Dear Editor and anonymous reviewers,

Thank you for your review and valuable comments for helping us improve the manuscript. Submitted is the revised version with changes highlighted and we include responses (in blue color) to each comment and corresponding text modifications (in green color) in this document. In summary, we followed your suggestions and added more details, comprehensive experiments, analyses, and discussions. These new revisions mainly include:

1) We added more details about the machine learning models applied in wildfire, and analyzed and discussed their strengths, potential limitations, and their interpretability differences. We also provided codes for all six machine learning models at https://zenodo.org/record/7416437#.Y5JnBXbMK5c to further help readers understand those machine learning models.
2) We provided more information about the datasets and the model validation method;
3) We added more background about the ocean indices, and further analyzed their impacts on wildfires;
4) We included all available earth system models (ESMs) of CMIP6, and projected and analyzed future burned area changes in African and South American regions under both low (SSP126) and high (SSP585) emission scenarios.
5) We added more discussions about AttentionFire model, including its computational cost (memory and time consumption) and potential limitation, its application in other regions, the potential ways for narrowing future projection uncertainty, and the full coupling of AttentionFire into the ESMs.

Details of the revisions are provided in the following response letter and revised manuscript.

Thank you for considering our manuscript for publication with the journal and we look forward to hearing your decision.

Qing Zhu on the behalf of all coauthors

Reviewer #2

Li et al. presents in this work an attention-augmented LSTM machine learning model framework used to predict burned area over tropics. Attention-augmented models aim to provide interpretability to LSTM models and improve driver selection by adaptively assigning weights to inputs. The authors use this capability to explicitly capture controlling factors of fire predictions with various time-lags (e.g., climate wetness).

I would also like to appreciate the authors' preparation of the source code to include data preparation scripts and a brief tutorial python script to get users started with the model with examples.

The manuscript is generally well written and the AttentionFire model could be useful for burned area predictions.

Thank you for the positive comments.

However, there are some sections which need substantial revisions for clarity and for more details. I will be happy to further consider this manuscript for publication after my concerns are addressed.

Major comments:

1.The authors compare against other models (in Section 2.2), i.e., RF, DT, GBDT, ANN, and naïve LSTM. While Table S1 discusses the hyperparameter configuration of these models, it would be more helpful for model users to read here about the specific strengths and shortcomings of the models chosen – e.g., have these been used for burned area predictions before? Why were these particular models chosen for comparison? Not all models here lack interpretability (DT, RF, …), do they give the same important features as AttentionFire (shown in Fig. 3)? How much more computational cost (memory/data, training time) is incurred with training this more complex, attention-augmented LSTM model, compared to others?

Overall, the comparison needs to have more context (for readers who are interested in fire models but not necessarily well-versed in machine learning), and more detail (justifying that the model presented is better and its potential shortcomings). A table similar to Table S1 with a summary of all the models would be helpful in the main text.

Thanks for the suggestion. We added more context about the machine learning (ML) models used, including their strengths, potential limitations, applications in wildfire, and corresponding references. Accordingly, we included a table (Table 1) to summarize the aforementioned information. Among the ML models, DT, RF, and GBDT provided variable importance scores, and we therefore compared and analyzed their variable importance against the variable importance of AttentionFire model. In addition, we compared the computational cost (memory usage and training time) among all ML models, and discussed the potential shortcomings of AttentionFire model. We also provided the code for all baseline models to help readers understand the machine learning models. Bellows are the revisions.

We added more details about the black box nature of machine learning models, and the reasons why they are less interpretable. L111-122, section 1:

For example, the commonly used neural network or deep learning models (Zhu et al., 2022; Joshi and Sukumar, 2021) themselves are complex and built upon hidden neural layers with non-linear activation functions and thus cannot directly identify the relative importance of different drivers for wildfires (Murdoch et al., 2019; Jain et al., 2020). A few ML models (e.g., decision tree and random forest) provide variable importance, however, such importance scores are constant across the entire dataset rather than spatiotemporally varied (Wang et al., 2021; Yuan et al., 2022b). While post-hoc analyses could interpret ML models (Altmann et al., 2010; Lundberg and Lee, 2017), inconsistent and unstable explanations can be derived with different post-hoc methods or settings (Slack et al., 2021; Molnar et al., 2020). Such limitations impede an interpretable and reliable way to understand the critical spatiotemporal processes from wet season to dry season (Reichstein et al., 2019; Jain et al., 2020).

