

Supplementary information

Forecasting carbon-risk hotspots ahead of the extreme 2026 El Niño

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Supplementary Text S1-3

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Supplementary References

Supplementary Text S1. Evaluation of ECMWF forecasts against ERA5

To assess the continuity of climate forcing across the June–July 2026 transition, we compared European Centre for Medium-Range Weather Forecast (ECMWF) ensemble forecasts¹ with ERA5^{2,3} during the overlapping period in June 2026. Each variable used to drive the model was evaluated separately (Table S1). The consistency was quantified using the coefficient of determination (R^2) and the root mean squared error (RMSE). First, we compared regional monthly mean values, showing strong agreement across all variables ($R^2 > 0.80$) (Fig. S26). Instantaneous variables show the closest agreement with ERA5, including R^2 values of 0.99 for 2-m air and dewpoint temperature, and 0.93 for mean sea-level pressure (Fig. S26c–e). Some accumulated variables (surface downward shortwave radiation and surface downward longwave radiation) also showed highly consistent regional patterns, with R^2 values exceeding 0.97. In contrast, total precipitation and snowfall exhibited larger spatial discrepancies ($R^2 = 0.92$ and 0.80 , respectively) relative to other variables. For example, precipitation was overestimated over Asia, whereas snowfall was slightly underestimated in the same region (Fig. S26h, i).

Secondly, we evaluated the temporal evolution of global mean values for each variable during June 2026 (Fig. S27). The ECMWF ensemble reproduced the temperature evolution well, capturing most of the fluctuations observed in ERA5 (Fig. S27c). For wind components and snowfall, the forecasts also captured the overall temporal patterns, although their day-to-day variability was weaker than that in ERA5 (Fig. S27a, b, i). Systematic biases were also identified for some variables: surface shortwave radiation was consistently underestimated throughout June, while precipitation was overestimated during the second half of the month (Fig. S27f, h). The weaker day-to-day variability may introduce uncertainties in simulated terrestrial carbon-cycle responses. Nevertheless, the generally consistent temporal evolution and monthly mean values between ECMWF and ERA5 support the use of ECMWF forecasts for assessing terrestrial carbon-cycle responses to El Niño at the monthly scale (Fig. S28).

We further evaluated the spatial differences between ECMWF and ERA5 (Fig. S29). Spatial differences varied across variables and regions. For wind components, temperature and air pressure, spatial differences were relatively small in the tropics but larger at higher latitudes. Precipitation showed the largest relative differences among the variables, with particularly pronounced discrepancies over Central Asia and Africa (Fig. S29h). Overall, the ECMWF ensemble reproduced the large-scale meteorological patterns captured by ERA5, while regional discrepancies remained for individual variables, with precipitation showing the largest relative differences.

To evaluate how forecast errors evolve with lead time, we used ECMWF hindcasts initialized on 1 June for 1993–2016 and calculated the RMSE between ECMWF and ERA5 at each forecast timestep. RMSEs for the 10-m u- and v-components of wind remained relatively stable with increasing lead time, whereas RMSEs for air temperature, dewpoint temperature, and mean sea-level pressure increased gradually (Fig. S25a–e). In contrast, the RMSEs of shortwave radiation, precipitation, and snowfall showed non-monotonic variations with lead time, without a consistent increase or decrease (Fig. S25f,h,i). Overall, the magnitude and evolution of forecast errors varied among variables and with lead time, but the errors remained small relative to the absolute magnitude of the corresponding variables, indicating that ECMWF forecasts retained reasonable reliability over the forecast period.

We quantified ensemble spread as the standard deviation across the 51 ECMWF ensemble members (Fig. S24). For wind components, 2-m air temperature, sea-level pressure, and downward shortwave radiation, ensemble spread was generally higher at

mid- to high latitudes in the Northern Hemisphere and lower in the tropics. Moreover, relatively high spread in 2-m dewpoint temperature and downward longwave radiation was also observed over North Africa and southern South America, respectively. In contrast, the areas of relatively high spread for precipitation and snowfall were more spatially localized, occurring mainly over parts of South and East Asia for precipitation and over high-latitude and mountainous regions for snowfall.

Supplementary Text S2. Evaluation of DGVMs performance in simulating NBP anomalies

To evaluate the ability of the dynamic global vegetation models (DGVMs) (ORCHIDEE-MICT⁴ and JULES^{5,6}) to reproduce global terrestrial net biome productivity (NBP) anomalies, we compared ORCHIDEE and JULES simulations with atmospheric CO₂ inversion products. We used the 1° GCP2024 atmospheric inversion dataset for 1990–2023⁷, and the land carbon flux adjusted for fossil fuel and cement emissions (land_flux_only_fossil_cement_adjusted) was used to represent terrestrial carbon exchange. Three inversion systems from the GCP2024 ensemble, including the Copernicus Atmosphere Monitoring Service (CAMS) atmospheric inversion v21r2⁸, the Jena CarboScope inversion v2022⁹, the NISMON-CO2¹⁰, were selected because they cover the two strongest El Niño events of 1997–1998 and 2015–2016.

We first evaluated annual global NBP anomalies from the DGVM simulations against atmospheric inversion estimates. For each DGVM and inversion product, detrended annual anomalies were calculated as residuals from a linear trend fitted over 1990–2023. Both ORCHIDEE and JULES captured the interannual variations in global NBP anomalies (Fig. S30). The DGVMs NBP showed a regression slope of 0.93 relative to the inversions estimate (Fig. S30b). Although its correlation was slightly lower than that of JULES alone, the two-model mean exhibited a regression slope closer to one and the lower RMSE.

To further evaluate the ability of DGVMs to reproduce NBP variations during strong El Niño events, we further compared the global monthly NBP anomalies during over 1997–1998 and 2015–2016 period. The DGVMs reproduced the temporal evolution of the inversion-derived anomalies during both events (Fig. S31). For 1997–1998 El Niño event, the correlation between DGVMs and the inversions was 0.745, and the regression of inversion anomalies against model anomalies yielded a slope of 0.951. Despite capturing the main progression of the anomalies, the models underestimated the cumulative reduction in the land carbon sink: the two-model estimate was -1.16 ± 0.45 Pg C, compared with -3.39 ± 0.27 Pg C from the inversions. ORCHIDEE and JULES simulated cumulative anomalies of -0.71 and -1.61 PgC, respectively, indicating underestimation by both models (Fig. S31a). For 2015–2016 El Niño event, the two-model mean showed stronger agreement with the inversion mean, with a regression slope of 1.018 and an RMSE of 0.099 PgC month⁻¹. These results indicate good agreement in monthly variability, but the cumulative anomaly (-1.2 ± 0.89 PgC) remained smaller in magnitude than the inversion estimate (-2.2 ± 0.14 PgC) (Fig. S31b). Thus, the two-model mean reproduced the main monthly evolution of global NBP anomalies during both strong El Niño events, while underestimating the cumulative reduction in the land carbon sink.

Supplementary Text S3. Evaluation of burned area predictions

To evaluate the ability of our machine-learning framework to reconstruct burned area, we conducted leave-one-year-out validation for 2004–2020. Predicted and observed multi-year mean burned-area fractions (BAF) showed strong spatial agreement globally ($R^2 = 0.94$; Fig. S33), with the highest regional agreement in NHAF and SHAF ($R^2 = 0.95$ and

0.96, respectively). These results indicate that the framework reproduced the spatial distribution of mean burned area across the validation period.

We further evaluated the predictions against independent satellite burned-area products, including FireCCI51 for 2021–2022^{11,12}, C3S Fire Burned Area for 2021–2023¹³, and FireCCIS311 for 2021–2024¹⁴ (Table S3). In terms of global monthly burned areas, the prediction showed strong agreement with the C3S and FireCCI51 products, while the FireCCIS311 generally reported higher burned areas (Fig. S34). Differences in sensors and retrieval algorithms allow FireCCIS311 to detect more small fires, resulting in higher burned area estimates and discrepancy among the three satellite products. Grid-cell comparisons further showed strong spatial agreement between the predictions and all three satellite products, with global R^2 values of 0.73–0.74 (Fig. S35). Predicted burned area closely matched FireCCI51 and C3S estimates, with regional agreement highest in NHAF and SHAF (Figs. S36, S37). Overall, the framework captured global spatial patterns and seasonality in burned areas, although biases remained in regions with low burned areas.

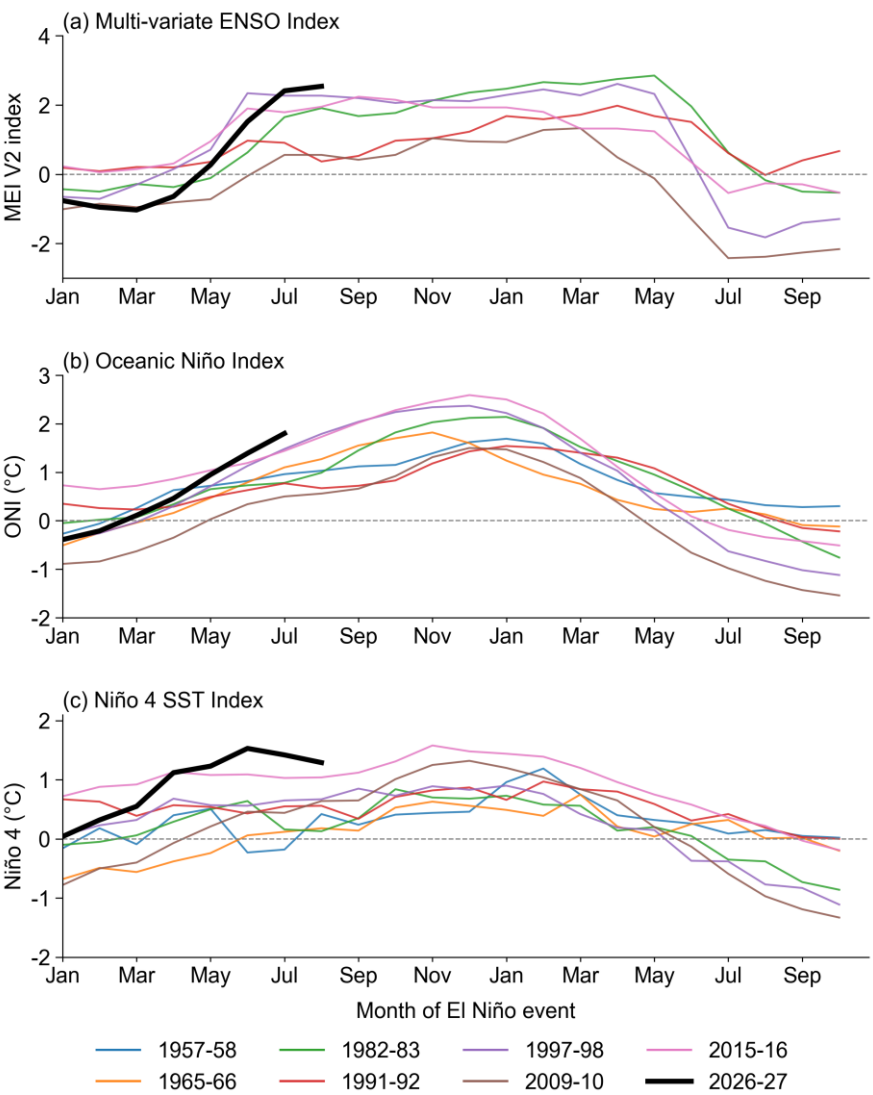


Figure S1. Evolution of ENSO indices during major El Niño events. The index records are obtained from NOAA¹⁵. The lines represent El Niño events ranked among the strongest events in the historical record since 1950.

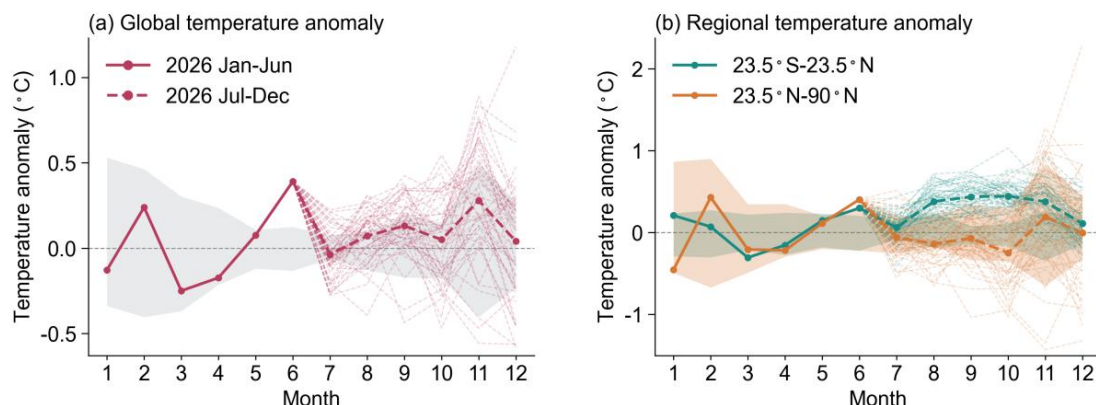


Figure S2. Global and regional temperature anomalies during the 2026 El Niño event. (a) Monthly anomalies in global mean temperature. The grey shading represents the 10th–90th percentile range of monthly anomalies during the reference period, 2016–2025 (excluding the El Niño years), and the pale red dashed lines show individual forecasts from the 51 ECMWF ensemble members. (b) Monthly temperature anomalies over the tropics (23.5°S–23.5°N) and the extra-tropical Northern Hemisphere (23.5°–90°N). The shadings represent the 10th–90th percentile range of monthly anomalies during the reference period, and the pale dashed lines show individual forecasts from the 51 ECMWF ensemble members.

