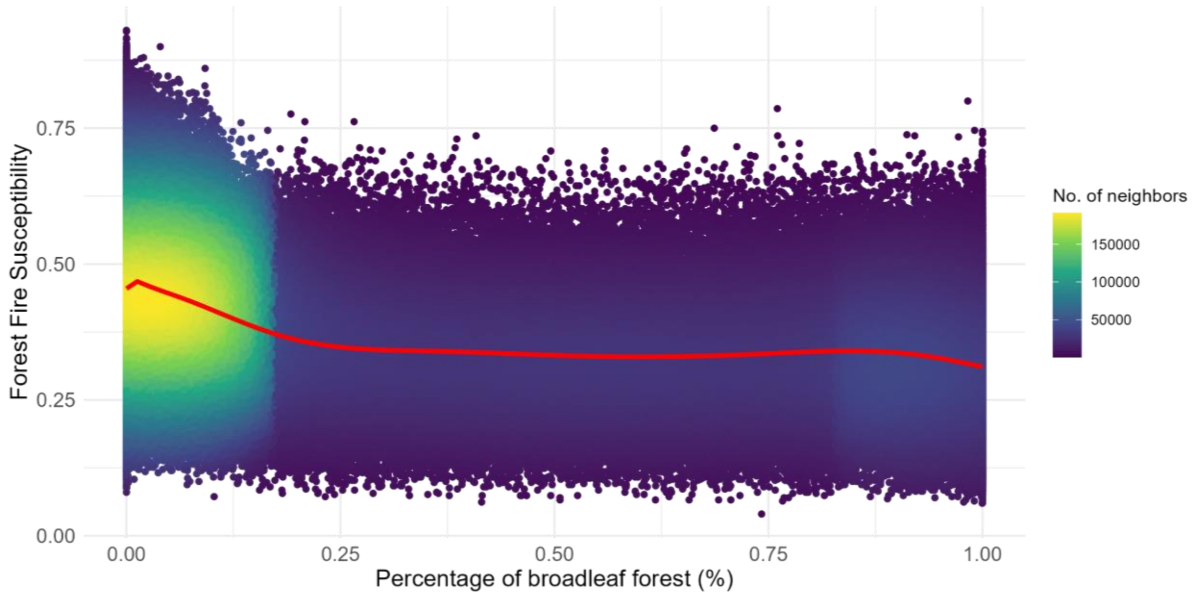


Figure S 8. Partial dependence plot for precipitation and forest fire susceptibility. To compute this plot, a random subset of 100,000 pixels from each of the four FFS predictions (2016, 2022, 2081-2100 under SSP 3.70 and SSP 5.85) was combined (400,000 data points in total). Data for June 2016 and June 2022: DWD Climate Data Center (CDC): Hourly station observations of precipitation for Germany, version v24.03. Data for June 2081-2100: Multi-annual monthly total precipitation (mm) of GCM MPI-ESM1-2-HR (SSP 3.70 and SSP 5.85) from CMIP6 multi-model ensemble derived from WorldClim (2023).

"Figures S 7 and S 8 show the partial dependence plots for the dynamic variables and the predicted FFS. Fig. S 7 underlines that when air temperatures are higher, the FFS increases as well. Fig. S 8 shows that higher or lower precipitation sums overall did not substantially increase or decrease FFS, indicating that there is no clear relation between precipitation and FFS. This was already reflected by the variable importance results (see Fig. 3 in the manuscript)."





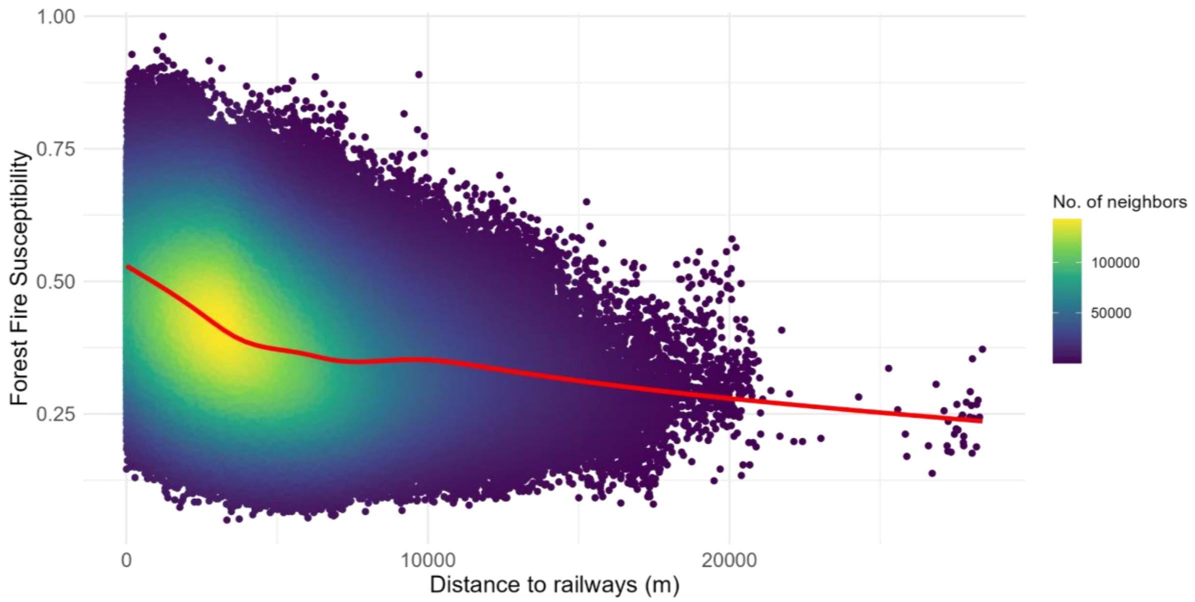


Figure S 9. Partial dependence plot for the three most important predictors and FFS. Similarly to Fig. S 7 and S 8, a subset of 100,000 pixels was extracted from each prediction (2016, 2022, 2081-2100 under SSP 3.70 and SSP 5.85) to compute the partial dependence plots.

*"**The partial dependence plots of the three most important predictors and the related FFS (Fig. S 9) show the relation between the parameter and the FFS. With an increasing distance of up to ~2500 m from urban settlements, an increasing distance to railways, and an increasing percentage of broadleaf trees, FFS decreases.**"*

We added the following sentence in the manuscript to refer to supplemental figure S 9 (Results, 3.2 Importance of predictor variables, ll. 290 f.):

*"**To more deeply explore the relationship between key variables and FFS, partial dependence plots were created (see Figure S 9 in the Supplement).**"*

2. <u>Analysis of false positives and false negatives</u>

To further assess the model's mechanisms, we computed the false positive and false negative rates (FPR and FNR) for each year left out, as well as for the model including all years. False positives are those observations, where the model predicted "fire", although the actual value was "non-fire". False negatives on the other hand are those observations, where the model predicted "non-fire", although the actual value was "fire".