We provided more context about the LSTM model. L136-143, section 2.1:

Like the traditional artificial neural network (ANN) models, the LSTM is also built upon neurons and the non-linear activation functions; specifically, the LSTM deployed the gating mechanism (i.e., forget, input, and output gates) (Hochreiter and Schmidhuber, 1997; Wang and Yuan, 2019) to filter out useless information while keeping useful information underlying in the time series as hidden states (Fig. 1). Relative to traditional ANN, the LSTM has shown advantages in capturing short- and long-term dependencies in input time series (Hochreiter and Schmidhuber, 1997), implying good potential of LSTM on representing time-lagged controls from wet-to-dry season climate conditions on wildfires.

We added a table and provided more context about the ML models including ANN, DT, RF, GBDT, and LSTM. L206-220, 234-235 section 2.2:

The details of baseline models selected, including strengths, potential limitations, and their applications in wildfire studies and references are listed in Table 1. The ANN and LSTM have shown good performance on multiple earth science problems (Yuan et al., 2022a; Reichstein et al., 2019) including wildfires (Joshi and Sukumar, 2021; Zhu et al., 2021; Liang et al., 2019), however, the black-box nature of such models makes them lack interpretability. The DT method provides variable importance and is easily interpretable with its single tree structure, but prone to overfitting compared to RF and GBDT. The RF alleviates the overfitting through feature selection and ensemble learning (Breiman, 2001) while the GBDT avoids overfitting by constructing multiple trees with shallow depth (Ke et al., 2017). DT, RF, and GBDT provide variable importance scores for dominant driver inference, however, such importance scores are constant across the entire dataset and thus impede detailed interpretation of the variable importance like over space and time. The aforementioned ML models have been commonly used in wildfire science (Jain et al., 2020).

Table 1. Strengths, potential limitations, and applications of selected baseline models in wildfire studies.

Model (acronym)	Strengths	Potential limitations	Applications
Random Forest (RF) (Breiman, 2001)	Provide variable importance; Alleviate overfitting through feature selection and ensemble learning;	Constant variable importance rather than varied; time-consuming when building large trees; may not perform well on time series with lags	(Gray et al., 2018b; Yu et al., 2020)
Decision Tree (DT) (Safavian and Landgrebe, 1991)	Provide variable importance; easy to interoperate the single tree	Prone to overfitting; constant variable importance rather than varied; time-consuming when building a large tree; may not perform well on time series with lags	(Amatulli et al., 2006; Coffield et al., 2019)
Gradient Boosting Decision Tree (GBDT) (Ke et al., 2017)	Alleviate overfitting by building multiple shallow trees; generally fast because of the shallowness of each tree built	Constant variable importance rather than varied; may not perform well on time series with lags	(Coffield et al., 2019; Jain et al., 2020)
Artificial Neural Network (ANN) (Ke et al., 2017)	Show good performance on complex and non-linear problems; alleviate overfitting through techniques like dropout and regularization	Lack of interpretability; hard to know the optimal neural network structures for different problems	(Joshi and Sukumar, 2021; Zhu et al., 2021)
Long-Short-Term-Memory (LSTM) (Hochreiter and Schmidhuber, 1997)	Show good performance on time series predictions; alleviate overfitting through techniques like dropout and regularization	Lack of interpretability; may not be suitable for non-time series problems; vanishing gradient problem when deployed to long time series (Li et al., 2020; Liang et al., 2018)	(Liang et al., 2019; Natekar et al., 2021)

We discussed the variable importance differences between AttentionFire and three tree-based models (i.e., DT, RF, and GBDT) and compared their computational cost. L506-525, section 3.5:

We revealed the dominant, spatially heterogenous, and time lagged controls of climate wetness on ASA wildfires. Such climate wetness importance on ASA wildfires was consistent with previous findings (Andela and Van Der Werf, 2014; Chen et al., 2011) and also confirmed by the other three tree-based ML models (i.e., DT, RF, and GBDT) with variable importance (e.g., precipitation and VPD were regarded as the top-five most important variables in Fig. S7). However, differences existed across model identified most important drivers (Fig. 3 versus Fig. S7). The variable importance of AttentionFire model was spatiotemporally varied (Fig. 4) while tree-based model provided variable importance was constant over the entire dataset. We showed that the climate wetness was more (less) important in areas with large (small) burned areas and its importance also varied over time (Fig. 4), but the other MLs did not explicitly distinguish such differences. Albeit the higher accuracy and generally acceptable computation speed of AttentionFire (Table S2), its memory consumption and model training time could be up to 141% and 22 times higher than the other ML models. The implementation of LSTM in AttentionFire model is series instead of parallel, therefore, future work could improve the model efficiency by deploying some easy-for-parallel-computing time series prediction frameworks (e.g., temporal convolutional attention (Lin et al., 2021) and self-attention (Mohammadi Farsani and Pazouki, 2020; Vaswani et al., 2017)).