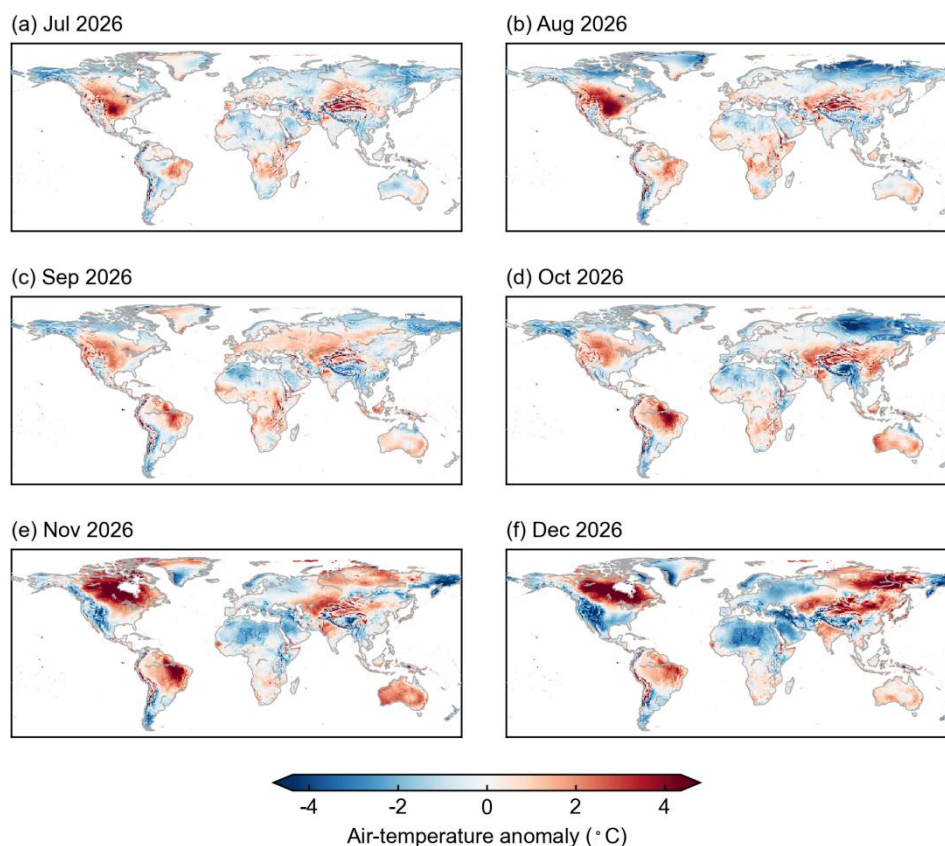


Figure S3. Spatial patterns of projected temperature anomalies during July–December 2026 based on the 51-member ECMWF ensemble mean.

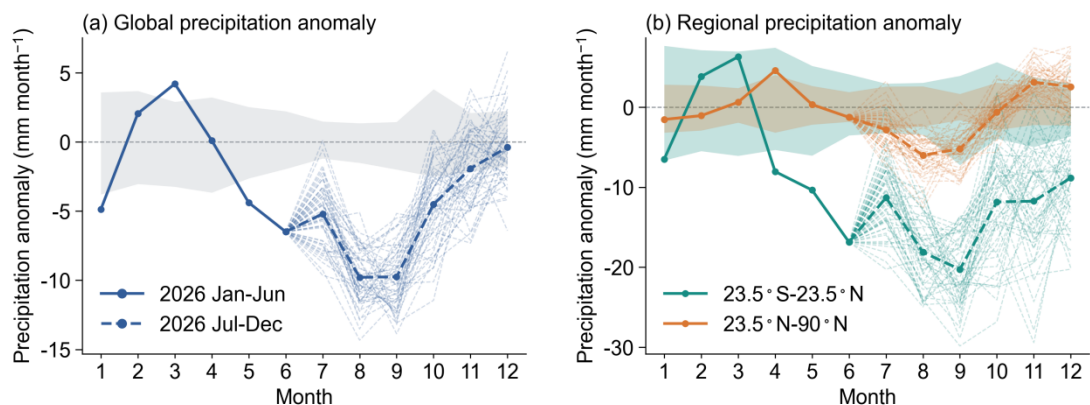


Figure S4. Global and regional precipitation anomalies during the 2026 El Niño event. (a) Monthly anomalies in global precipitation. The grey shading represents the 10th–90th percentile range of monthly anomalies during the reference period, 2016–2025 (excluding the El Niño years), and the pale blue dashed lines show individual forecasts from the 51 ECMWF ensemble members. (b) Monthly precipitation anomalies over the tropics (23.5°S–23.5°N) and the extra-tropical Northern Hemisphere (23.5°–90°N). The shadings represent the 10th–90th percentile range of monthly anomalies during the reference period, and the pale dashed lines show individual forecasts from the 51 ECMWF ensemble members.

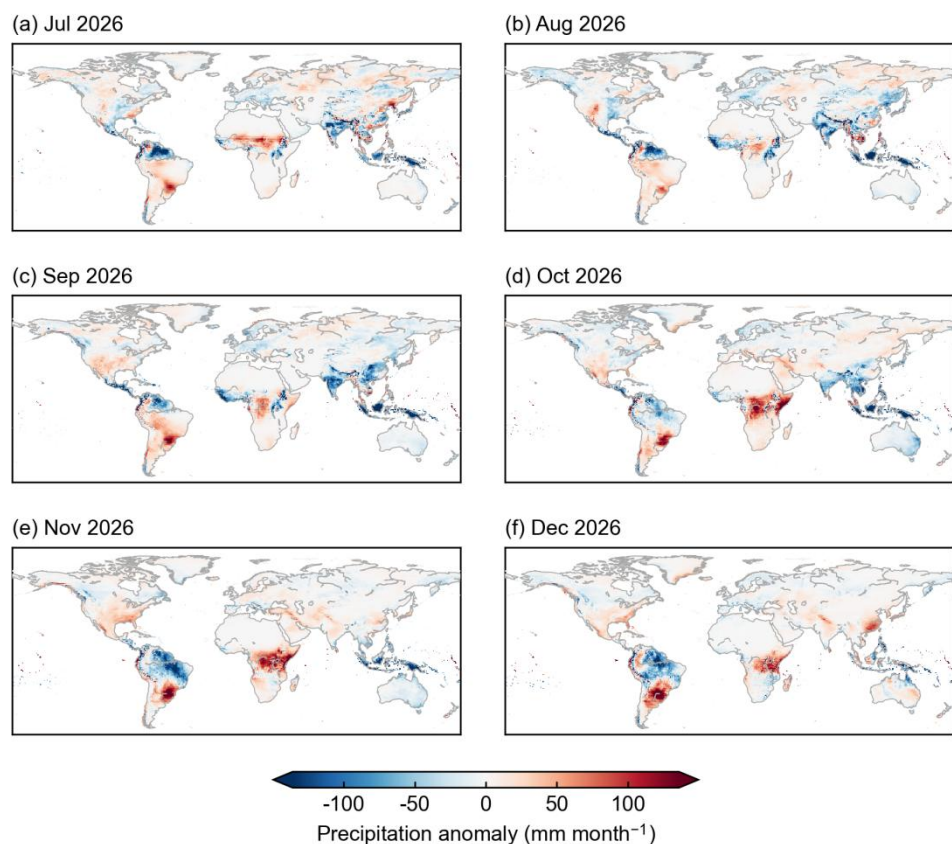


Figure S5. Spatial patterns of projected precipitation anomalies during July–December 2026. Figures show the 51 ECMWF member ensemble-mean precipitation anomaly.

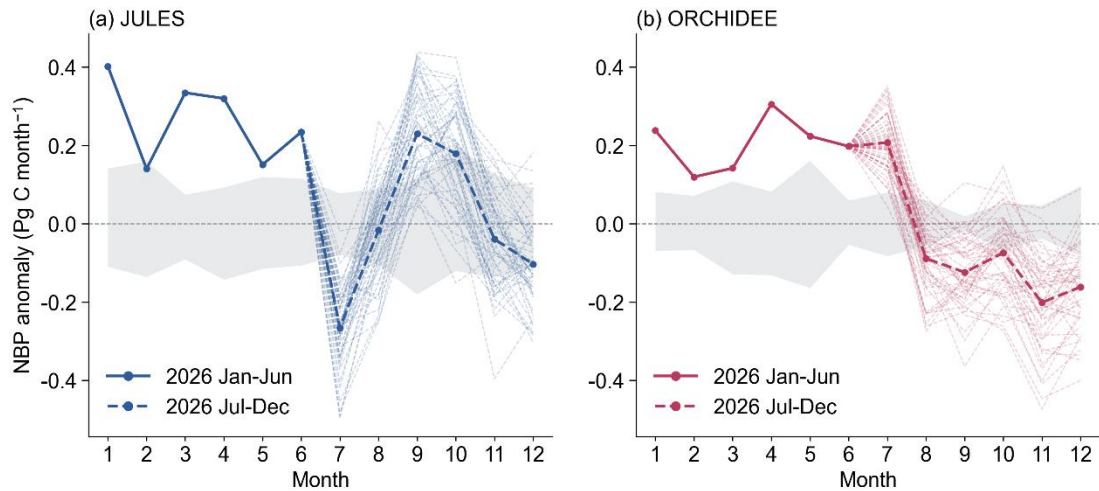


Figure S6. DGVM projections of global monthly net biome productivity (NBP) anomalies during the 2026 El Niño event. The grey shading represents the 10th–90th percentile range of NBP anomalies during the reference period, 2016–2025 (excluding the El Niño years), and the pale dashed lines show individual predictions driven by the 51 ECMWF ensemble members.

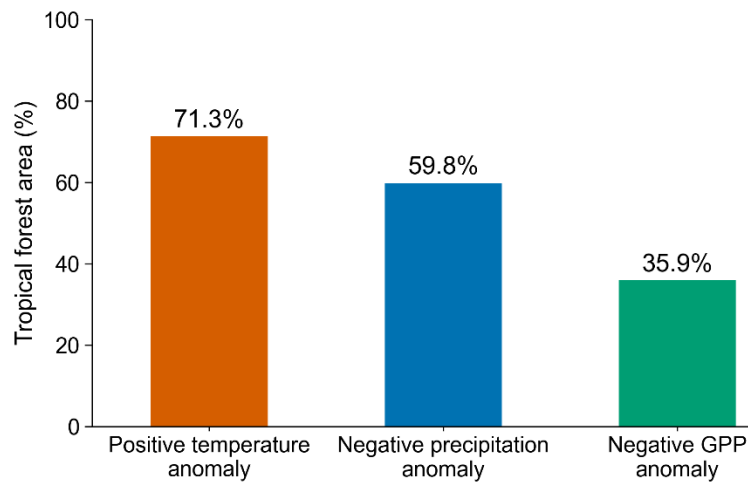


Figure S7. Proportion of tropical forests experiencing positive temperature anomalies, negative precipitation anomalies, and negative GPP anomalies during July–December 2026.