We added the Fig. S 6 and its description to the Supplement:

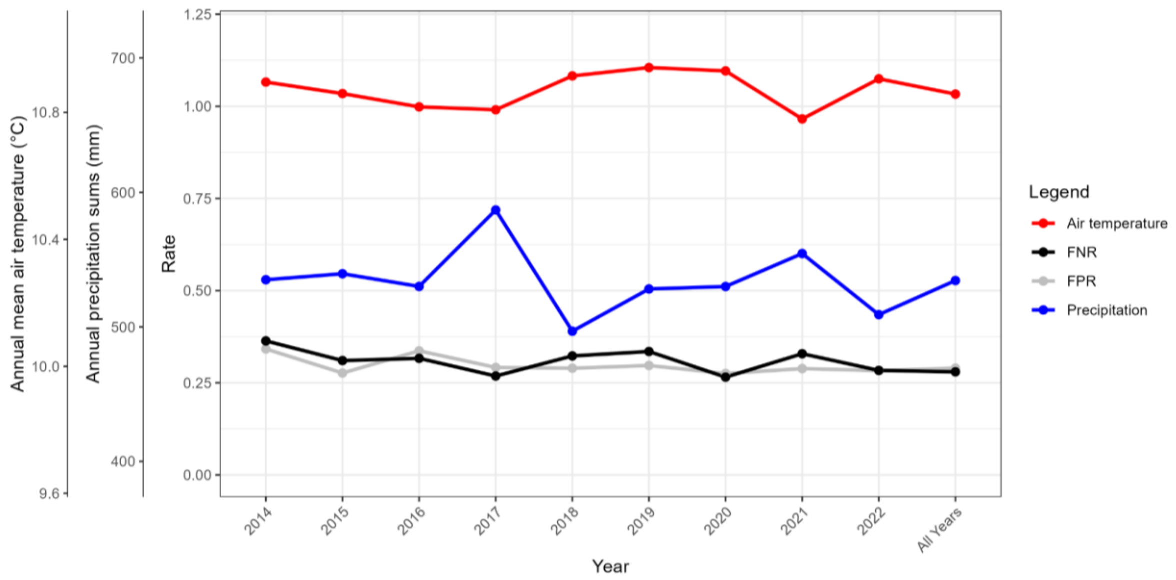


Figure S 6. False Positive Rate (FPR) and False Negative Rate (FNR) of the RF models for each year (2014 to 2022) and all years combined. In order to analyse the influence of climate parameters on the FNR and FPR, the graph additionally shows annual means of monthly precipitation and annual mean air temperatures. These were computed based on data by the DWD Climate Data Center (CDC): Grids of monthly averaged daily air temperature (2m) over Germany, version v1.0 and DWD Climate Data Center (CDC): Hourly station observations of precipitation for Germany, version v24.03.

"Figure S 6 illustrates the False Positive Rate (FPR) and False Negative Rate (FNR) of the RF models. The grey and black lines show the FPR and FNR, respectively. The red line illustrates the mean air temperature per year, computed based on monthly mean air temperatures. The blue line shows mean precipitation sums per year, based on monthly precipitation sums.

The figure shows that across the years, FPR and FNR only differ slightly. Whereas air temperature and precipitation values change more substantially across all years, this did not appear to significantly influence the FPR and FNR. These results underline that the model was not so sensitive to changing weather conditions. Therefore, it can be assumed that the

model has more of a spatial than temporal influence. This means that the model is better at distinguishing where forest fires may occur but has more difficulties to understand forest fire prone weather conditions. This drawback could be addressed by future research that could for example utilise a Long Short-Term Memory (LSTM) model. By introducing an internal memory unit known as the 'cell state' and three gate units: the forget gate, input gate, and output gate, LSTM is able to process short and long-term meteorological trends and the subsequent effects on forest fire susceptibility more adequately."

To address this in the manuscript, we added the following paragraph (ll. 455 ff.):

*"**Apart from the spatial resolution of forest fire products, the modelling approach to predict FFS should be carefully selected. As previously discussed, meteorological parameters did not have a significant influence on the model. Therefore, future research may consider applying a Long Short-Term Memory (LSTM) model to better incorporate meteorological trends and to improve the understanding of how forests react to droughts and heat waves (Burge et al., 2021; Natekar et al., 2021).**"*

Furthermore, we added the reference to the figure in the Discussion section (ll. 335 f.):

*"The results reflect that climatic parameters do not appear to play a pivotal role for FFS **(see Fig. S 6 in the Supplement)**."*

Additional references:

Burge, J., Bonanni, M., Ihme, M., and Hu, L.: Convolutional LSTM Neural Networks for Modeling Wildland Fire Dynamics, https://doi.org/10.48550/arXiv.2012.06679, arXiv:2012.06679 [cs], 2021

Natekar, S., Patil, S., Nair, A., and Roychowdhury, S.: Forest Fire Prediction using LSTM, in: 2021 2nd International Conference for Emerging Technology (INCET), pp. 1–5, https://doi.org/10.1109/INCET51464.2021.9456113, 202

RC2: Finally, the study's future projections are problematic. The authors adjust only climate variables—despite finding them to have minimal effect—while leaving all other factors static. If the distance to urban settlements is the main driver of fire susceptibility, as the study suggests, then future projections should incorporate urban development trends, not just climate.

A: We thank the reviewer for pointing this out. We agree with the estimation that the future projections would highly benefit from the inclusion of further dynamic parameters such as future urban development. To address this matter, we researched available data sets of future *urban cover. We decided to use Esri's "Land Cover 2050 - Global" data set (Esri Environment, 2021) that models different land cover classes at 300 m spatial resolution on a global scale for the year of 2050 as it had a higher spatial resolution than other data products. We extracted the information for the land cover class "Artificial Surface or Urban Area", resampled it to 50 m spatial resolution and computed the distance to "Artificial surface or Urban Area". Consequently, we decided to replace the scenario 2081-2100 (SSP 3.70) by the scenario June 2081-2100 (SSP 5.85) including this projected land cover change data. Therefore, the two future scenarios presented in the manuscript main text now both refer to the time period of June 2081-2100 under SSP 5.85. The scenario of June 2081-2100 (SSP 3.70) was moved to the Supplement (see Fig. S 10 to S 13).*

Accordingly, we now present the following four scenarios within the main text of the manuscript:

- *June 2016,*
- *June 2022,*
- *June 2081-2100 (SSP 5.85), and*
- *June 2081-2100 (SSP 5.85) incl. projected land cover data.*

Despite the fact that the future land cover data set for 2050 does not cover the same time period as the future climatic data sets, we consider it valuable in reflecting future trends in urban development affecting future FFS. Furthermore, projected land cover data for 2081-2100 was not available; thus, we selected the Esri product due to it being a dataset with an acceptable spatial resolution which was closest to this time period.

Since we replaced the future scenario of June 2081-2100 (SSP 3.70) with the new future scenario June 2081-2100 including projected land cover data for 2050, we changed several sections, figures, and tables in the main text and the Supplement.

Specifically, we applied the following changes to figures & tables:

<u>*Table 1:*</u> *We added the information for the projected land cover data set in the last row of Table 1.*