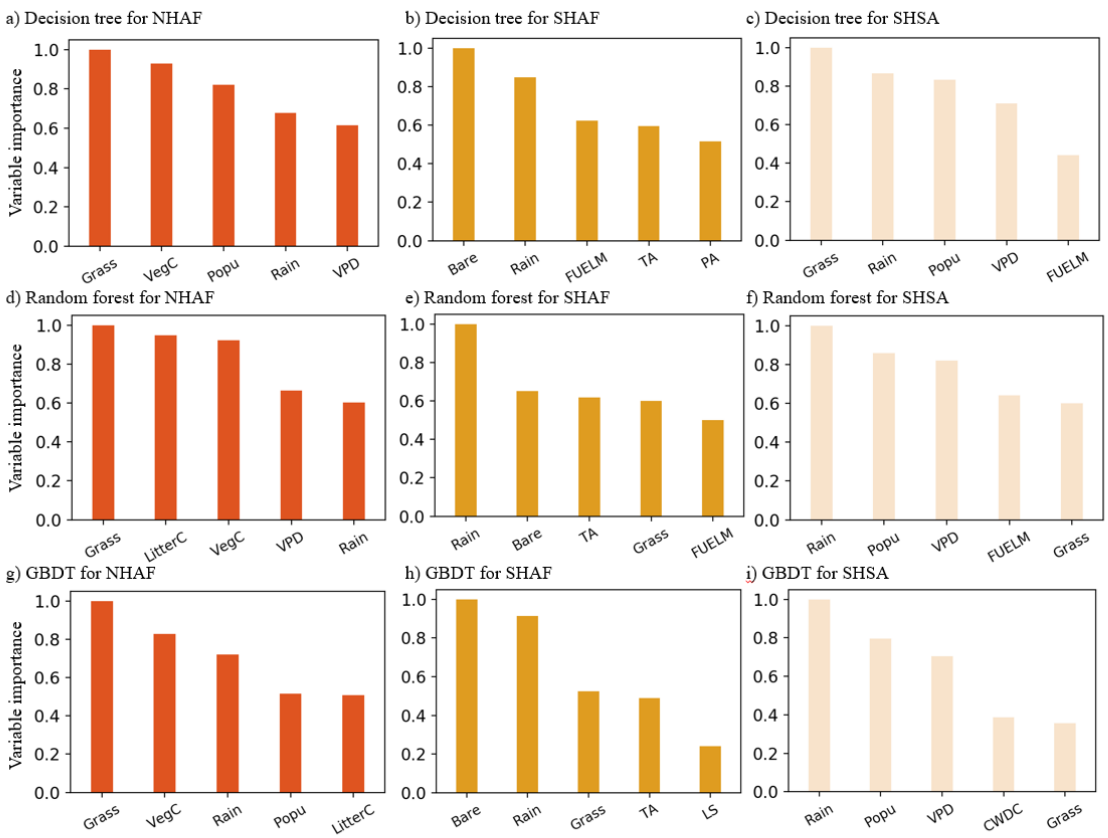

Fig. S7. Ranked top-five important variables for burned area in Northern Hemisphere Africa (NHAF) (a), Southern Hemisphere Africa (SHAF) (b), and Southern Hemisphere South America (SHSA) (c). For each region, the variable importance was normalized by the dominant variable importance. Three machine learning models that provide variable importance score are considered, including decision tree, random forest, and Gradient Boosting Decision Tree (GBDT). The full name of each abbreviated variable is listed in Table 2 in the main text.

We provided the link for the code of all baseline models used.

L582-583, Code availability:

"The source code of AttentionFire_v1.0 and all baseline machine learning models is archived at Zenodo repository: https://zenodo.org/record/7416437#.Y5JnBXbMK5c"

2. Section 3.3 regarding oceanic dynamics introduces four oceanic indexes into the model, but they are not defined (except in the legend of Fig. 5) nor introduced. There needs to be more context in this set of experiments: what are these oceanic indexes, why are they important or potentially affecting burned area, how much weight was assigned to these OIs by the model – how much relative importance are they compared to the other predictors, and source of data.