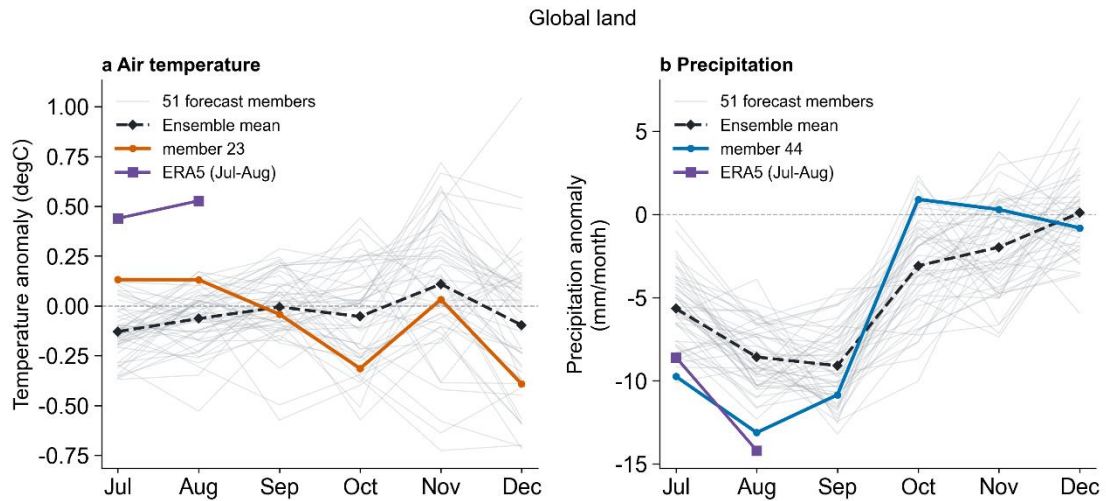


Figure S8. ECMWF ensemble members with the closest global temperature and precipitation anomalies to ERA5 during July–August 2026. The members with the lowest mean absolute error (MAE) among the 51 ECMWF ensemble members were selected for temperature (member 23) and precipitation (member 44), respectively. Purple lines represent the global mean July–August anomalies from ERA5, while grey lines represent the 51 ECMWF ensemble members.

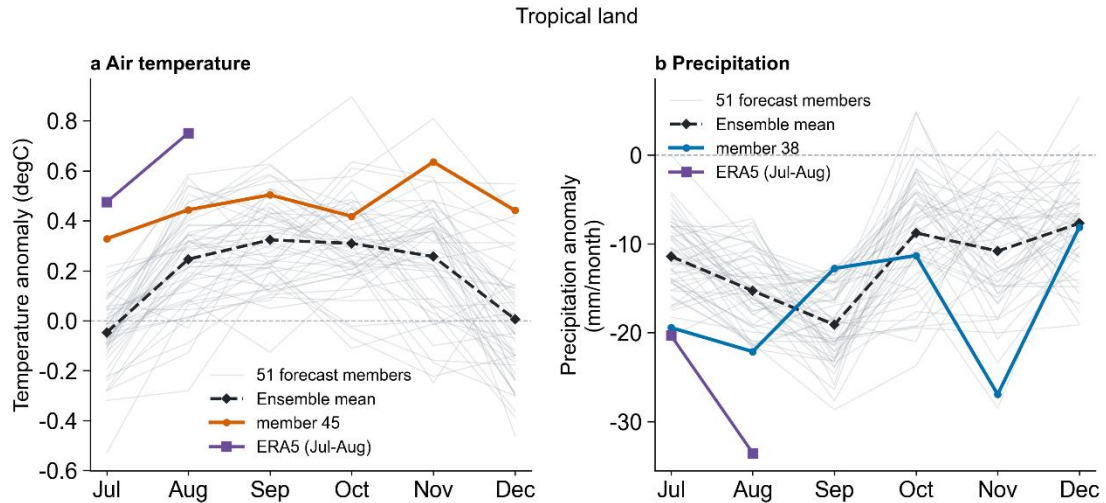


Figure S9. ECMWF ensemble members with the closest tropical temperature and precipitation anomalies to ERA5 during July–August 2026. The members with the lowest mean absolute error (MAE) among the 51 ECMWF ensemble members were selected for temperature (member 45) and precipitation (member 38), respectively. Purple lines represent the global mean July–August anomalies from ERA5, while grey lines represent the 51 ECMWF ensemble members.

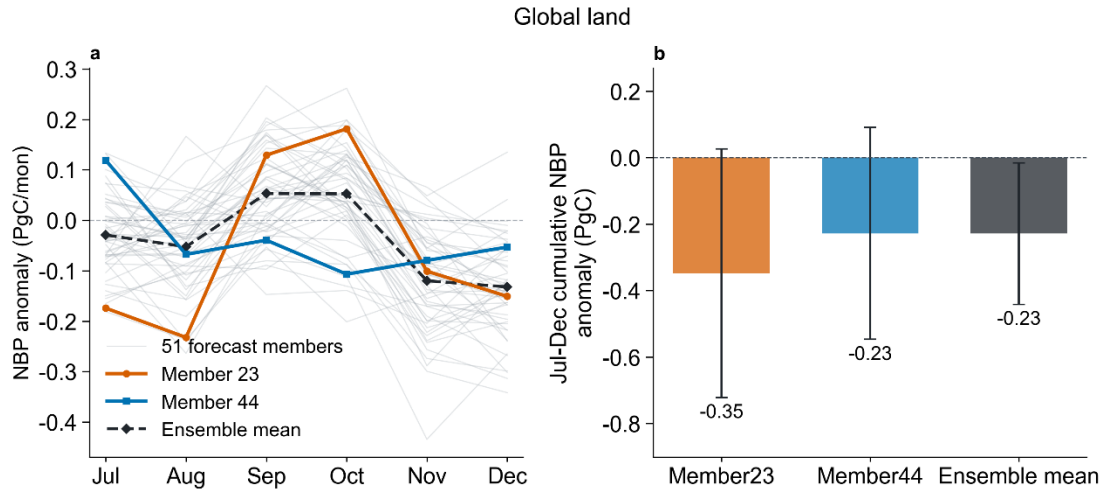


Figure S10. Global NBP anomalies simulated using DGVMs driven by the ensemble members with temperature and precipitation closest to ERA5. (a) Time series of global NBP anomalies during July–December 2026. Orange and blue lines show the DGVM simulations driven by the members with temperature and precipitation, respectively, closest to ERA5, while grey lines show simulations driven by all 51 ensemble members. (b) Cumulative global NBP anomalies during July–December 2026. Error bars indicate the standard deviation across the DGVMs.

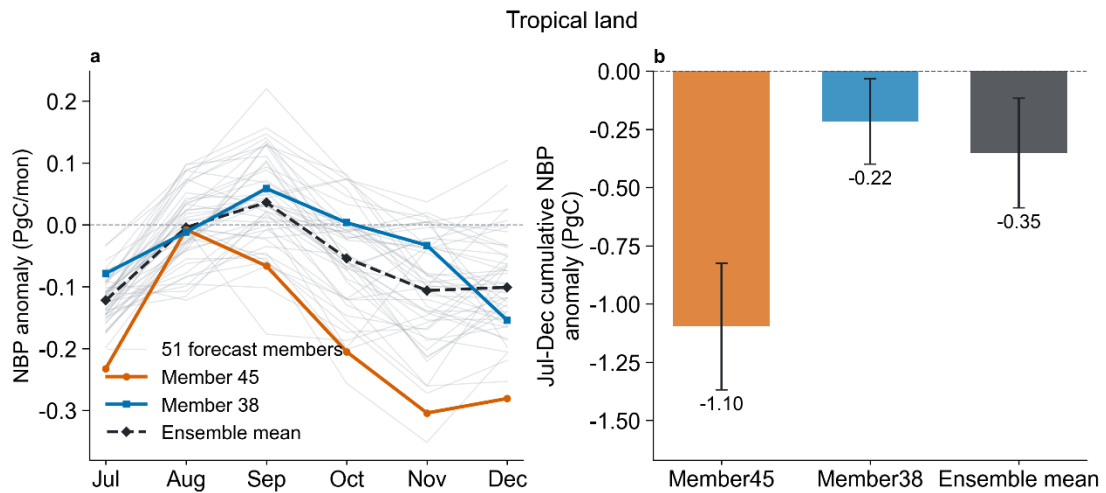


Figure 11. Tropical NBP anomalies simulated using DGVMs driven by the ensemble members with temperature and precipitation closest to ERA5. (a) Time series of global NBP anomalies during July–December 2026. Orange and blue lines show the DGVM simulations driven by the members with temperature and precipitation, respectively, closest to ERA5, while grey lines show simulations driven by all 51 ensemble members. (b) Cumulative global NBP anomalies during July–December 2026. Error bars indicate the standard deviation across the DGVMs.

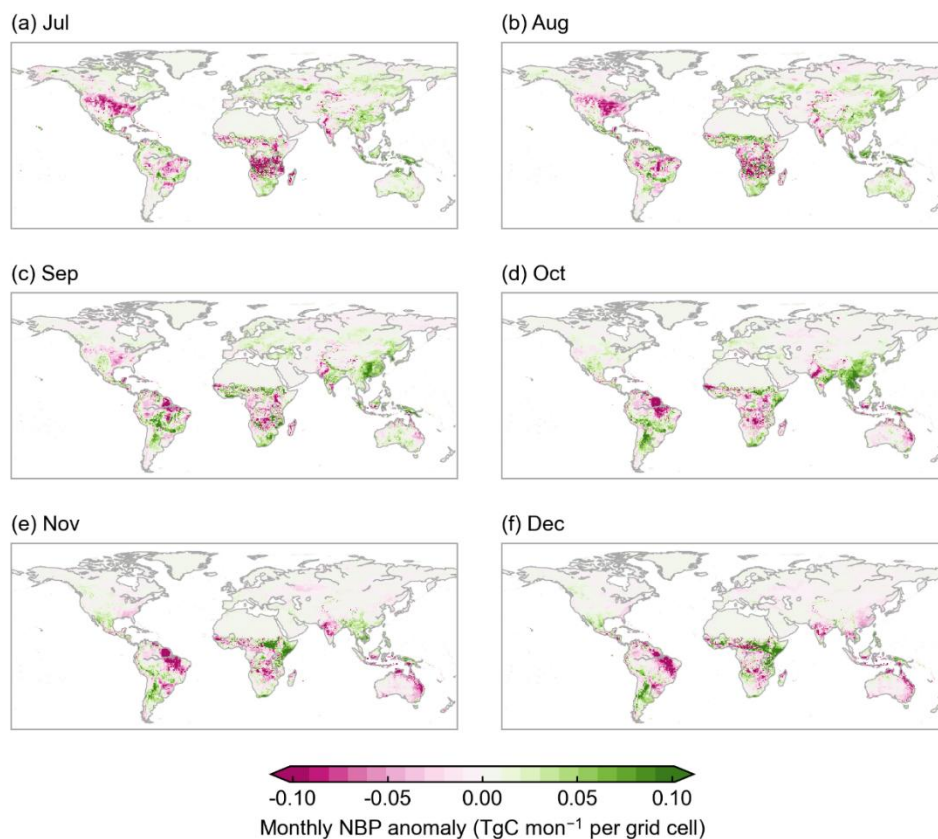


Figure S12. Spatial patterns of ECMWF ensemble-mean projected NBP anomalies during July–December 2026.

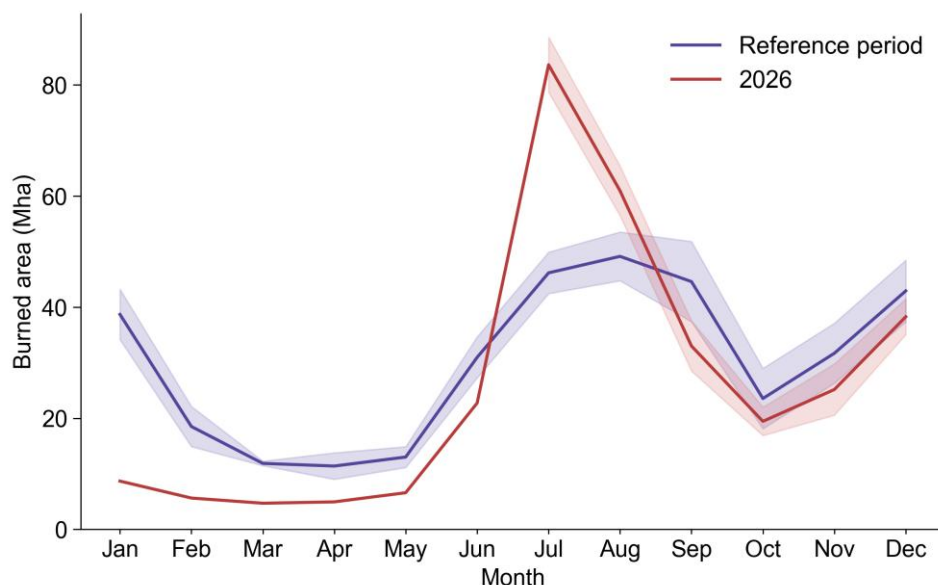


Figure S13. Monthly variation of global burned area (BA). The purple shading represents the standard deviation of monthly BA across years during the reference period, 2016–2025 (excluding the El Niño years), whereas the red shading represents the standard deviation among BA predictions driven by the 51-member ECMWF ensemble.