<u>*Figure 2:*</u> *We updated and replaced Figure 2.*

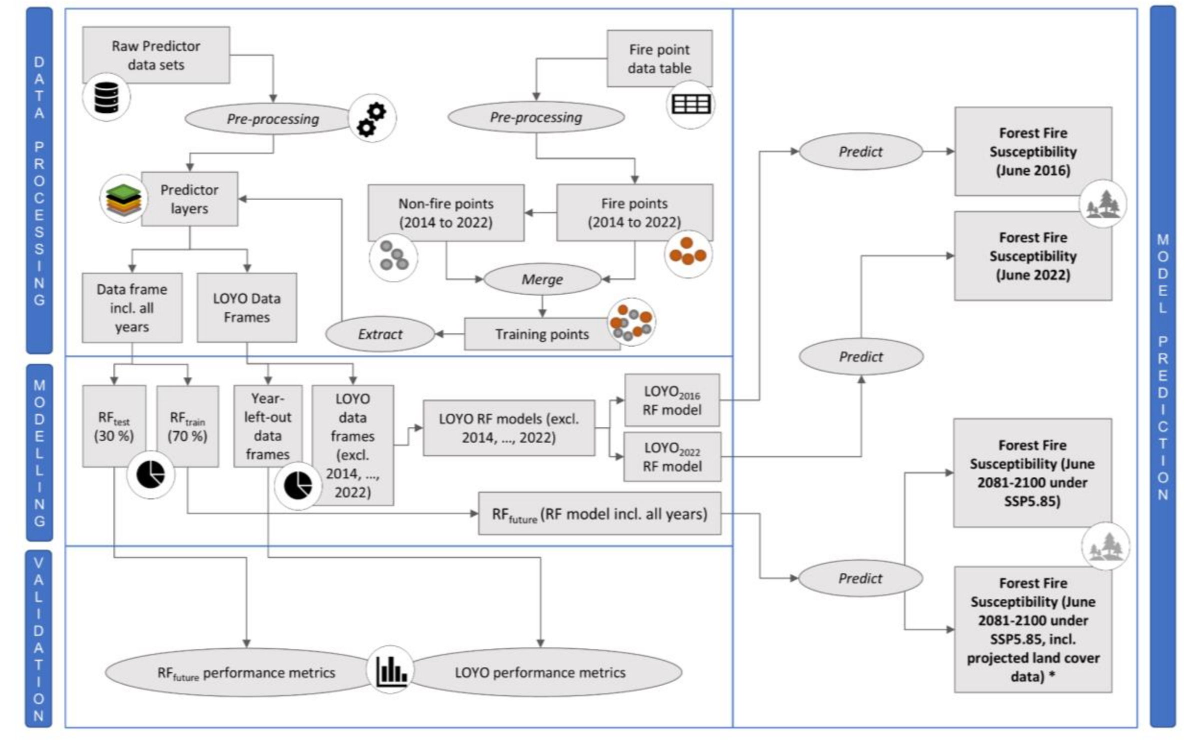


Figure 2. Methodological approach for modelling forest fire susceptibility under different scenarios.

<u>Figure 4:</u> We replaced Figure 4.

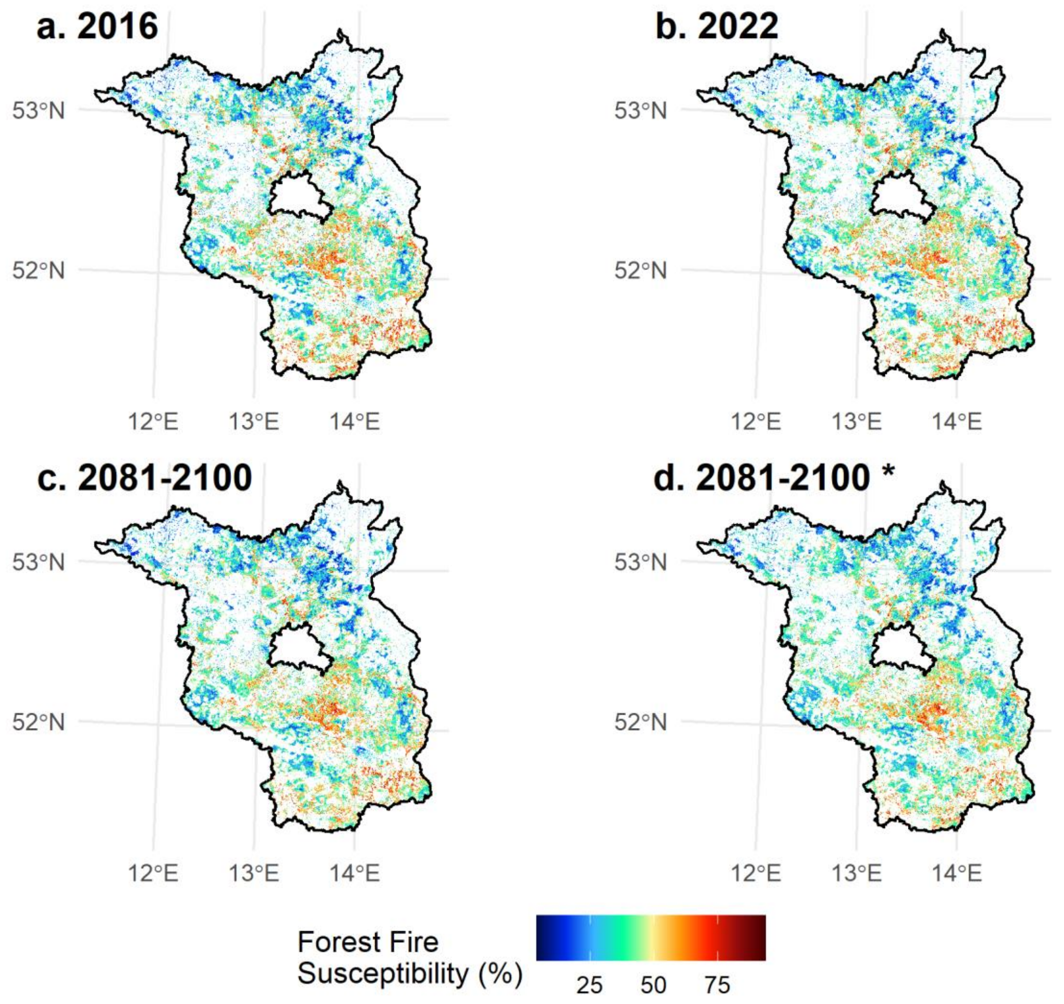


Figure 4. Forest fire susceptibility in Brandenburg under different scenarios. Scenarios c and d both show predicted FFS in June 2081-2100 under SSP 5.85. Scenario d includes projected land cover data, whereas scenario c does not. Border layer © 2018-2022 GADM.