Sorry for the missing. We added more context to explain ocean indices (OIs), their importance on wildfire prediction, and the source of data. We also compared the attention weights of OIs with other predictors and quantified their impacts on burned area prediction. We updated the Introduction, Methods, and Results and Discussions. Bellows are the revisions.

L71-78, section 1:

Meanwhile, ocean dynamics (e.g., El Niño-Southern Oscillation, ENSO) may also exert considerable influences on ASA wildfires through influencing wet and wet-to-dry season climate and fuel conditions (Yu et al., 2020; Chen et al., 2016; Andela and Van Der Werf, 2014; Chen et al., 2011; Chen et al., 2017). The time-lags between ocean dynamics and wildfires can be even longer than that between climate and wildfires (Chen et al., 2020), which enable wildfire predictions ahead of fire season (Chen et al., 2011; Chen et al., 2016; Chen et al., 2020; Turco et al., 2018).

L249-267, section 2.3:

In addition to the local socio-environmental drivers, we also explored the impacts of ocean indices on burned area predictions. Chen et al. (2011) found that wildfires in South America were closely linked to the Oceanic Niño Index (ONI), and Atlantic multidecadal Oscillation (AMO) index. The ONI and AMO reflected the sea surface temperature (SST) anomalies in the tropical Pacific and north Atlantic. The SST anomalies directly affected ocean-atmosphere interactions and thus the wet, wet-to-dry, and onset of dry season climate in South America (Chen et al., 2011). The two indexes were significantly correlated with peak fire month wildfires 3 to 7 months later and could predict fire season wildfires in many regions of South America with lead times of 3 to 5 months (Chen et al., 2011). The controls of SST anomalies in tropical Pacific on climate and thus wildfires were also found in northern and southern Africa (Andela and Van Der Werf, 2014). In addition, SST anomalies in tropical northern and southern Atlantic could also affect wildfires in South America (Chen et al., 2016) and Africa (Yu et al., 2020; Chen et al., 2020). Therefore, we included ocean indices (Table 2) and investigated their impacts on wildfire predictions with the AttentionFire model (see section 3.4).

Table 2. Input and output variables and datasets of the AttentionFire model.

Variable category	**Variables (abbreviation, units)**	**Spatial (temporal) resolution**	**Dataset and reference**
Wildfire	Burned area (BA, hectares month^{-1})	0.25 degree (monthly)	Global Fire Emissions Database 4 (Giglio et al., 2013)
Climate	Precipitation (RAIN, mm s^{-1}), temperature (TA, K), surface air pressure (PA, Pa), specific humidity (SH, kg kg^{-1}), downward short-wave radiation (SW, W m^{-2}), wind speed (WIND, m s^{-1}), vapor pressure deficit (VPD, hPa) (VPD calculated according to (Bolton, 1980))	~1.9 degree (monthly)	NCEP-DOE Reanalysis 2 (Kanamitsu et al., 2002)

Fuel conditions	Fuel moisture (FUELM, %), coarse wood debris (CWDC, gC m^{-2} s^{-1}), vegetation biomass (VegC, gC m^{-2} s^{-1}), litter biomass (LitterC, gC m^{-2} s^{-1})	~1.9 degree (monthly)	ELM prognostic simulations (Zhu et al., 2019)
Human activities	Population density (Popu, persons $grid^{-1}$)	~1km (yearly)	(Dobson et al., 2000)
	Road density (Road, km km^{-2})	0.5 degree (yearly)	(Meijer et al., 2018)
	Livestock density (LS, number of livestock $grid^{-1}$)	0.5 degree (yearly)	(Rothman-Ostrow et al., 2020)
Land cover	Bare soil (Bare, %), Forest (Forest, %), and Grass (Grass, %)	0.25 degree (yearly)	LUH2 (Hurtt et al., 2020a)
Oceanic indices	Ocean Niño Index (ONI), Atlantic multidecadal Oscillation (AMO) index, Tropical Northern Atlantic (TNA) Index, and Tropical Southern Atlantic (TSA) Index	monthly	NOAA Climate Indices (Noaa, 2021)

L431-435, section 3.3:

While the mean variable importance of OIs was consistently lower that of local climate (Fig. S4) across the three regions, the OIs did provide additional information for long-term predictions with lower biases (Fig. 5). The results demonstrated the potential usage of teleconnections for long leading time burned area predictions (Chen et al., 2020; Chen et al., 2016; Chen et al., 2011).