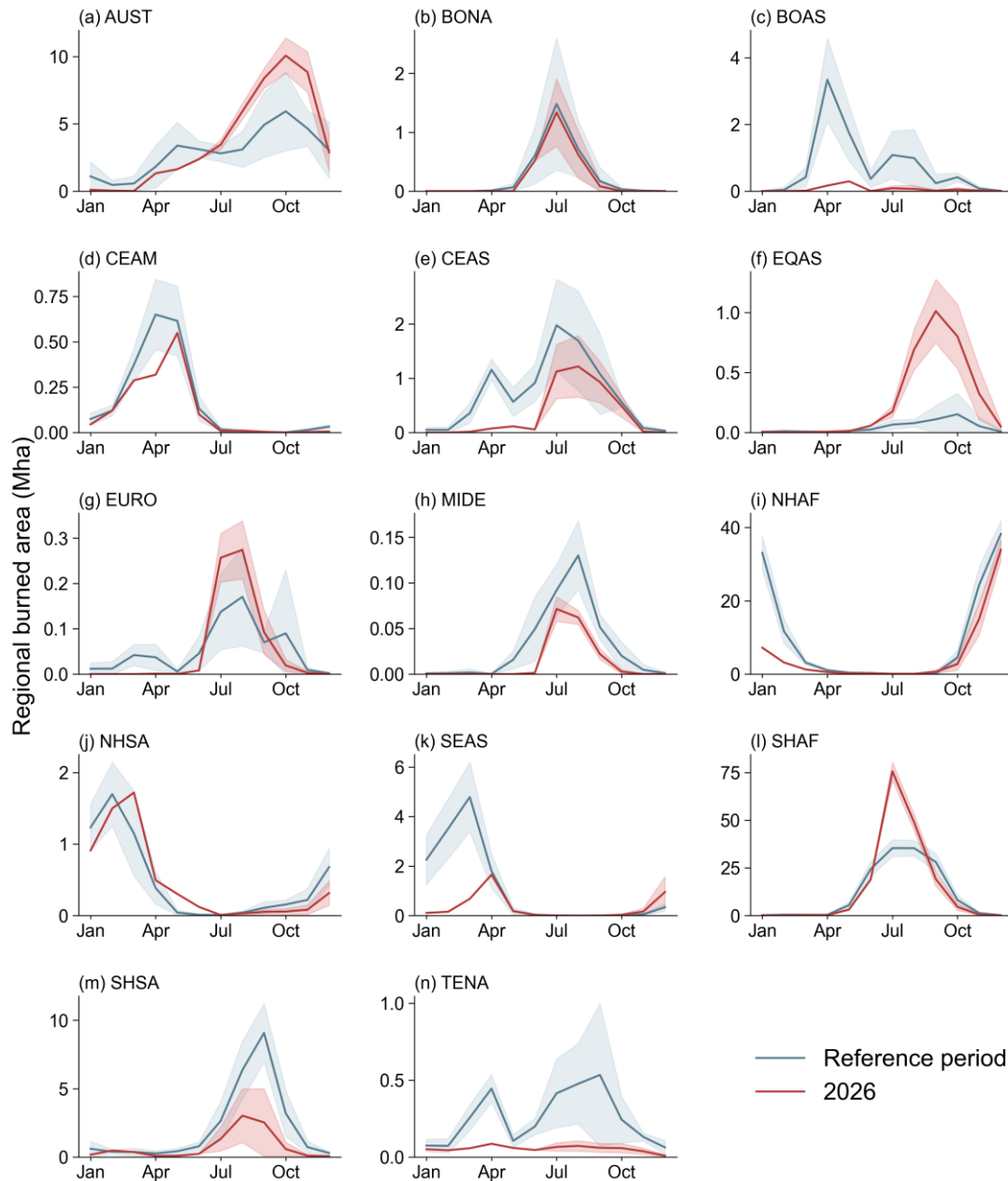


Figure S14. Regional monthly burned area (BA) in GFED regions, including Boreal North America (BONA), Temperate North America (TENA), Central America (CEAM), Northern Hemisphere South America (NHSA), Southern Hemisphere South America (SHSA), Europe (EURO), Middle East (MIDE), Northern Hemisphere Africa (NHAF), Southern Hemisphere Africa (SHAF), Boreal Asia (BOAS), Central Asia (CEAS), Southeast Asia (SEAS), Equatorial Asia (EQAS), Australia and New Zealand (AUST), as shown in Fig. S18. The blue shading represents the standard deviation of monthly BA across years during the reference period, 2016–2025 (excluding the El Niño years), whereas the red shading represents the standard deviation among BA predictions driven by the 51-member ECMWF ensemble.

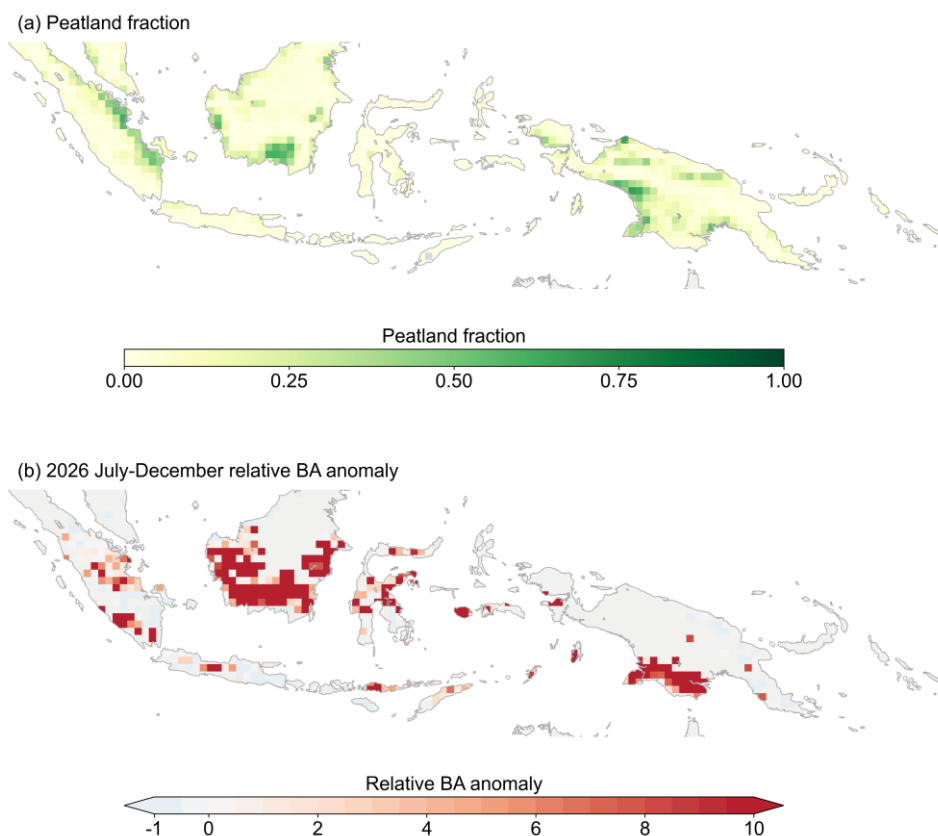


Figure S15. Spatial distribution of peatland extent¹⁶ and machine learning-based burned area anomaly predictions in equatorial Asia (EQAS).

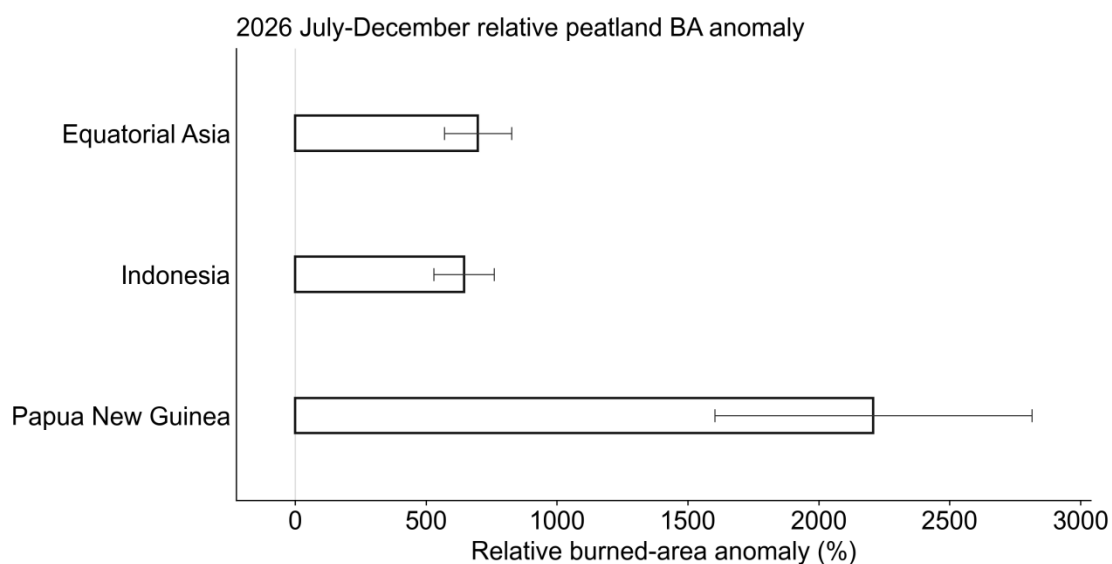


Figure S16. Projected peatland burned area anomaly in equatorial Asia. The error bars represent standard deviation across forecast ensemble members.

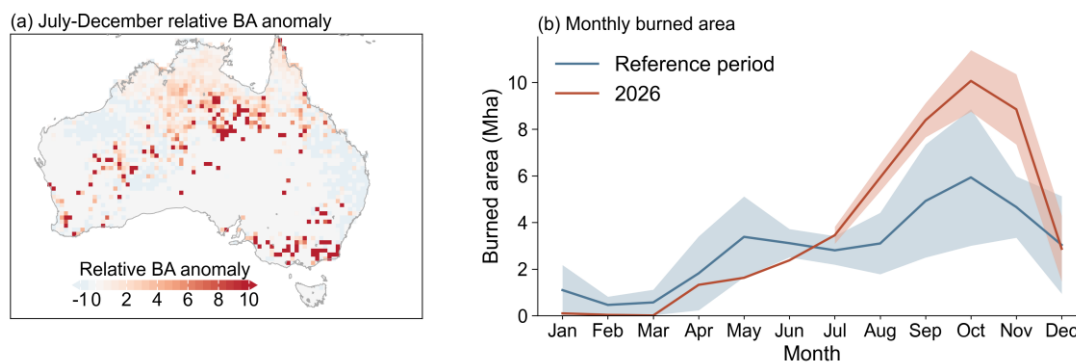


Figure S17. Machine learning (ML)-based prediction of burned area (BA) in Australia and New Zealand (AUST). (a) Ensemble-mean relative burned area anomaly relative to the reference period, 2016-2025 (excluding the El Niño years) July-December mean. (b) Monthly BA in AUST, comparing the reference period mean. The blue shading represents standard deviation across reference period, and the red shading represents standard deviation across BA based on 51 ECMWF member ensemble.

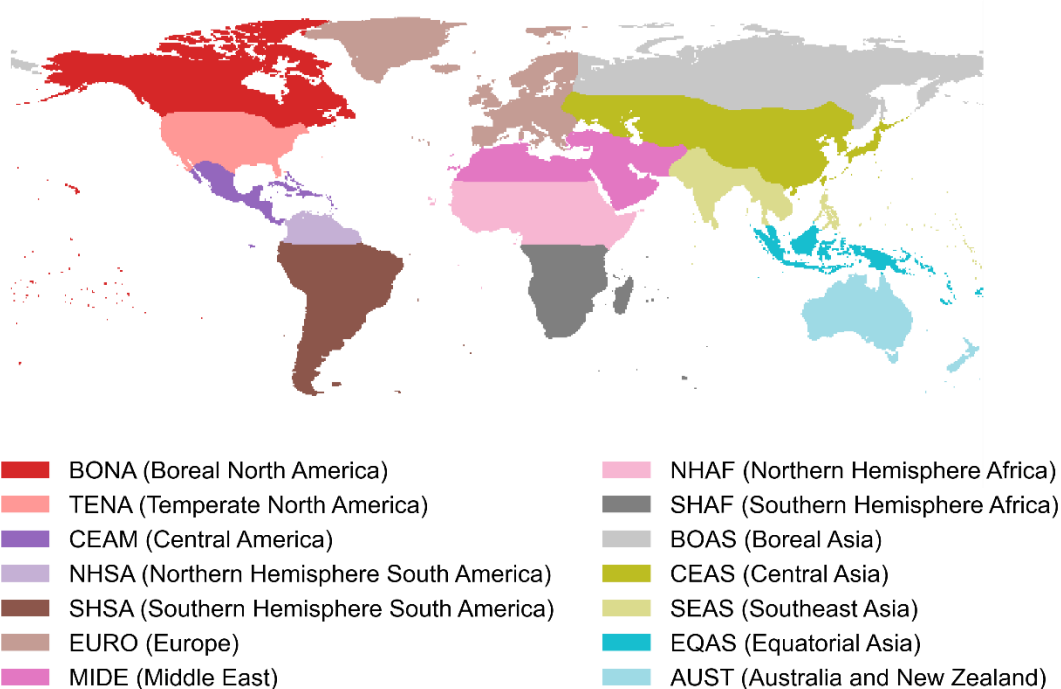


Figure S18. Map of the GFED¹⁷ 14 regions used in this study.