<u>Figure 5:</u> *We replaced Figure 5.*

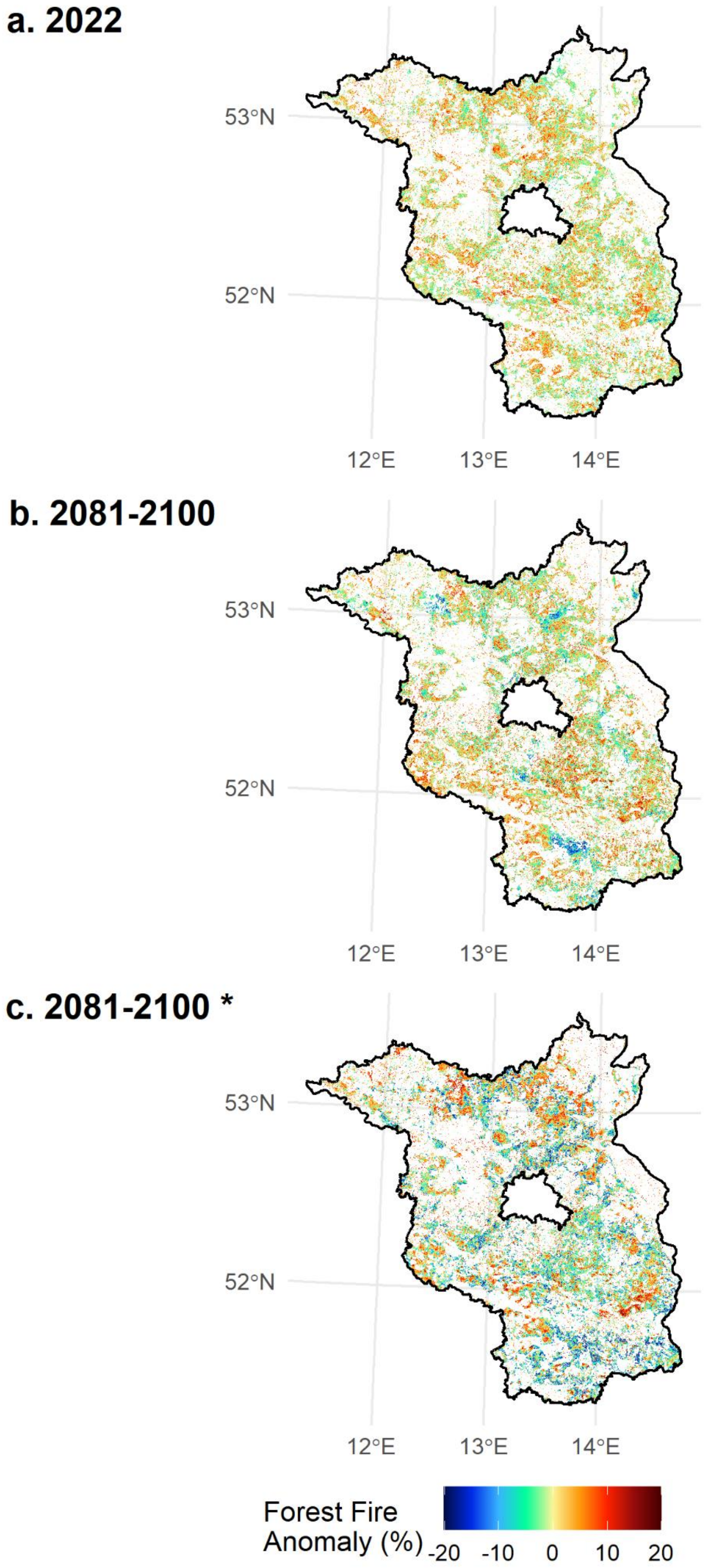


Figure 5. Forest fire anomalies compared to 2016. Scenarios b and c both show predicted FFS in June 2081-2100 under SSP 5.85. Scenario d includes projected land cover data, whereas scenario c does not. Border layer © 2018-2022 GADM.

<u>Figure 6:</u> We replaced Figure 6 and moved the previous version to the Supplement (Fig. S 12).

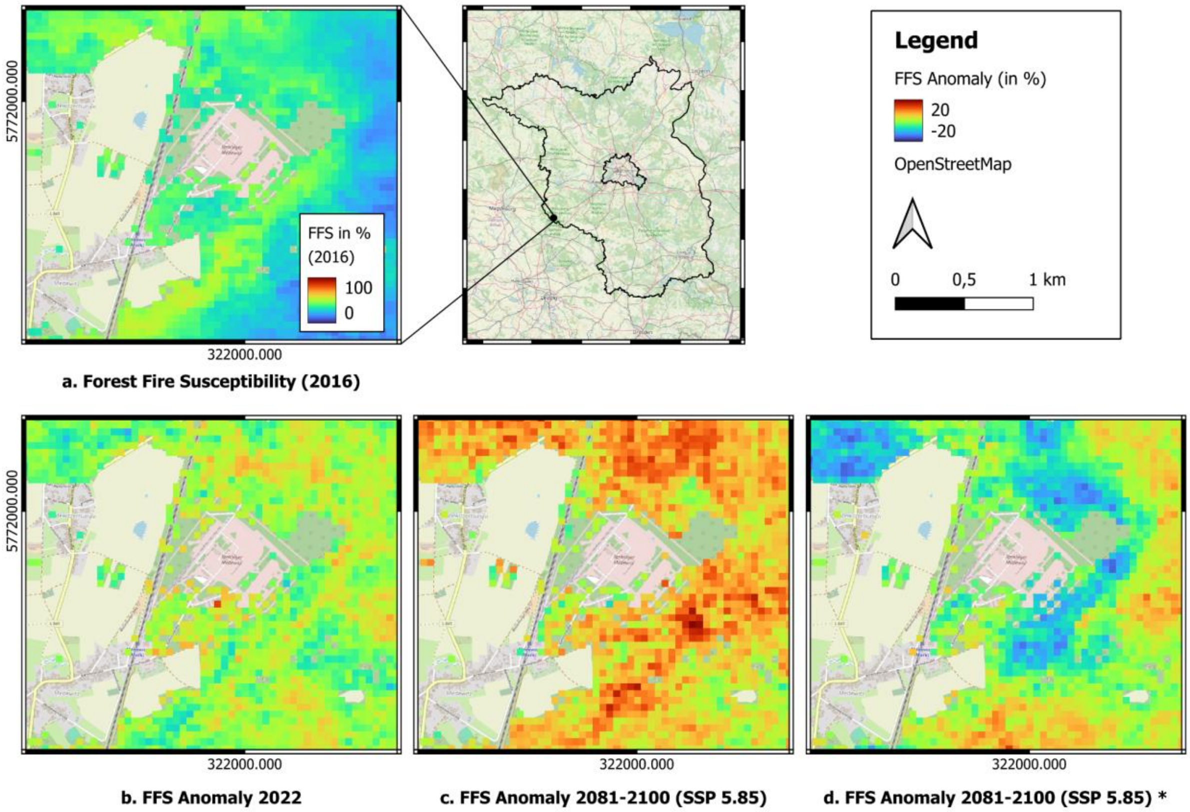


Figure 6. Detailed maps of FFS anomalies in the municipality of Medewitz (Brandenburg). Scenarios c and d both show predicted FFS in June 2081-2100 under SSP 5.85. Scenario d includes projected land cover data, whereas scenario c does not. Base Map © OpenStreetMap contributors 2024. Distributed under the Open Data Commons Open Database License (ODbL) v1.0, Border layer © 2018-2022 GADM.

<u>Figure 7:</u> We replaced Figure 7 and moved the previous version to the Supplement (Fig. S 13).