3. Section 3.4 mentions "considering land use changes, population growth, and projected climate under the SSP585". Is AttentionFire using outputs from a fully coupled CESM simulation? More details about the simulation setup (compsets, any customization to the namelists, input data, etc.) need to be provided (supplement). I understand that the choice for 2016-2055 was due to the model being trained under the historically available data; but I would also suggest testing the AttentionFire model under a different SSP for more complete projections. As it stands section 3.4 heavily leans on the SSP585 CESM model output data for predictions, and the prediction results must be presented carefully, especially when some results are not statistically significant.

We clarified that the AttentionFire model used the outputs of Earth System Models (ESMs) of CMIP6 for future projection. Given the large uncertainty across different ESMs, in the revised version, we included all available ESMs of CMIP6, and analyzed burned area changes with multi-model ensemble mean under different scenarios (SSP126 versus SSP585) for 2016-2055 and 2016-2100. We found that under SSP585, the future burned area trends (i.e., decreasing trend in NHAF, dampened trend in SHAF, and increasing trend in SHSA) were robust with multiple ESM ensemble mean. The burned area trends were consistent for 2016-2055 and 2016-2100. Under SSP126, the decreasing trend in NHAF disappeared (Fig. S5a) and the increasing trend in SHSA was reduced by ~69% (Fig. S5c), implying the big influences of climate changes and socioeconomic development pathways on future burn area changes. In addition, we discussed the uncertainty for future projections. We revised the manuscript as follows.

We included more ESMs, and clarified how we processed the data and made future projections. L279-290, section 2.3:

All available ESMs with outputs of historical and future (SSP126 and SSP585) fuel availability (i.e., biomass of coarse wood debris, vegetation, and litter) and climate variables (Table 2) were selected, including ACCESS-ESM1-5 (Ziehn et al., 2020), CESM2 (Danabasoglu et al., 2020), NorESM2-LM (Seland et al., 2020), NorESM2-MM (Seland et al., 2020), and TaiESM1(Wang et al., 2021b). For each

ESM, the variable bias was corrected with the mostly used linear scaling method (Maraun, 2016; Dangol et al., 2022; Shrestha et al., 2017) which adjusted the bias in model simulations based on the ratio of modeled and observed variable mean value. Then the bias corrected variables of each ESM were used to drive AttentionFire model for future burned area projection. Finally, given the uncertainty of each ESM, the multi-model ensemble (MME) mean of projected burned area was calculated (Li et al., 2022) and analyzed. Details of the bias correction method can be found in Maraun (2016).

We analyzed burned area changes with multi-model ensemble mean under different scenarios. L468-480, section 3.4:

Considering land use changes, population growth, and projected climate and fuel conditions under the SSP585 high emission scenario, our model predicted that burned areas in the NHAF region will continue to decline; the currently increasing trend will be dampened in the SHAF region, and the currently decreasing trend will be reversed in SHSA region (Fig. 6). The increasing trend in SHSA, decreasing trend in NHAF, and dampened trend in SHAF under SSP585 were robust when projecting burned area till the end of 21st century (Fig. S5). Over NHAF and SHSA, burned area trends at the gridcell level were mostly robust (Fig. 6a, c; $p < 0.05$) and of the same sign, thus resulting in a robust trend at regional scale. Under the low emission scenario (i.e., SSP126), the decreasing trend in NHAF disappeared (Fig. S5a) and the increasing trend in SHSA was reduced by ~69% (Fig. S5c), implying the big influences of climate changes and socioeconomic development pathways on future burn area changes in the two regions.

We acknowledged that the AttentionFire model did not couple with ESMs and discussed such limitation.

L539-553, section 3.5:

With the fully coupled ESMs of CMIP6, we analyzed future burned area changes under high (SSP585) and low (SSP126) emission scenarios in the ASA region. While the MME mean was considered, substantial uncertainty has been found across different ESMs in history (Yuan et al., 2022a; Yuan et al., 2021; Wu et al., 2020) and future (Li et al., 2022; Lauer et al., 2020). Further work therefore is needed to narrow the projection uncertainty of ESMs (e.g., with constraints of causality (Nowack et al., 2020; Li et al., 2022) and observations (Tokarska et al., 2020; Lauer et al., 2020)). Meanwhile, for future projections, although land use and land cover changes, population growth, and climate and fuel changes were considered, constant livestock and road density were adopted due to lack of data. The impacts of livestock and road density therefore need further exploration with available data under different future scenarios. In addition, the AttentionFire model currently is not coupled with the ESM, therefore, the feedbacks among fires, climate, and biomass were ignored. To analyze such feedbacks, the AttentionFire model needs to surrogate the original fire module and be coupled within the ESM (Zhu et al., 2021).