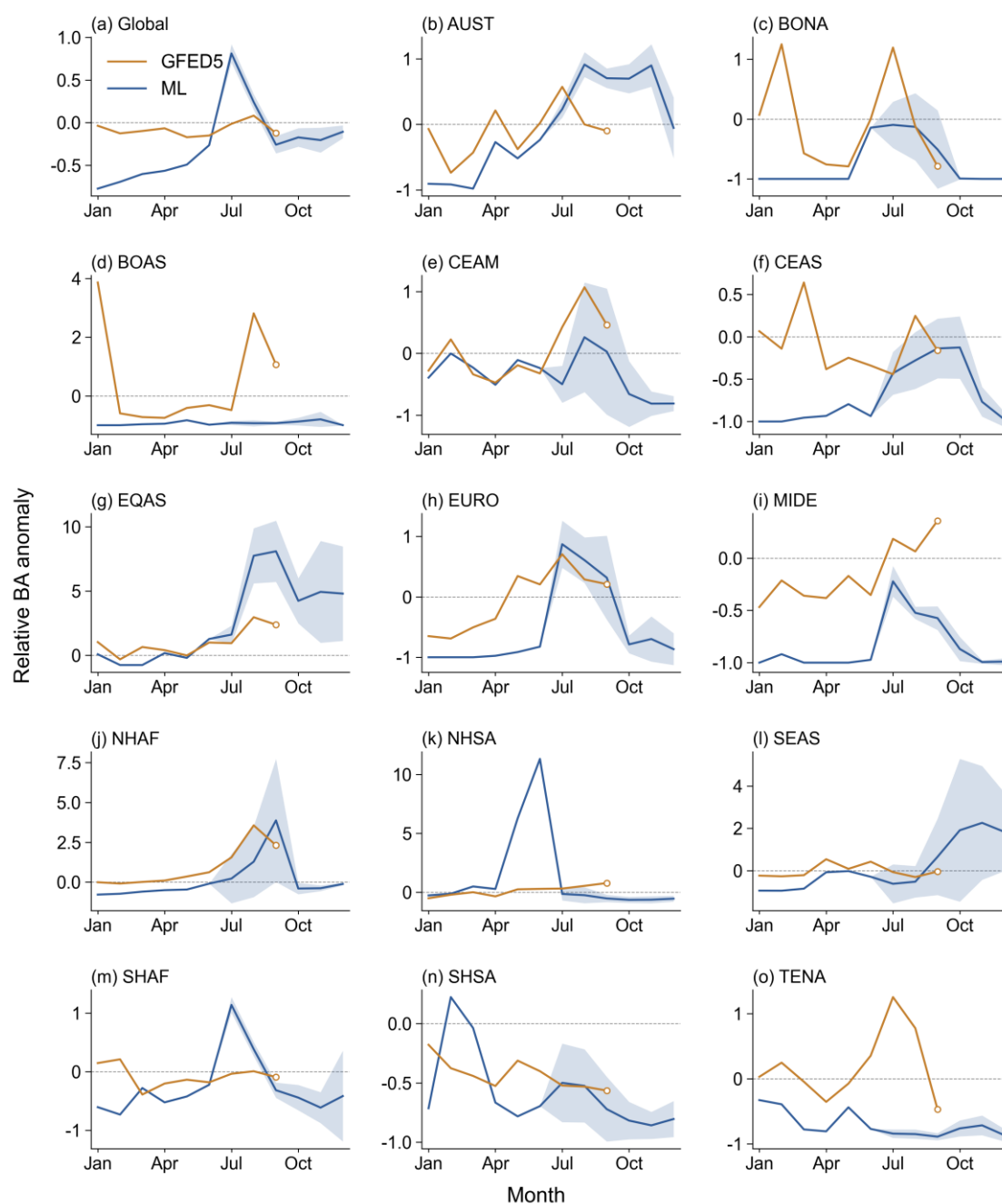


Figure S19. Comparison of machine-learning-predicted and GFED5 NRT¹⁸ burned-area anomalies in 2026 at global and regional scales. Blue shading indicates the standard deviation across ensemble members, and orange lines show GFED5 estimates for January–September 2026.

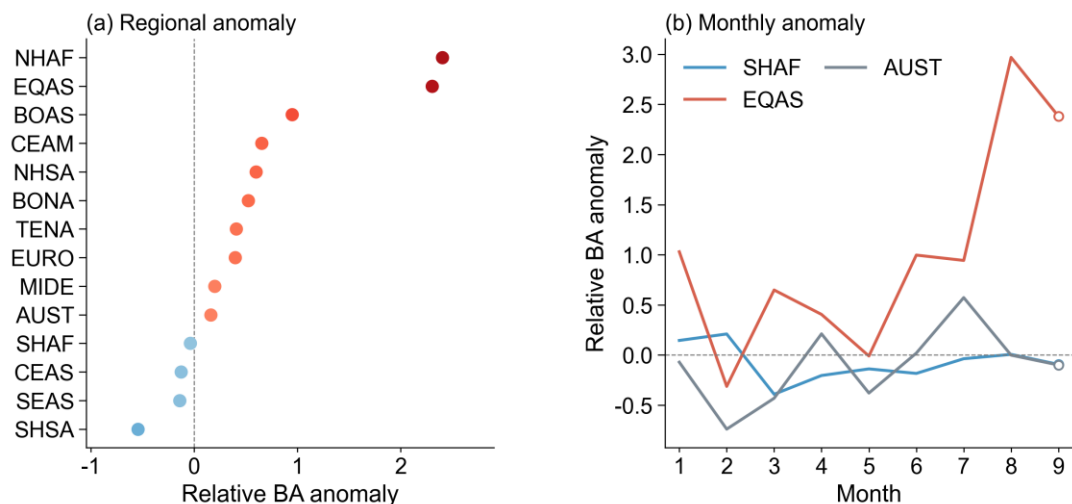


Figure S20. Regional relative burned area (BA) anomalies in 2026 from GFED5 NRT¹⁸. (a) Cumulative relative BA anomalies from July to September 2026 across the 14 GFED regions. (b) Monthly relative BA anomalies from January to September 2026 in Southern Hemisphere Africa (SHAF), Equatorial Asia (EQAS) and Australia and New Zealand (AUST). September 2026 data cover 1–28 September.

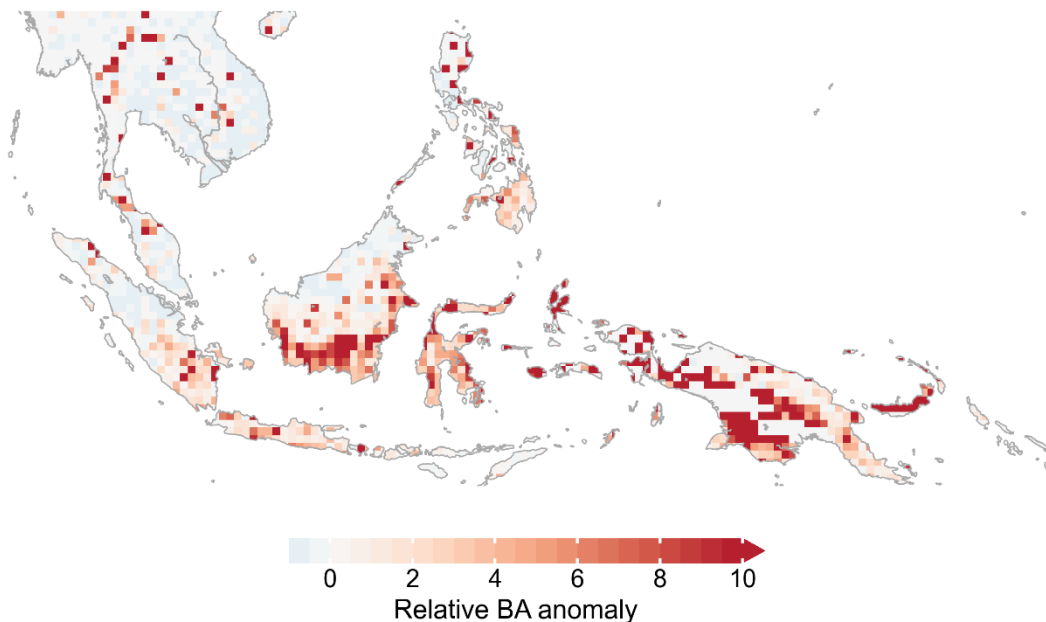


Figure S21. Spatial distribution of relative burned area (BA) anomalies in Equatorial Asia (EQAS) during July–September 2026 estimated from GFED5 NRT¹⁸. September 2026 data cover 1–28 September.

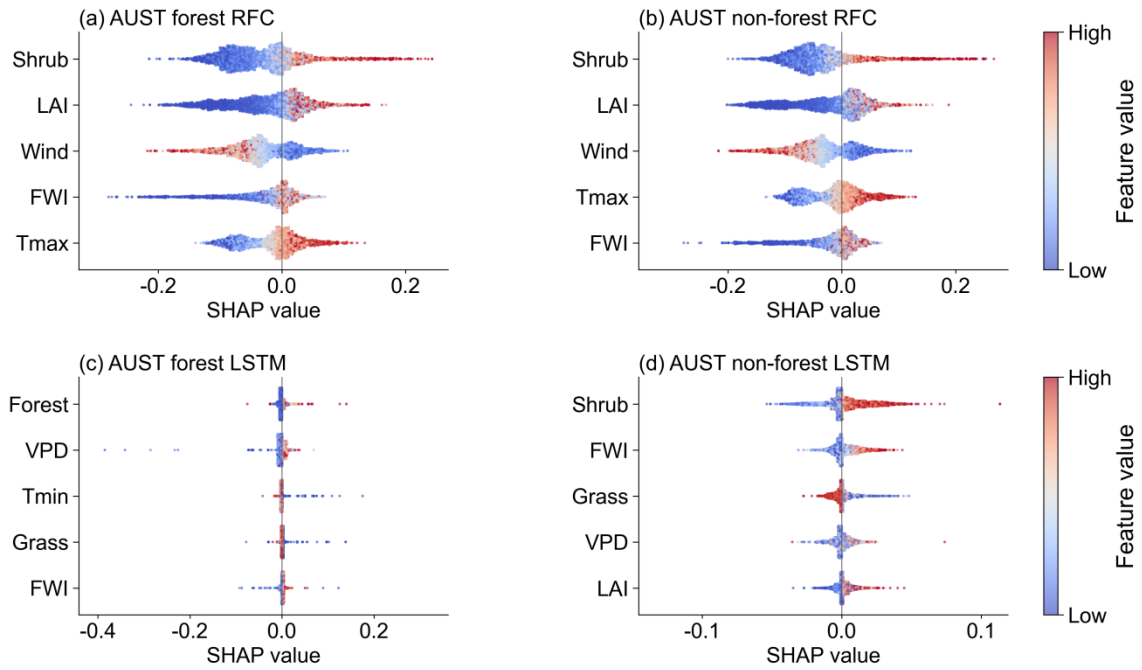


Figure S22. Feature importance in predicting burned area (BA) in Australia and New Zealand (AUST) based on a two-stage machine learning framework. The SHapley Additive exPlanations (SHAP) plots illustrate the contribution of input features to BA predictions. The random forest classifier (RFC) first predicts fire occurrence, followed by a long short-term memory (LSTM) model that predicts BA.