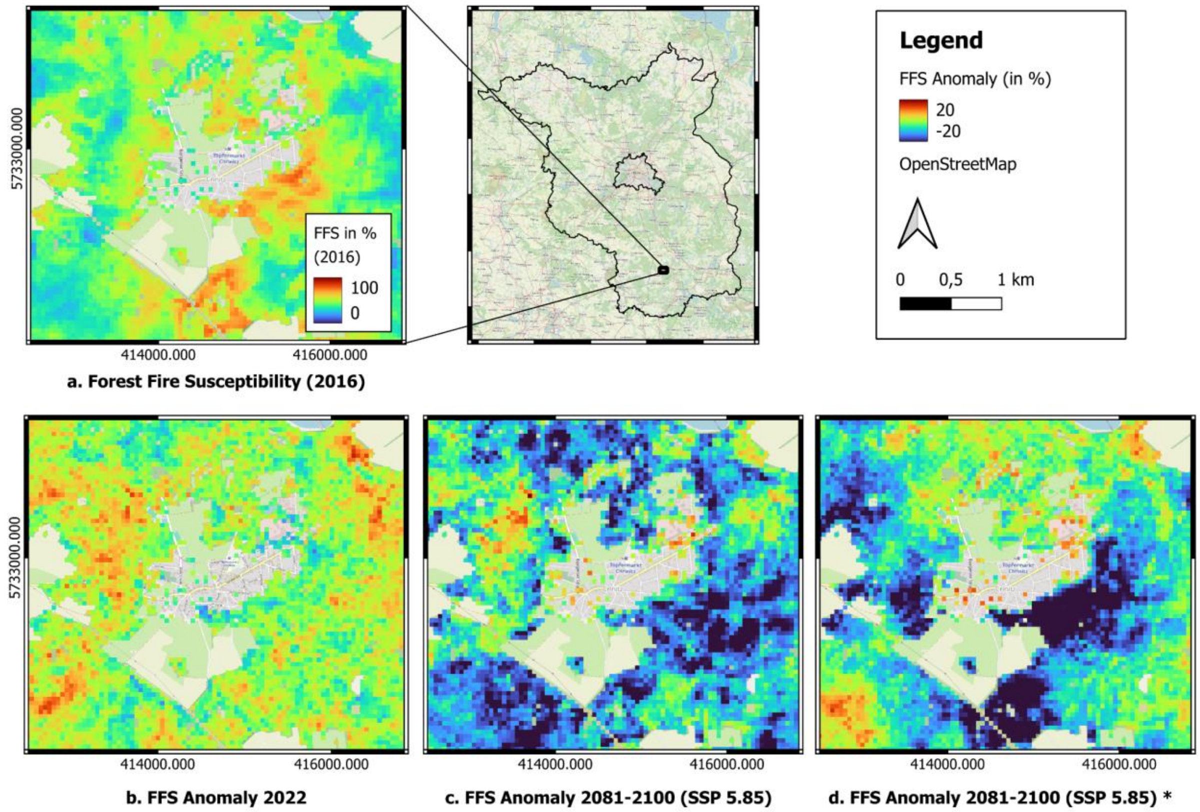


Figure 7. Detailed maps of FFS anomalies in the municipality of Crinitz (Brandenburg). Scenarios c and d both show predicted FFS in June 2081-2100 under SSP 5.85. Scenario d includes projected land cover data, whereas scenario c does not. Base Map © OpenStreetMap contributors 2024. Distributed under the Open Data Commons Open Database License (ODbL) v1.0, Border layer © 2018-2022 GADM.

We updated the results of this table according to the new future predictions including projected land cover data:

Table 3. Statistical overview of the four forest fire susceptibility scenarios. ***Scenarios "2081-2100" and "2081-2100 *" both show predicted FFS in June 2081-2100 under SSP 5.85. Scenario "2081-2100 *" includes projected land cover data, whereas scenario "2081-2100" does not.***

	2016	*2022*	***2081-2100***	***2081-2100 ****
Minimum	*0.040*	*0.040*	***0.042***	***0.072***
Maximum	*0.936*	*0.964*	***0.976***	***0.878***
Mean	*0.409*	*0.419*	***0.414***	***0.393***

Standard Deviation	*0.147*	*0.146*	***0.144***	***0.116***

We added the following figures to the Supplement:

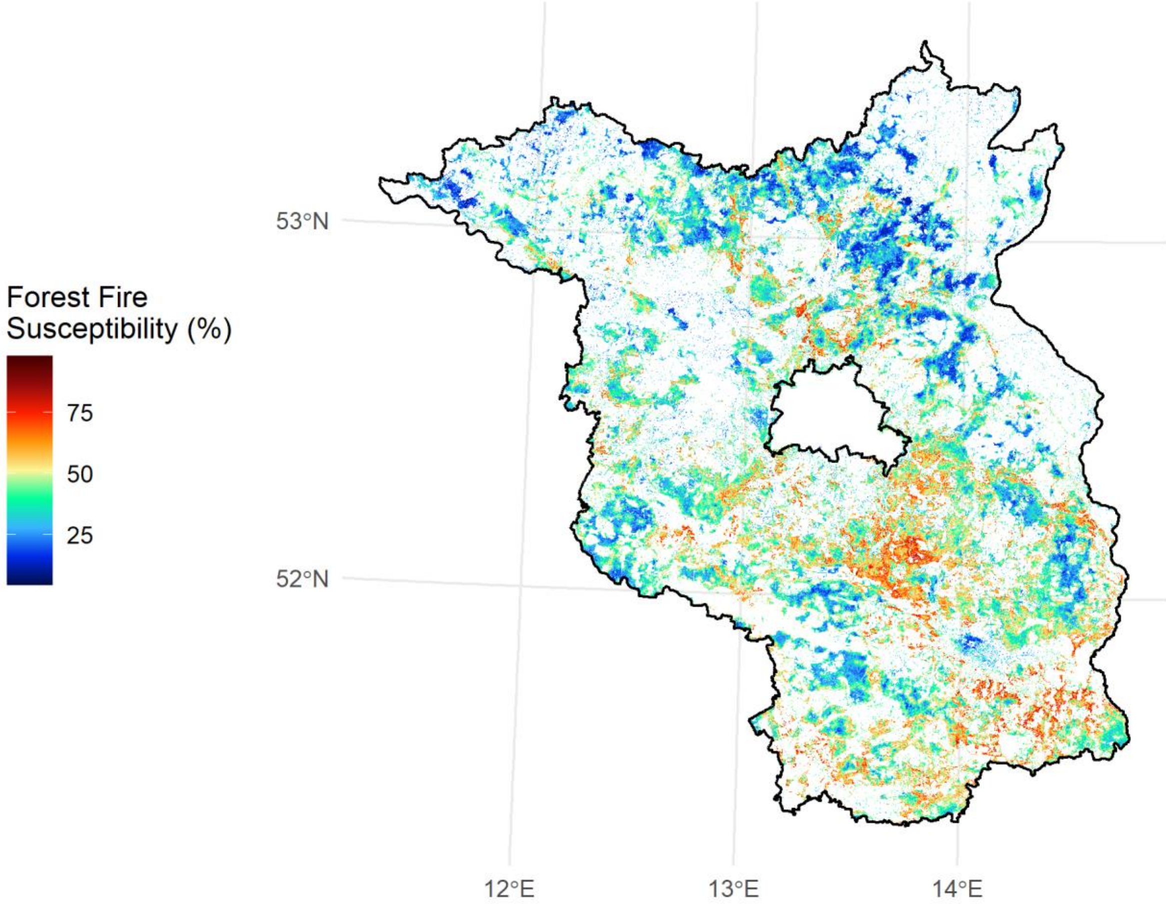


Figure S 10. Predicted forest fire susceptibility in June 2081-2100 (SSP 3.70) excluding projected land cover data. Border layer © 2018-2022 GADM.