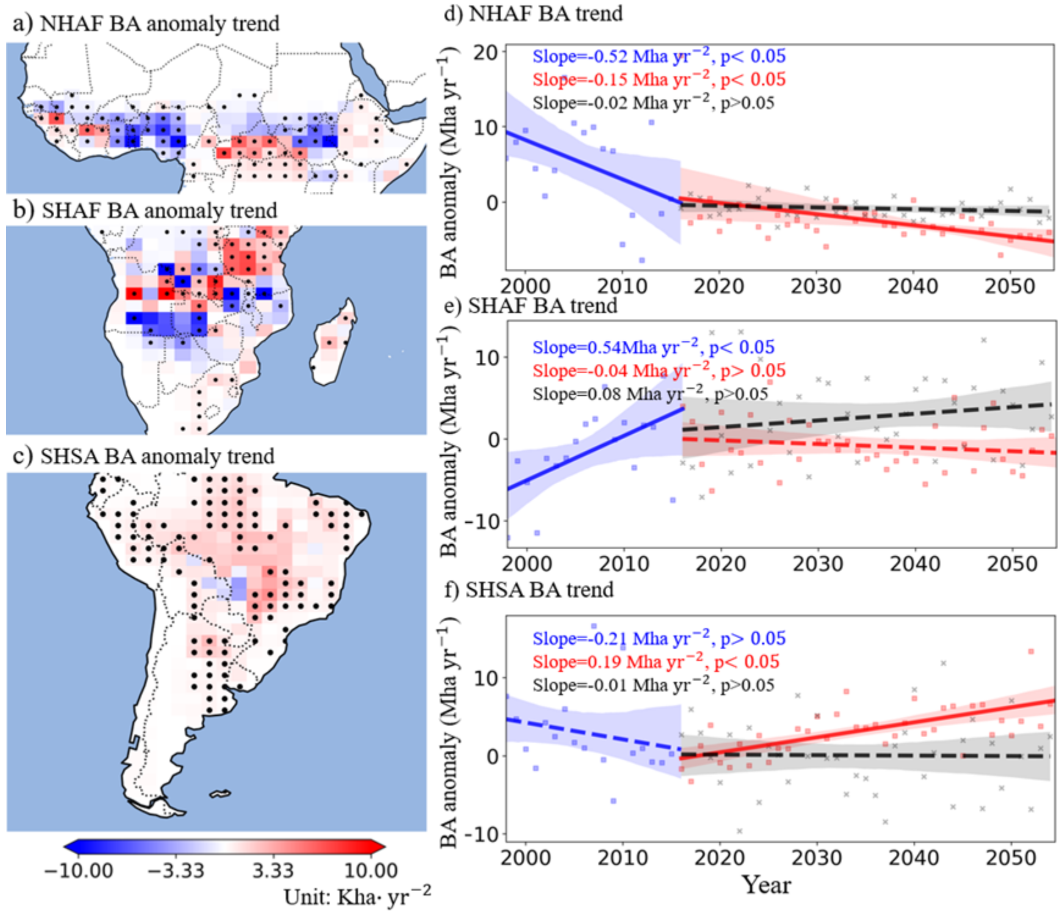

Fig. 6: Future burned area trends under the SSP585 high emission scenario. (a-c) spatial distribution of fire season burned area trends using drivers with interannual variations; dots in (a-c) indicate gridcells with statistically significant changes in the trend. (d-f) regionally aggregated burned area changes with historical mean subtracted. Blue and red lines respectively represent burned area anomaly in history and future; the black line represents future burned area trend while removing the interannual variations of the dominant variable. Solid lines represented significant BA trends (p value <0.05) while dashed lines represented non-significant BA trends.