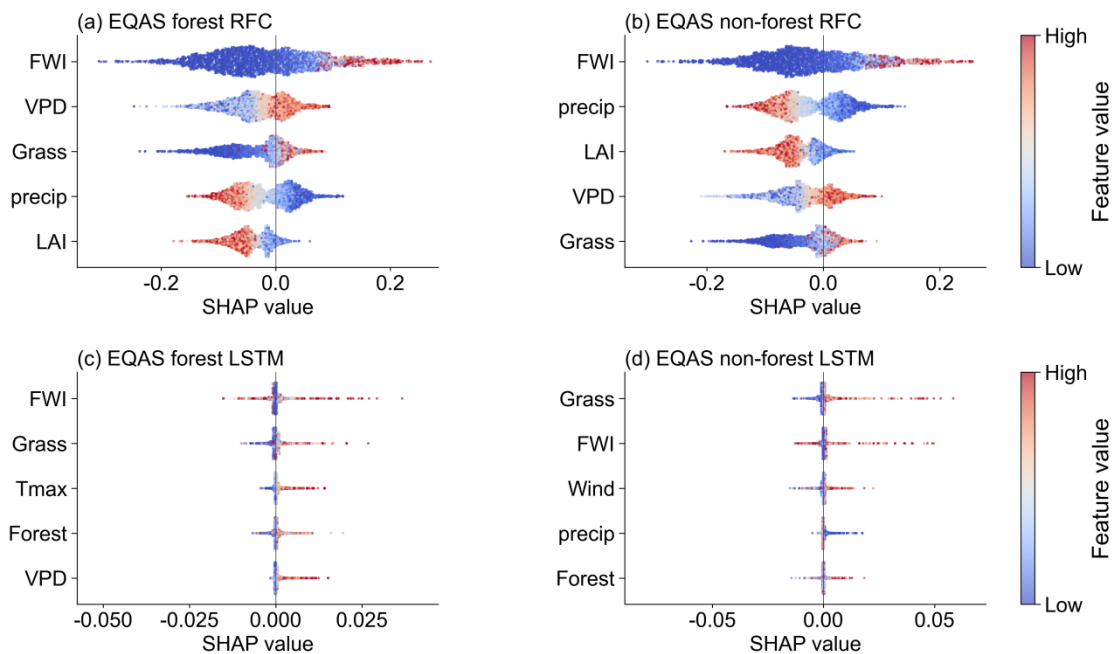


Figure S23. Feature importance in predicting burned area (BA) in equatorial Asia (EQAS) based on a two-stage machine learning framework. The SHapley Additive exPlanations (SHAP) plots illustrate the contribution of input features to BA predictions. The random forest classifier (RFC) first predicts fire occurrence, followed by a long short-term memory (LSTM) model that predicts BA.

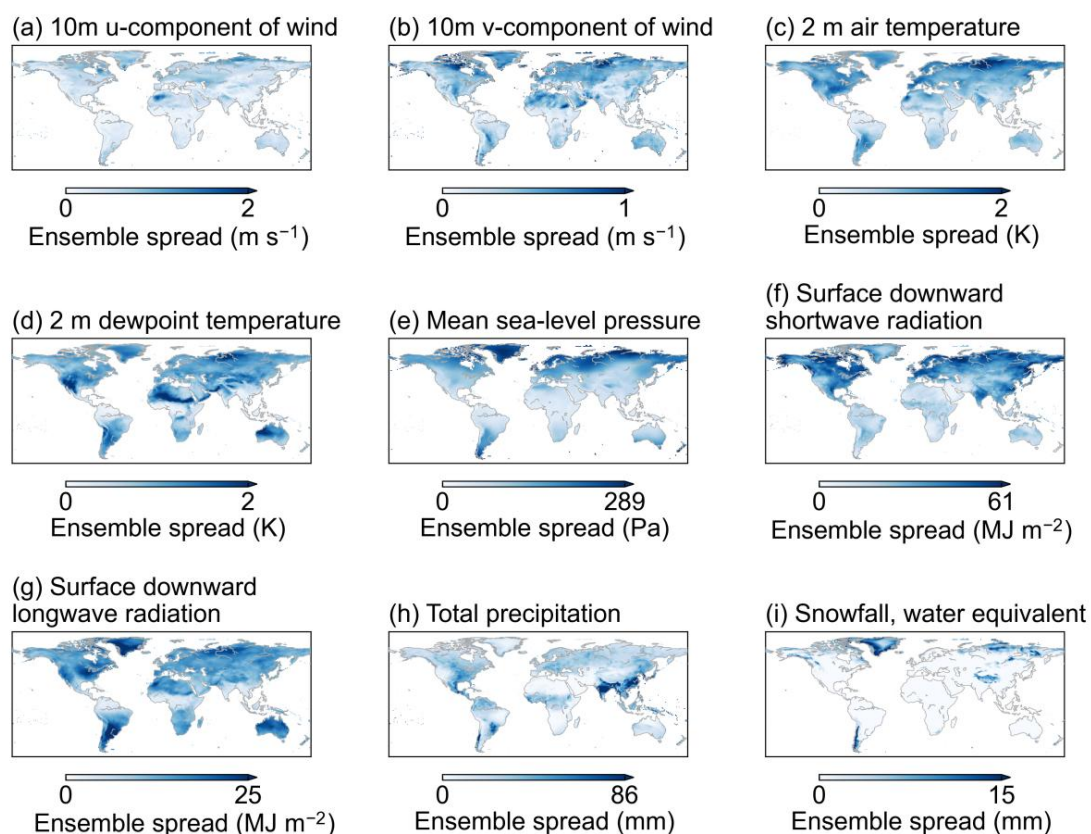


Figure S24. Spatial distribution of ECMWF ensemble spread in June 2026. Ensemble spread is calculated as the standard deviation among the 51 ECMWF ensemble members.

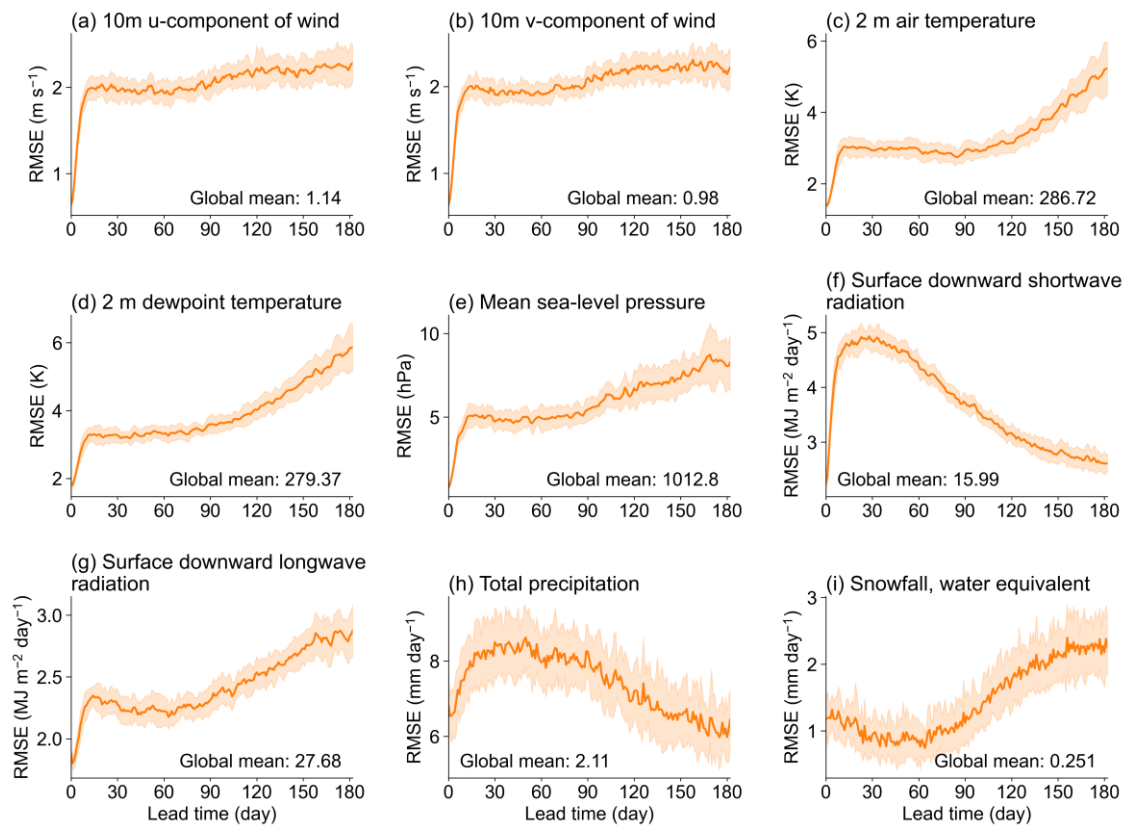


Figure S25. Lead-time evolution of daily global-land RMSE for ECMWF hindcasts relative to ERA5 during 1993–2016. The orange shading indicates the interannual standard deviation of the ECMWF ensemble-mean hindcasts. Numbers in the corners indicate the 1993–2016 mean values from ERA5.

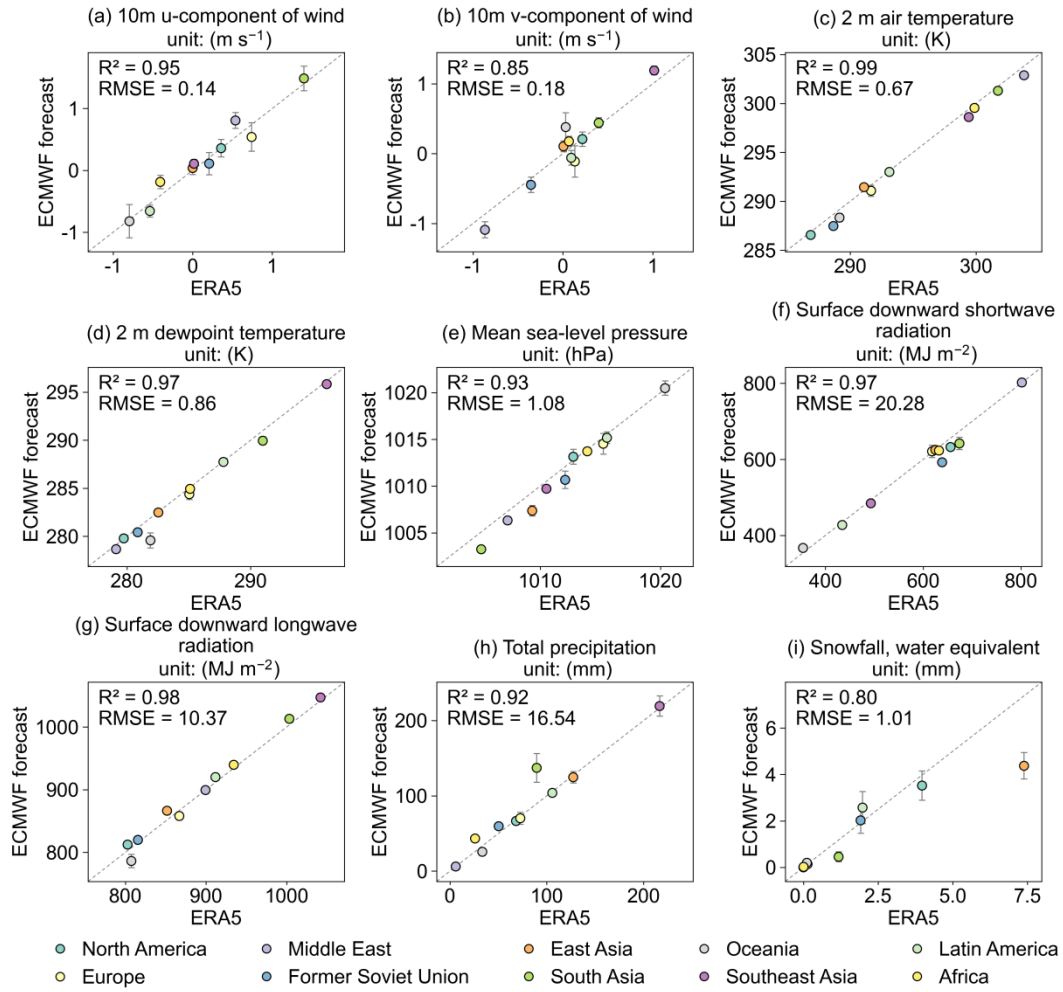


Figure S26. Regional comparison between ECMWF forecasts and ERA5 reanalysis in June 2026. Instantaneous variables are shown as monthly means, whereas accumulated variables are shown as monthly totals. Spatial averages are calculated across global land grid cells within each region. Error bars represent the standard deviation among the 51 ECMWF ensemble members. Dashed lines indicate the 1:1 relationship.