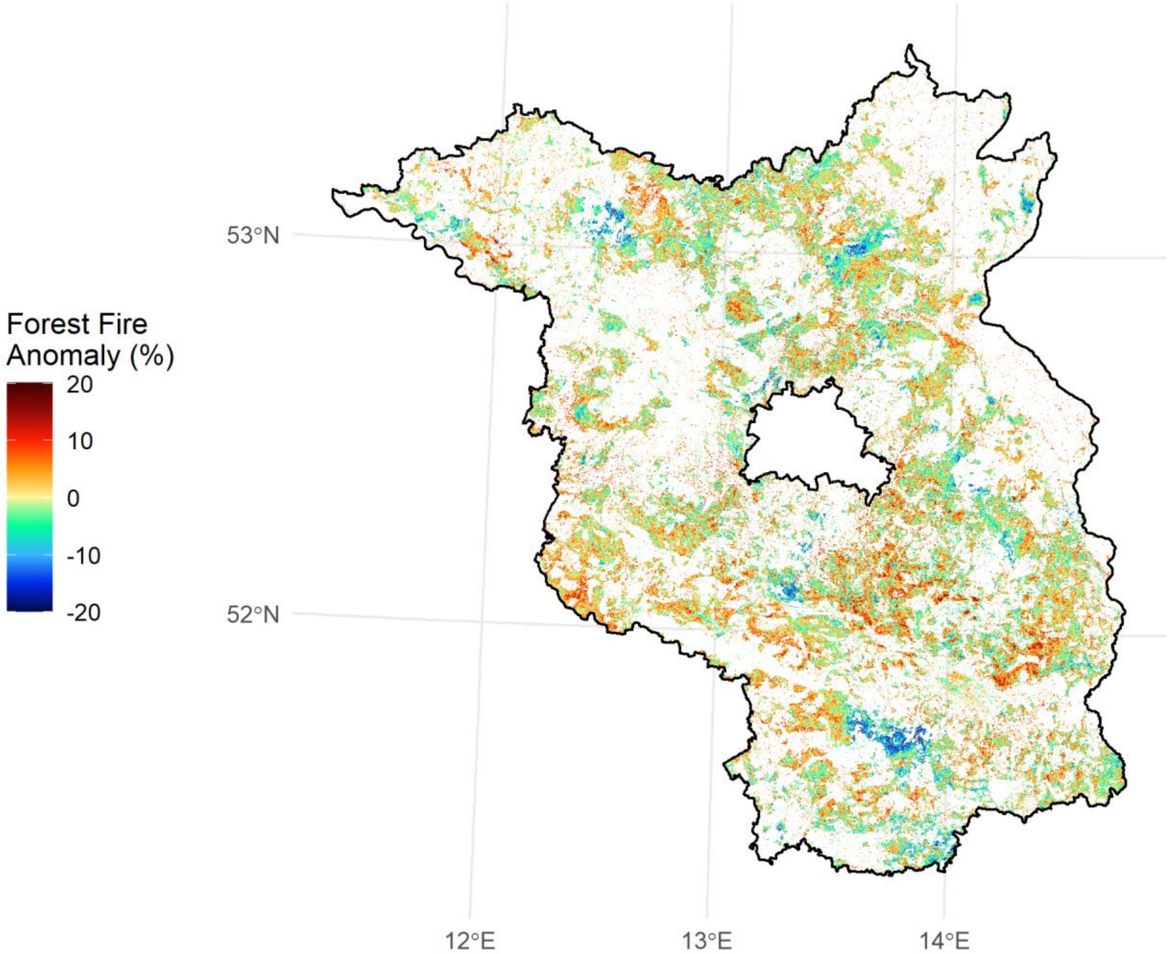


Figure S 11. Forest fire anomaly in June 2081-2100 (SSP 3.70) excluding projected land cover data compared to the reference scenario of June 2016. Border layer © 2018-2022 GADM.

We moved the previous versions of Figures 6 and 7 in the main text to the Supplement:

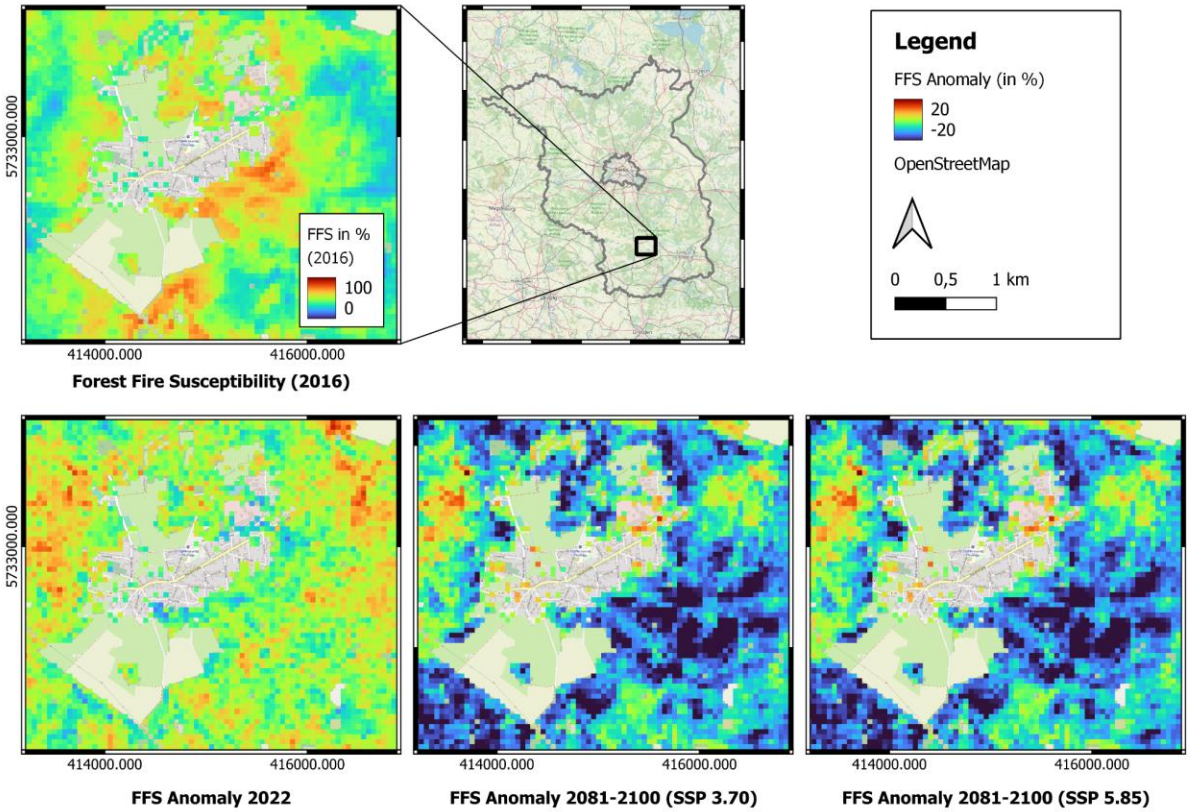


Figure S 12. Detailed maps of FFS anomalies in the municipality of Medewitz (Brandenburg). Base Map © OpenStreetMap contributors 2024. The future scenarios were computed excluding projected land cover data. Distributed under the Open Data Commons Open Database License (ODbL) v1.0, Border layer © 2018-2022 GADM.