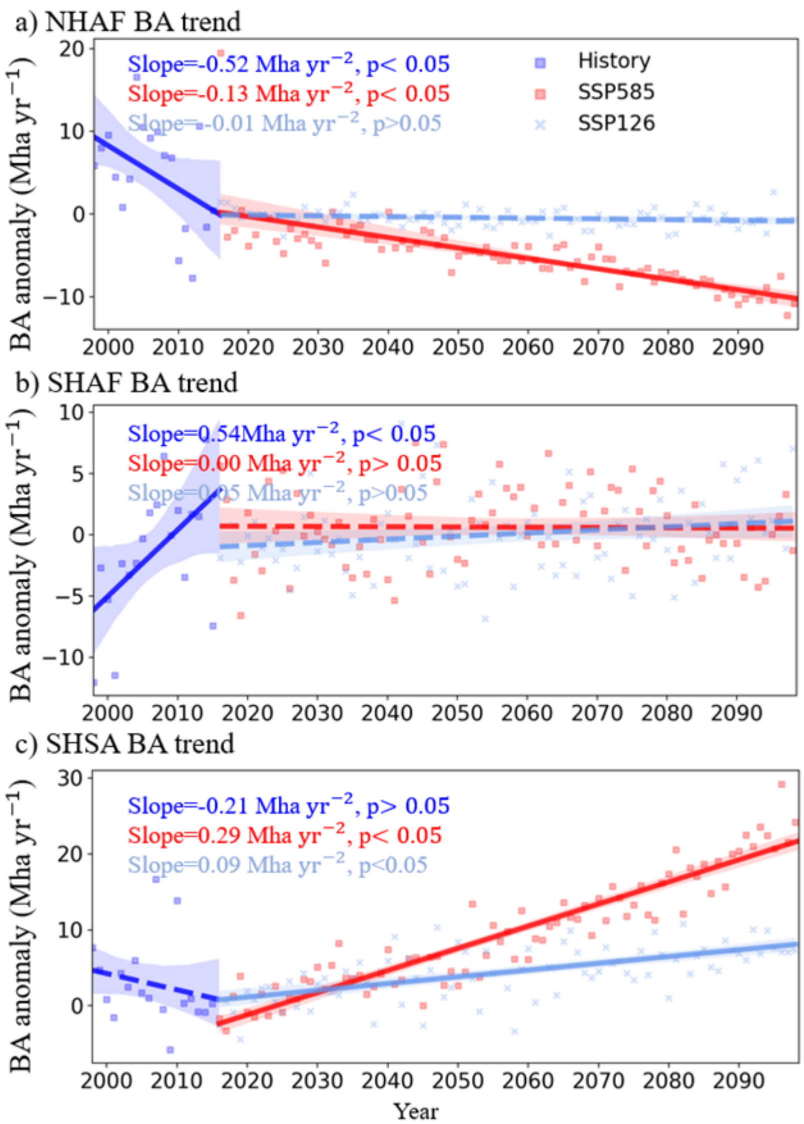

Fig. S5. Burned area changes in history and future. Deep blue and light blue lines represent burned area changes under SSP585 and SSP126, respectively, and red lines represent burned area changes in history. Solid lines represented significant (p <0.05) burned area trends while dashed lines represented non-significant trends.

4.Finally, the manuscript focuses on predicting ASA wildfires using AttentionFire. Can the AttentionFire model be readily applied for interpretable burned area predictions to other regions with wildfires as well?

The AttentionFire model is readily appliable for burned area predictions in other regions, while whether AttentionFire model can also outperform other machine learning models in other regions depends on the dependency strength and time lags between wildfires and local climate conditions. One reason for the performance improvement of AttentionFire model is its advance on capturing the time-lagged controls of climate, which dominated ASA wildfires. Therefore, the AttentionFire model could be potentially useful in regions where the time-lagged controls showed dominant impacts on dry-season wildfires. We discussed the potential of AttentionFire model for wildfire predictions in other regions. Bellows are the revisions.

L526-538, section 3.5:

This study focused on wildfire prediction in ASA region and we showed the performance improvement of AttentionFire model by representing the time-lagged controls of climate on wildfires. Whether the AttentionFire model can also outperform other ML models in other regions may depend on the dependency strength and time lags between wildfires and climate variables. For example, in North American boreal forests, lightning was identified as the major driver of the interannual variability in burned area by influencing the number of ignitions in dry-season (Veraverbeke et al., 2017). In such region, AttentionFire model might not outperform other ML models due to the less dominance of time-lagged controls. In regions like western US and India where wildfires showed time-lagged dependencies with local climate (Littell et al., 2009; Kale et al., 2022) and some extreme wildfires were caused by persistent drought from wet to dry seasons with multi-month lags (Taufik et al., 2017; Littell et al., 2016), the AttentionFire model could be potentially useful.

Specific comments and technical corrections:

1. Line 110: define LSTM acronym here as its used directly in below text.

Revised as suggested.

2. Line 206: "T62 resolution: 94x192". I suggest noting the approximate resolution (at equator) here, ~210km, for the spectral resolution.