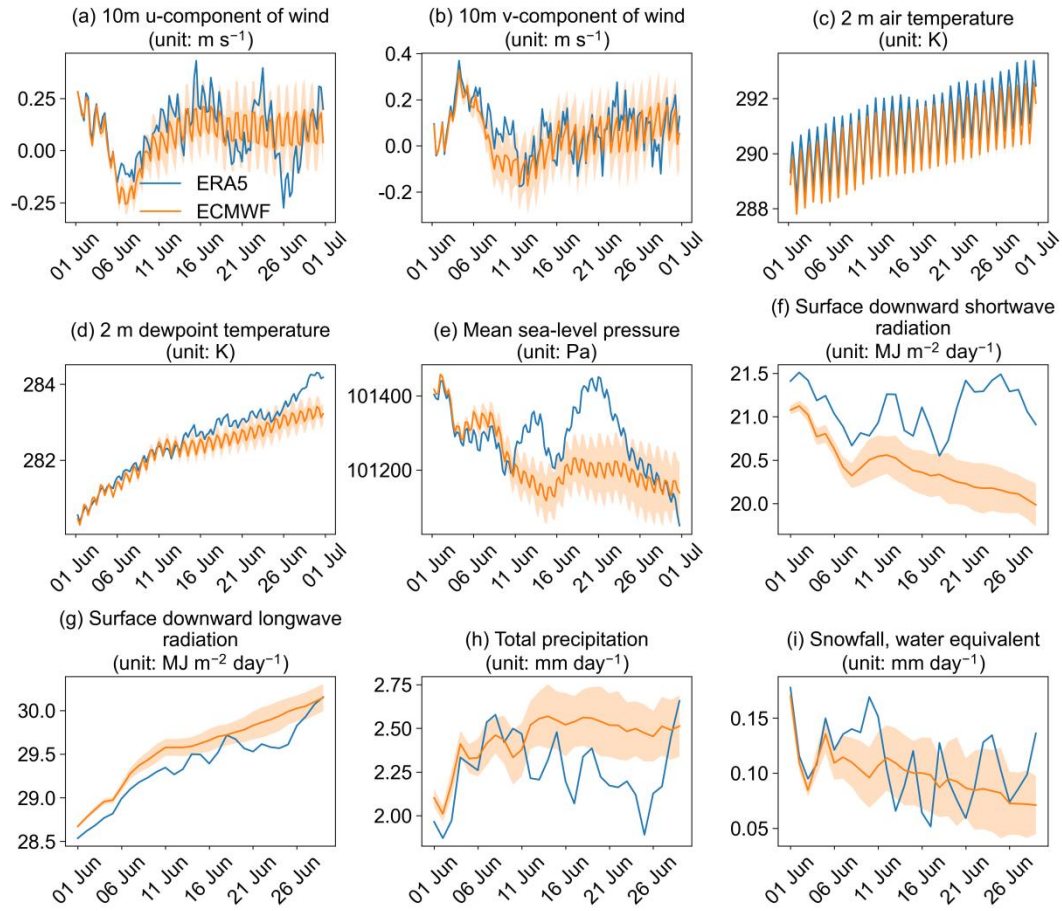


Figure S27. Temporal evolution of global land meteorological conditions throughout June 2026. The shading represents the ensemble spread (standard deviation) among ECMWF ensemble members.

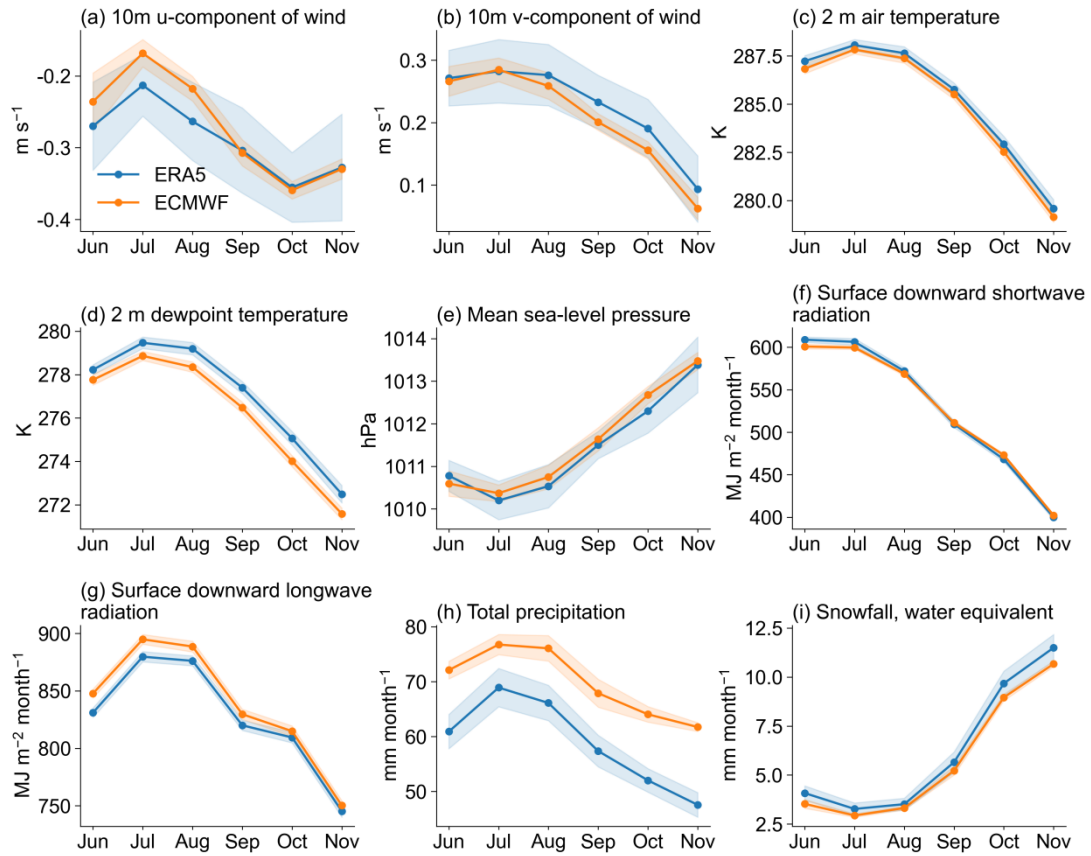


Figure S28. Monthly evolution of ECMWF hindcasts and ERA5 during June–November 1993–2016. The orange shading indicates the interannual spread (standard deviation) of the ECMWF ensemble-mean hindcasts, while the blue shading indicates the interannual standard deviation of ERA5.

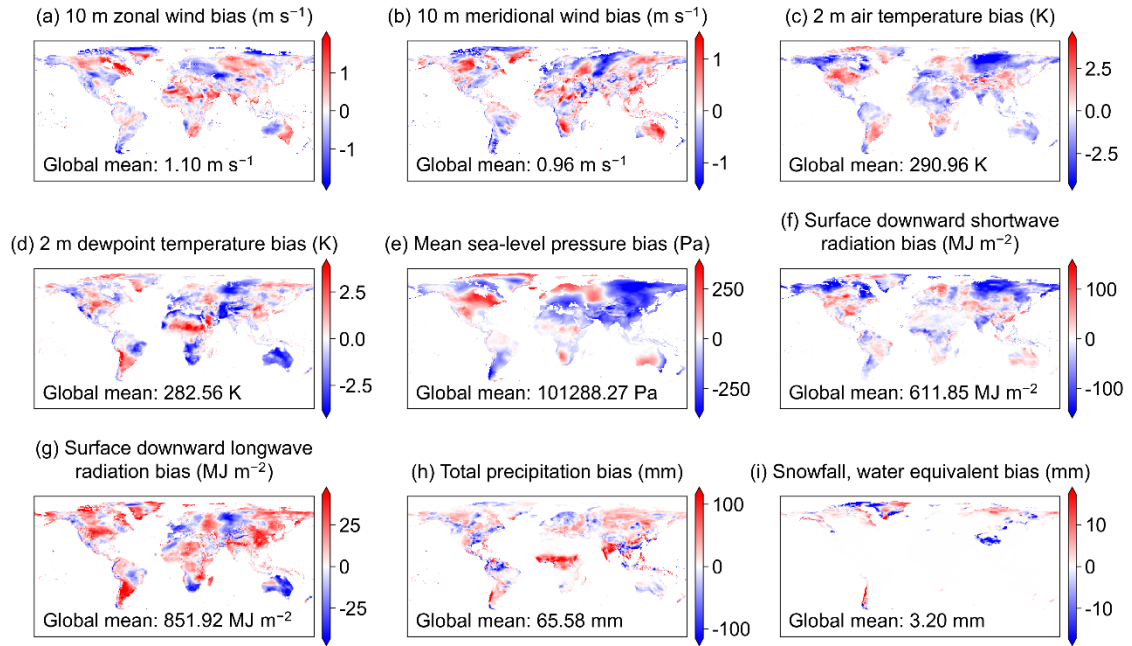


Figure S29. Spatial biases of ECMWF seasonal forecasts relative to ERA5 in June 2026. Biases were calculated at each grid cell as ECMWF minus ERA5. Numbers in the lower-left corners indicate the global mean values from ERA5. For instantaneous variables, values represent June 2026 monthly means, whereas accumulated variables represent monthly totals over June 2026.

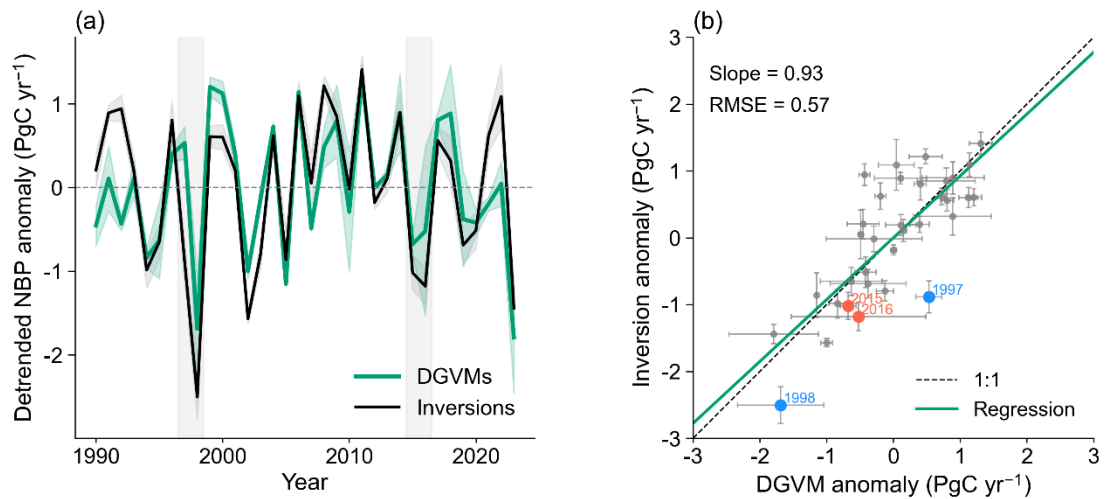


Figure S30. Comparison of annual NBP anomalies simulated by DGVMs and derived from atmospheric inversions during 1990–2023. (a) Interannual variations of annual NBP anomalies from DGVM ensembles and atmospheric inversion products. Green and black shading represent the standard deviation across DGVM simulations and atmospheric inversion products, respectively. Light gray ranges denote the El Niño years (1997-1998, 2015-2016). (b) Relationship between DGVM-simulated and inversion-based NBP anomalies. Years associated with El Niño events are highlighted with colored markers.

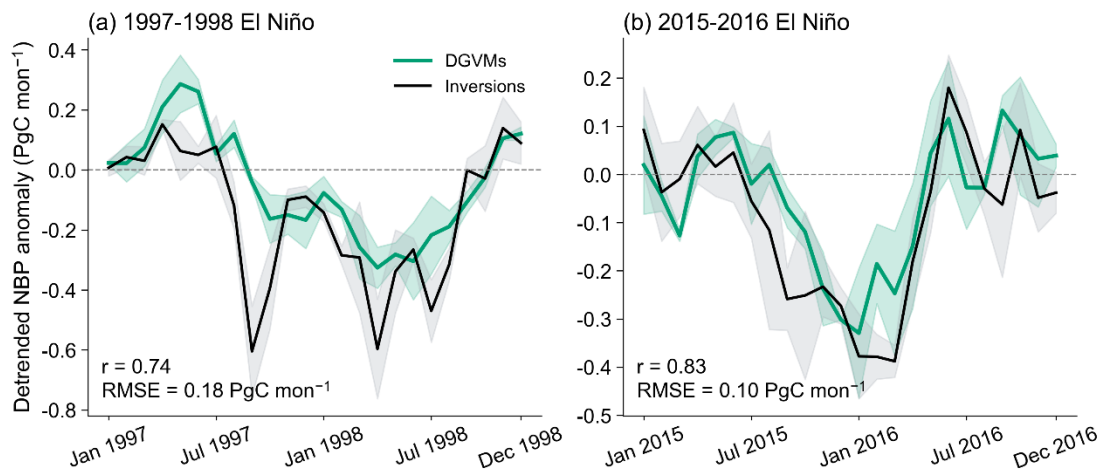


Figure S31. Monthly NBP anomalies during the 1997-1998 and 2015-2016 El Niño events. Green and black shading represent the standard deviation across DGVM simulations and atmospheric inversion products, respectively.