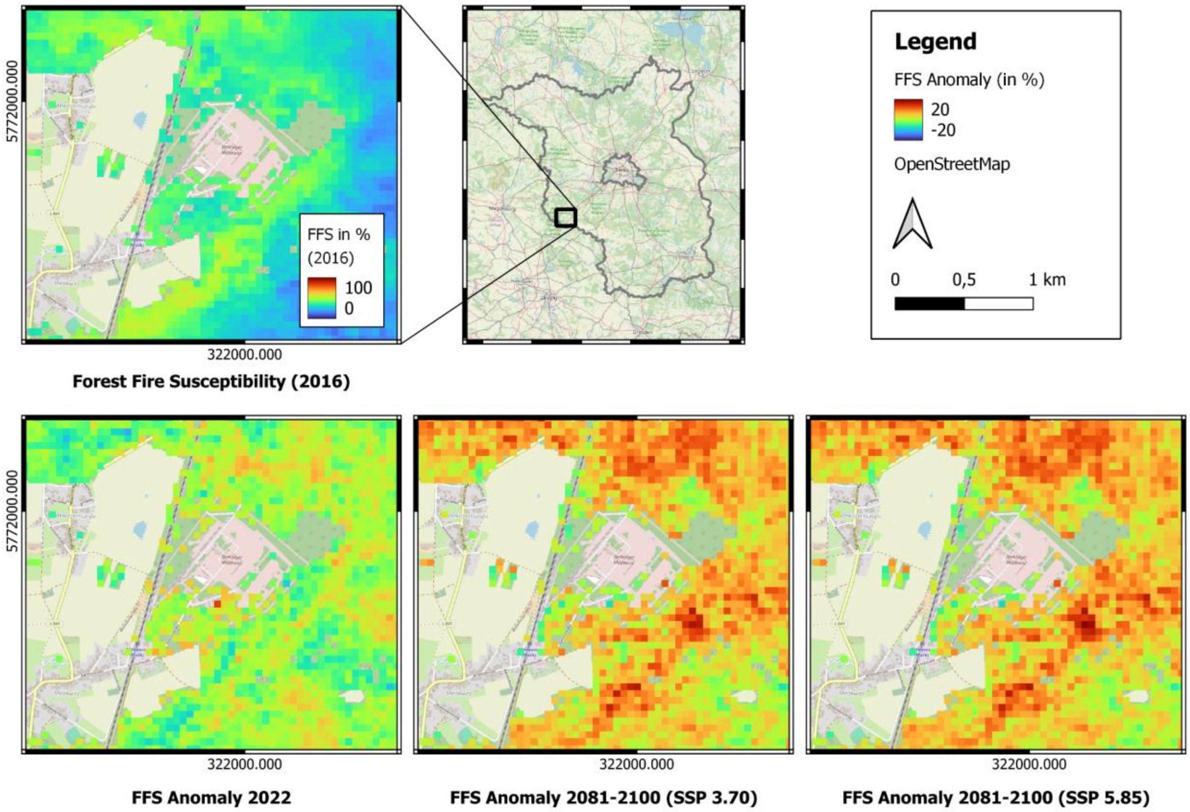


Figure S 13. Detailed maps of FFS anomalies in the municipality of Crinitz (Brandenburg). The future scenarios were computed excluding projected land cover data. Base Map © OpenStreetMap contributors 2024. Distributed under the Open Data Commons Open Database License (ODbL) v1.0, Border layer © 2018-2022 GADM.

According to the updated figures and tables, we modified / added the following sections to the main text of the manuscript:

<u>Abstract</u>

We deleted "considering different shared socioeconomic pathways (SSP 3.70 and SSP 5.85)". Further minor changes to the abstract were made based on the feedback from reviewer #1 (see answer to the first review comment).

<u>2.2 Current and future forest fire susceptibility scenarios</u> (ll. 85 ff.)

"The future scenarios of FFS cover the period of 2081 to 2100 ***using the socio-economic pathway (SSP) 5.85****. SSPs are different projections of future greenhouse gas emissions under distinct potential political and socioeconomic developments. The SSPs range from SSP1.19 to SSP 5.85, covering CO2 concentrations ranging from 393 to 1135 ppm until 2100. SSP 5.85*

represents "a high fossil-fuel development world throughout the 21st century" (Meinshausen et al., 2020). ***In order to include future land cover changes into the future predictions, future FFS was predicted twice: a) including only projected meteorological data for 2081-2100; and b) including projected meteorological data for 2081-2100 and projected land cover data. Within the Figures 2, 4, 5, 6, and 7, as well as in Table 3 the latter will be labeled with "*". Additionally, a third future scenario based on the SSP 3.70 was predicted. The results can be found in the Supplement (Fig. S 10 to S 13).**"*

2.3.2 Predictor variables. e) Anthropogenic influences and land use and land cover (LULC) (ll. 172 ff.):

"Consequently, to include anthropogenic influences as well as aspects of LULC, distance to urban settlements, streets, railways, campsites, water bodies and military sites were selected as predictor variables. ***Furthermore, to address future land cover changes, we included a data set on projected land cover change in 2050 provided by Esri Environment (2021). To our knowledge, this was the only available data set with a high spatial resolution to show future land cover changes, which is why it was selected for this study.*** *Table 1 provides an overview of the predictors as well as their characteristics and origin."*

3.3 Forest fire susceptibility under current and future scenarios

We rewrote the first part of the first paragraph (ll. 293 ff.):

"Figure 4 shows the FFS in Brandenburg for the two current scenarios, June 2016 and June 2022, as well as for the two future scenarios, June 2081-2100 ***under SSP 5.85 and June 2081-2100 under SSP 5.85 including projected land cover data****.* ***For comparison, the FFS for June 2081-2100 under SSP 3.70 can be found in the Supplement (Fig. S 10).****"*

We entirely rewrote the second paragraph (ll. 299 ff.):

"Figure 5 illustrates the anomalies in FFS relative to the reference scenario of June 2016. In the June 2022 scenario ***(scenario a),*** *FFS exhibits notable positive anomalies across various regions of the federal state, with anomalies ranging from + 5 to + 15 % compared to June 2016. Many areas across Brandenburg maintain similar FFS levels as the 2022 scenario. Only a few selected small regions in the south-east and south-west* ***exhibit*** *negative FFS anomalies compared to June 2016.* ***Regarding future FFS anomalies relative to June 2016, the future scenarios differ rather substantially from one another. Whereas the scenario neglecting land cover changes (b) shows positive FFS anomalies up to 15 % and more in southern, eastern, and western parts of Berlin, one area in the south shows negative FFS anomalies up to - 20 %. In comparison to the scenario based on only climatological projections, the scenario incorporating land cover changes (c) shows mostly negative FFS anomalies ranging from 0 to - 20%, especially in the southern part of Brandenburg. The northern part of Brandenburg***

however is characterised by an increase in FFS in many areas, reaching anomalies up to + 20 %. Additionally, some areas in the South and West also show positive FFS anomalies. For comparison, the FFS anomalies for 2081-2100 under SSP 3.70 can be found in the Supplement (Fig. S 11 to S 13).*"*

We rewrote parts of the following paragraph (ll. 311 ff.):

"Table 3 presents summary statistics of the FFS for the four scenarios. Upon comparing the values across all scenarios, it is evident that the 2016 scenario exhibits the lowest minimum value among the four. Conversely, the 2022 scenario demonstrates higher maximum and mean FFS values, suggesting a greater susceptibility compared to 2016. Notably, the mean susceptibility value for 2022 (0.419) is the highest among the four scenarios ***indicating the highest mean FFS. The future scenario excluding projected land cover data shows the highest maximum value and only a slightly lower mean value (0.414) than the scenario of June 2022. Finally the future scenario including land cover data (*) shows the lowest maximum, mean and standard deviation FFS values compared to the other scenarios.***"

We rewrote parts of the following paragraphs (ll. 318 ff.):

"To assess variabilities in FFS on a local scale, a detailed zoom to an area in the west of Brandenburg is shown in Fig. 6. The four maps show the municipality of Medewitz in the west of Brandenburg. The 2016 scenario shows a fairly low FFS (Fig. 6a). The three other maps show FFS anomalies compared to 2016 (Fig. 6b to d). Whereas the scenario of 2022 shows positive anomaly values of 10 to 15 %, anomaly values are even higher in the future scenario ***excluding projected land cover data****, reaching + 20 %.* ***In contrast, the scenario including land cover changes (d) shows negative anomalies up to - 15 %. However, pixels in the east and south of the map show positive FFS anomalies as well.***

The *four zoomed-in maps in Fig. 7 depict the Crinitz municipality located in the south of Brandenburg.* ***Whereas the June 2022 scenario (b) mainly shows anomalies close to 0, except for some pixels reaching up to + 16 %, the future scenario relying only on climatic projections (c) shows substantial negative anomalies reaching up to -20 %. Similarly, the scenario including projected land cover data (d) shows a substantial proportion of pixels with negative FFS anomalies. However, some areas in the north and southwest of the city show positive FFS anomalies.***

Figures 6 and 7 show that despite the trend of overall increase in FFS between 2016 and the future scenario of 2081-2100 excluding projected land cover data (Fig. 4 and 5), FFS differs significantly across the federal state. Furthermore, the future scenario incorporating land cover changes shows substantial differences to the scenario only relying on climatic projections.*"*

4.2 Assessing current and future forest fire susceptibility

We completely rewrote this chapter (ll. 372 ff.):