Thanks for the suggestion. We revised the sentence accordingly:

L246-247 section 2.3:

"The raw datasets were unified to the same spatial resolution (T62 resolution: **~210 km at the equator**) at the monthly scale"

3. Fig. 2: Are these observations from GFED? It is briefly mentioned in the introduction, but I suggest indicating such within the section 3.1.

The observations are from GFED, and we clarified GFED within section 3.1 accordingly.

L300-302 section 3.1:

The AttentionFire model had the lowest mean absolute errors (MAEs) between model predicted and observed (GFED) grided monthly burned areas among the six ML approaches.

4. Fig. 3: Please label the three regions in the figure.

We revised the labels of Fig. 3 accordingly.

L350-356 section 3.2:

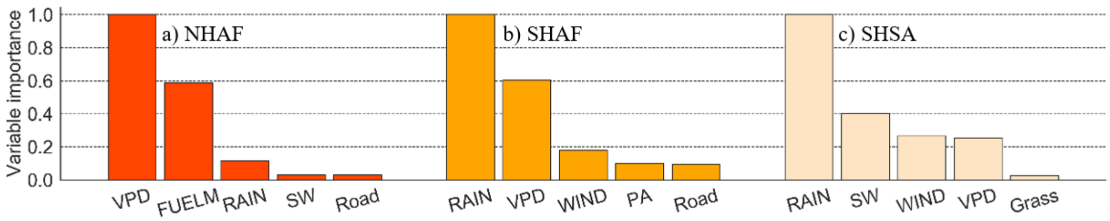

Fig. 3: Ranked top-five important variables for fire-season burned area in Northern Hemisphere Africa (NHAF) (a), Southern Hemisphere Africa (SHAF) (b), and Southern Hemisphere South America (SHSA) (c). For each gridcell within each study region, there is a mean variable weight, representing the importance of the variable for fire prediction in the gridcell. For each region, the variable weights are summed weighted by its corresponding mean burned areas, and normalized.

5. Section 3.3: Please avoid defining acronyms in the figure 5 legend, bring them into the main text of section 3.3.

We removed the acronyms in the legend of Figure 5 and defined the ocean indices in the main text of section 2.3. The revisions are shown as follows.

L249-267, section 2.3:

In addition to the local socio-environmental drivers, we also explored the impacts of ocean indices on burned area predictions. Chen et al. (2011) found that wildfires in South America were closely linked to the Oceanic Niño Index (ONI), and Atlantic multidecadal Oscillation (AMO) index. The ONI and AMO reflected the sea surface temperature (SST) anomalies in the tropical Pacific and north Atlantic. The SST anomalies directly affected ocean-atmosphere interactions and thus the wet, wet-to-dry, and onset of dry season climate in South America (Chen et al., 2011). The two indexes were significantly correlated with peak fire month wildfires 3 to 7 months later and could predict fire season wildfires in many regions of South America with lead times of 3 to 5 months (Chen et al., 2011). The controls of SST anomalies in tropical Pacific on climate and thus wildfires were also found in northern and southern Africa (Andela and Van Der Werf, 2014). In addition, SST anomalies in tropical northern and southern Atlantic could also affect wildfires in South America (Chen et al., 2016) and Africa (Yu et al., 2020; Chen et al., 2020). Therefore, we included ocean indices (Table 2) and investigated their impacts on wildfire predictions with the AttentionFire model (see section 3.4).

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Fuel conditions	Fuel moisture (FUELM, %), coarse wood debris (CWDC, gC m^{-2} s^{-1}), vegetation biomass (VegC, gC m^{-2} s^{-1}), litter biomass (LitterC, gC m^{-2} s^{-1})	~1.9 degree (monthly)	ELM prognostic simulations (Zhu et al., 2019)
Human activities	Population density (Popu, persons $grid^{-1}$)	~1km (yearly)	(Dobson et al., 2000)
	Road density (Road, km km^{-2})	0.5 degree (yearly)	(Meijer et al., 2018)
	Livestock density (LS, number of livestock $grid^{-1}$)	0.5 degree (yearly)	(Rothman-Ostrow et al., 2020)
Land cover	Bare soil (Bare, %), Forest (Forest, %), and Grass (Grass, %)	0.25 degree (yearly)	LUH2 (Hurtt et al., 2020a)
Oceanic indices	Ocean Niño Index (ONI), Atlantic multidecadal Oscillation (AMO) index, Tropical Northern Atlantic (TNA) Index, and Tropical Southern Atlantic (TSA) Index	monthly	NOAA Climate Indices (Noaa, 2021)

6. Line 426: “will dampened” ->“will be dampened”

Revised as suggested.