*"**Overall, the future scenario 2081-2100 (excl. projected land cover data) revealed a substantial increase in mean FFS compared to 2016. However, in 2022 the mean FFS was higher than in 2016 and the two future scenarios. The comparatively high mean FFS of 2022 can be explained by significantly drier and hotter conditions compared to 2016. Nevertheless, the mean FFS value of the future scenario neglecting land cover changes is only slightly below the mean FFS value of 2022 and higher than the mean FFS value of 2016. Considering exclusively future climatic conditions, this indicates an expected overall increase in FFS in Brandenburg until the end of the 21st century compared to June 2016. However, since the future modelled climate data relies on multi-annual monthly averages of air temperature and precipitation, future FFS is possibly underestimated in this study. The second future scenario including both projected land cover changes (*) and future climatic conditions paints a different picture. As shown in Table 3, mean FFS was lowest of all scenarios indicating an overall decrease in FFS. This result can most likely be explained by two aspects: First, Esri's "Land Cover 2050 - Global" data set (Esri Environment, 2021) used to plot future distance to urban settlements projects a decrease in urbanised areas in the future compared to the Impervious Built-up data set (European Environment Agency [EEA] 2020b). Shrinking urban areas can be explained by demographic changes, such as the ageing and decline of the German population, especially in the East of Germany (Kroll and Haase, 2010). Although Kroll and Haase (2010) state that the ageing of the German population has not yet influenced land use changes, they argue that this is likely to change in the future. Second, Esri's "Land Cover 2050 - Global" data set (Esri Environment, 2021) has a lower spatial resolution (300 m) than the COPERNICUS Imperviousness data set (European Environment Agency [EEA], 2020b) used to map the distance to "current" urban settlements (10 m). As a result, Esri's data set may show some inaccuracies due to mixed pixel effects. For instance, some smaller settlements may not appear in the future land cover data set. Our results underscore how the inclusion of projected land cover data significantly changes the projected FFS in the future, an aspect that can be further explored in future studies with new land cover projections.***

***Based on our findings, it can be argued that future urban development trends will significantly influence FFS. Hence, a population decline and abandonment of villages and rural areas may decrease FFS in those areas. However, new settlements due to continuous suburbanization processes may require additional forest fire prevention efforts in the future. Regardless of these trends, the expected increase in drought events in Brandenburg (Gnilke et al., 2022) may intensify the FFS in Brandenburg in the future. Consequently, effective forest fire management strategies in Brandenburg need to address these aspects. Therefore, the following chapter provides key strategies for the management of forest fires in the future.**"*

Additional references:

Esri Environment. (2021). Land Cover 2050 - Global. https://hub.arcgis.com/datasets/esri::land-cover-2050-global/about

Kroll, F., & Haase, D. (2010). Does demographic change affect land use patterns?: A case study from Germany. Land Use Policy, 27(3), 726–737. https://doi.org/10.1016/j.landusepol.2009.10.001

4.4 Shortcomings and future perspectives

We added the following paragraph (ll. 455 ff.):

*"**Apart from the spatial resolution of forest fire products, the modelling approach to predict FFS should be carefully selected. As previously discussed, meteorological parameters did not have a significant influence on the model. Therefore, future research may consider applying a Long Short-Term Memory (LSTM) model to better incorporate meteorological trends and to improve the understanding of how forests react to droughts and heat waves (Burge et al., 2021; Natekar et al., 2021).**"*

Additional references:

Burge, J., Bonanni, M., Ihme, M., and Hu, L.: Convolutional LSTM Neural Networks for Modeling Wildland Fire Dynamics, https://doi.org/10.48550/arXiv.2012.06679, arXiv:2012.06679 [cs], 2021

Natekar, S., Patil, S., Nair, A., and Roychowdhury, S.: Forest Fire Prediction using LSTM, in: 2021 2nd International Conference for Emerging Technology (INCET), pp. 1–5, https://doi.org/10.1109/INCET51464.2021.9456113, 202

We changed the following paragraph (ll. 459 ff.):

*"**Furthermore, the future land cover change data set (Esri Environment, 2021) had some limitations. First, it only included information on "Artificial Surface or Urban Area". Consequently, a differentiation of different anthropogenic land uses (e.g., campsites, streets, urban settlements, or railways) for the future scenarios was not possible. Instead, the data set was only used to project the future distance to urban settlements. Second, the projection of the data set was only available for 2050. Ideally, a data set reflecting the land use changes until the end of the 21st century would have led to more accurate results. Third, compared to the other land use and land cover data sets used in this study, the spatial resolution of the future land cover change data set (Esri Environment, 2021) was relatively coarse. Therefore, the data set may contain some inaccuracies, thus potentially decreasing the accuracy of the future FFS projections. Nevertheless, to our knowledge, this data set had a relatively high spatial resolution compared to other data sets, which is why it was selected for the study. In the end,** the expansion of renewable energies (Hilker et al., 2024), the settlement of new companies and factories (e.g., Tesla gigafactory in Grünheide) (Kühn, 2023), suburbanization **processes around Berlin driven by rising housing prices (Leibert et al., 2022), and finally the***

abandonment of smaller villages due to ageing and population decline is likely to lead to future land cover changes and either heightened or decreased pressures on forests. Consequently, including this data set into the analysis provides valuable information on potential land cover changes. Future research may consider including higher-spatial-resolution land cover change data to model FFS."

5. Conclusions

We modified the first part of the conclusions (ll. 479 ff.):

"This study successfully predicted FFS on a regional scale in the federal state of Brandenburg under different scenarios with the RF ML algorithm. The FFS maps show a high FFS in the south and south-east of the federal state. ***Considering only future meteorological conditions****, future FFS is expected to increase compared to the 2016 reference scenario. Extreme events such as droughts can significantly intensify FFS, which was demonstrated by the higher mean FFS value of 2022 compared to the other scenarios.* ***However, including both projected land cover change and future meteorological data into the future projections showed a decrease in FFS. This trend might be driven by demographic changes ultimately leading to future land use changes.****"*

RC2: Given these concerns, I must recommend the rejection of this manuscript for publication in its current form. I strongly encourage the authors to revisit and reevaluate their methodology and resubmit the paper once the results and conclusions are more reliable, as the study is generally very interesting and holds significant value for the field.

A: We understand and respect the evaluation of the reviewer. We thank the reviewer for all the relevant and valuable feedback. We hope that the answers to the reviewer's comments provided sufficient explanation. Furthermore, we hope that the changes we made to the manuscript substantially improved its quality and made it ready for a potential publication. Here is a summary of the major changes we made to address the reviewers' comments and improve the manuscript:

- *We provided additional information on the selection of the temporal resolution of the meteorological datasets (chapter 2.3.2).*
- *We included an additional data set (Land Cover Change in 2050 - Global) to address future land cover changes within the future predictions. Accordingly, we updated all related figures and tables and provided new aspects to the discussion sections 4.2 and 4.4 and to the conclusions (5.).*
- *We provided partial dependence plots for the three most important predictors and the related forest fire susceptibility. We further provided partial dependence plots for the meteorological parameters (air temperature, precipitation) and the related forest fire susceptibility.*

- *We provided an additional figure showing the false positive rate (FPR) and false negative rate (FNR) as well as annual air temperature and precipitation averages for comparison. We briefly discussed this figure to analyse the model's mechanisms.*

Further modifications:

We rephrased the sentence in 2.3.2 c) Anthropogenic influences & land use and land cover (LULC) (l. 167):

"Therefore, they **highly recommend** *including…"*

We rephrased the sentence in 4.4 Shortcomings and future perspectives (l. 432):

"Similarly, ***forest fire products based on remote sensing data with a high spatial and temporal resolution****…"*

*We capitalized the word "***Supplement***" along the whole manuscript and Supplement.*