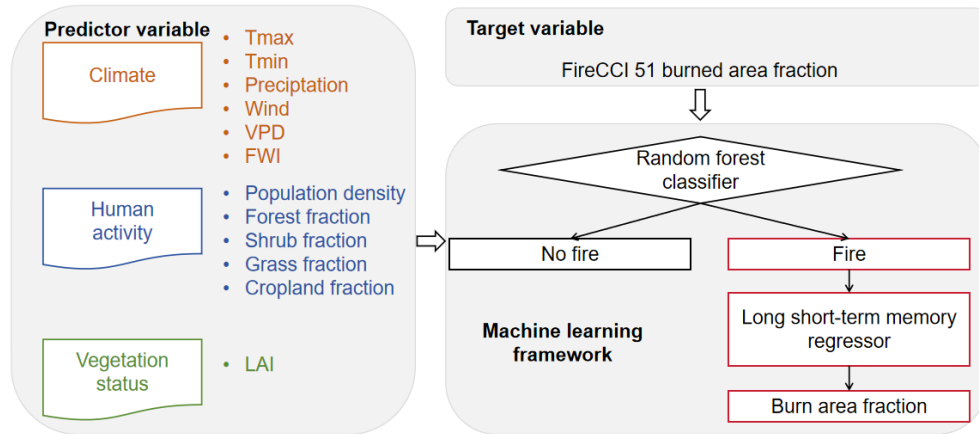


Figure S32. Workflow of the machine learning framework for burned area prediction.

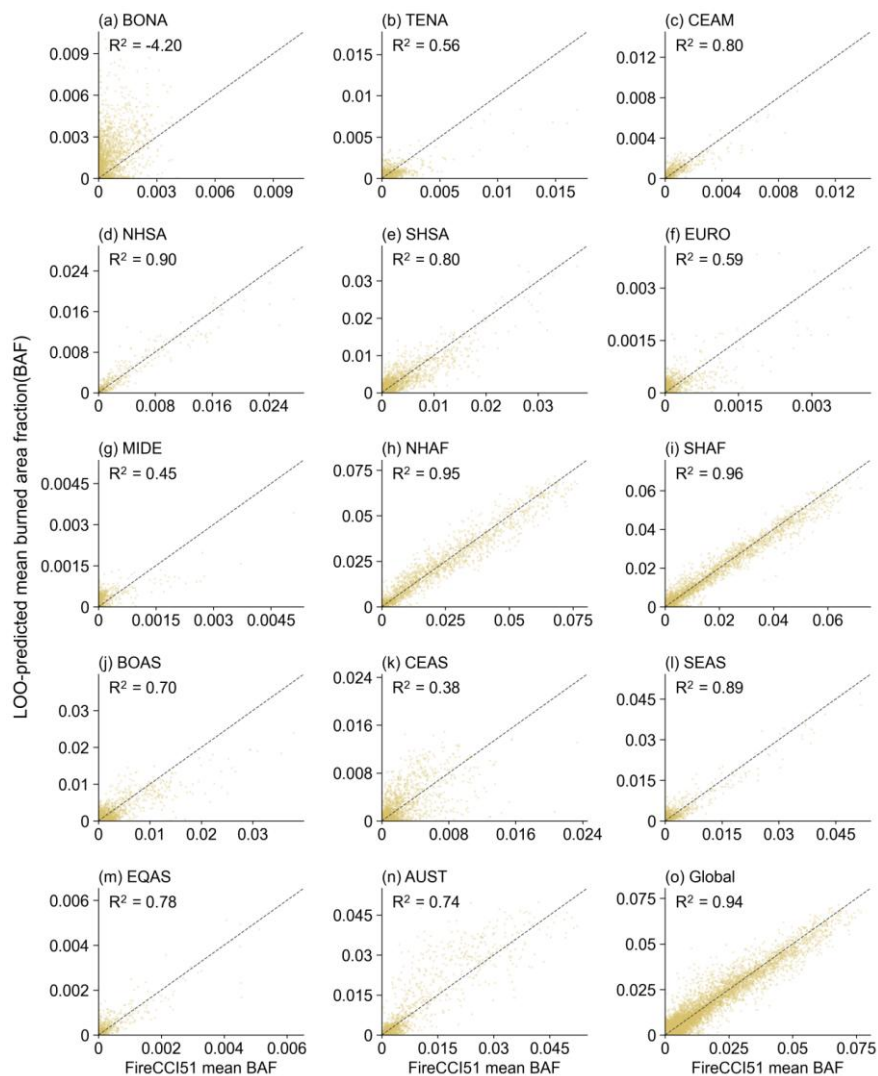


Figure S33. Spatial comparison of grid-cell burned area fraction (BAF) between leave-one-year-out (LOO) predictions and FireCCI51 observations. Each dot represents a $0.5^\circ \times 0.5^\circ$ grid cell where fire occurred during 2004–2020, with BAF values averaged over the study period. Dashed lines indicate the 1:1 relationship. R^2 represent the coefficient of determination between predicted and observed BAF.

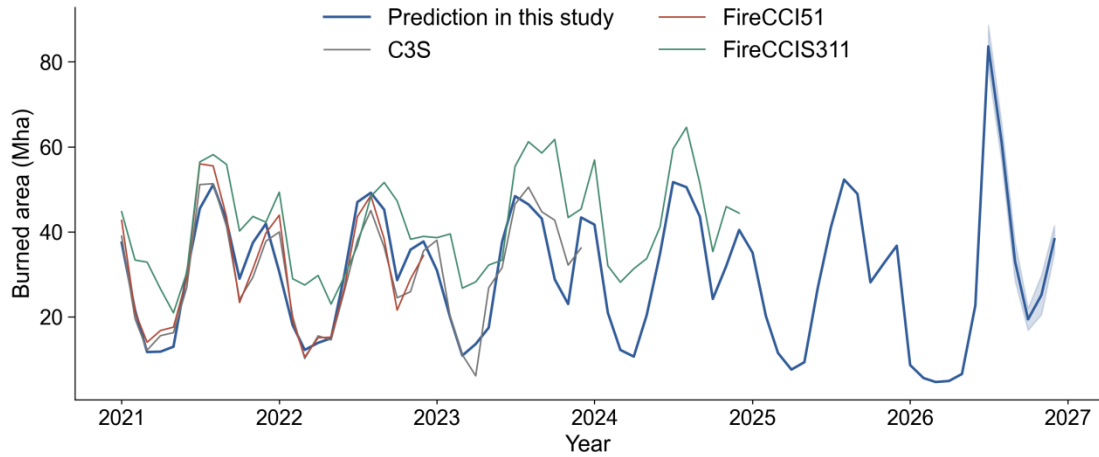


Figure S34. Comparison of global monthly burned area predicted by the machine learning framework and derived from satellite products. Shading represents the standard deviation among machine learning predictions driven by the 51 ECMWF ensemble members. Descriptions of the satellite products are provided in Table S3.

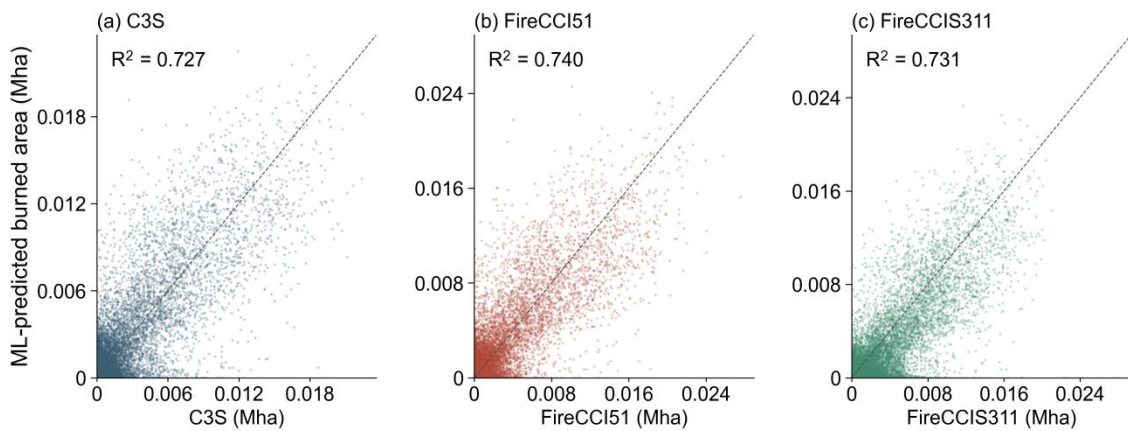


Figure S35. Spatial comparison of grid-cell burned area (BA) between machine-learning (ML) predictions and satellite observations. Each dot represents a $0.5^{\circ} \times 0.5^{\circ}$ grid cell where fire occurred during the evaluation period, with BA values averaged over that period. Dashed lines indicate the 1:1 relationship. R^2 represents the coefficient of determination between predicted and observed BA. For each satellite product, the evaluation is restricted to the years jointly covered by the ML predictions and that product: 2021–2022 for FireCCI51, 2021–2023 for C3S, and 2021–2024 for FireCCIS311.

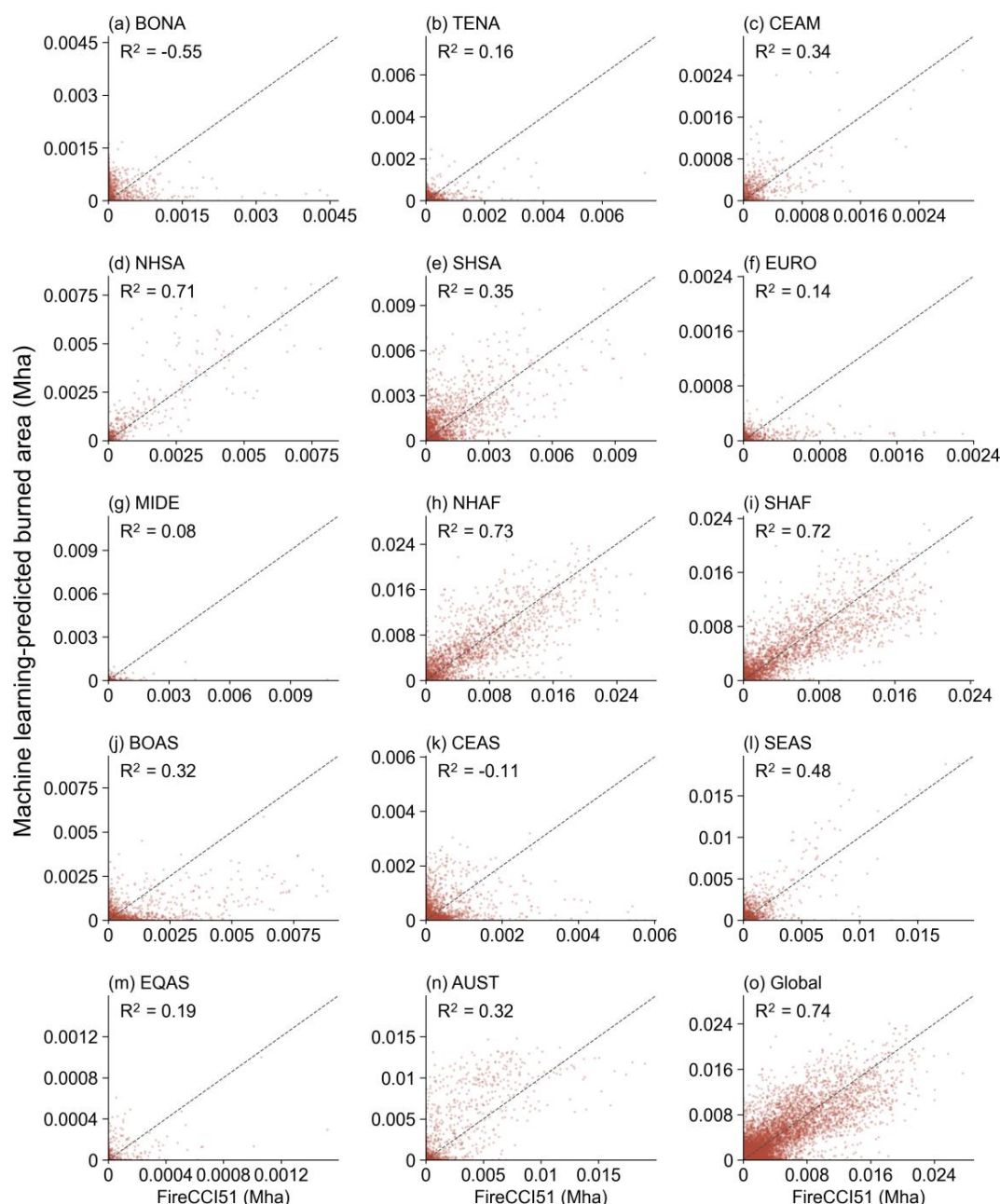


Figure S36. Spatial comparison of grid-cell burned area (BA) between machine-learning (ML) predictions and FireCCI51 observations. Each dot represents a $0.5^{\circ} \times 0.5^{\circ}$ grid cell where fire occurred during 2021–2022, with BA values averaged over that period. Dashed lines indicate the 1:1 relationship. R^2 represents the coefficient of determination between predicted and observed BA. The evaluation is restricted to 2021–2022, the period jointly covered by the ML predictions and the FireCCI51 product.

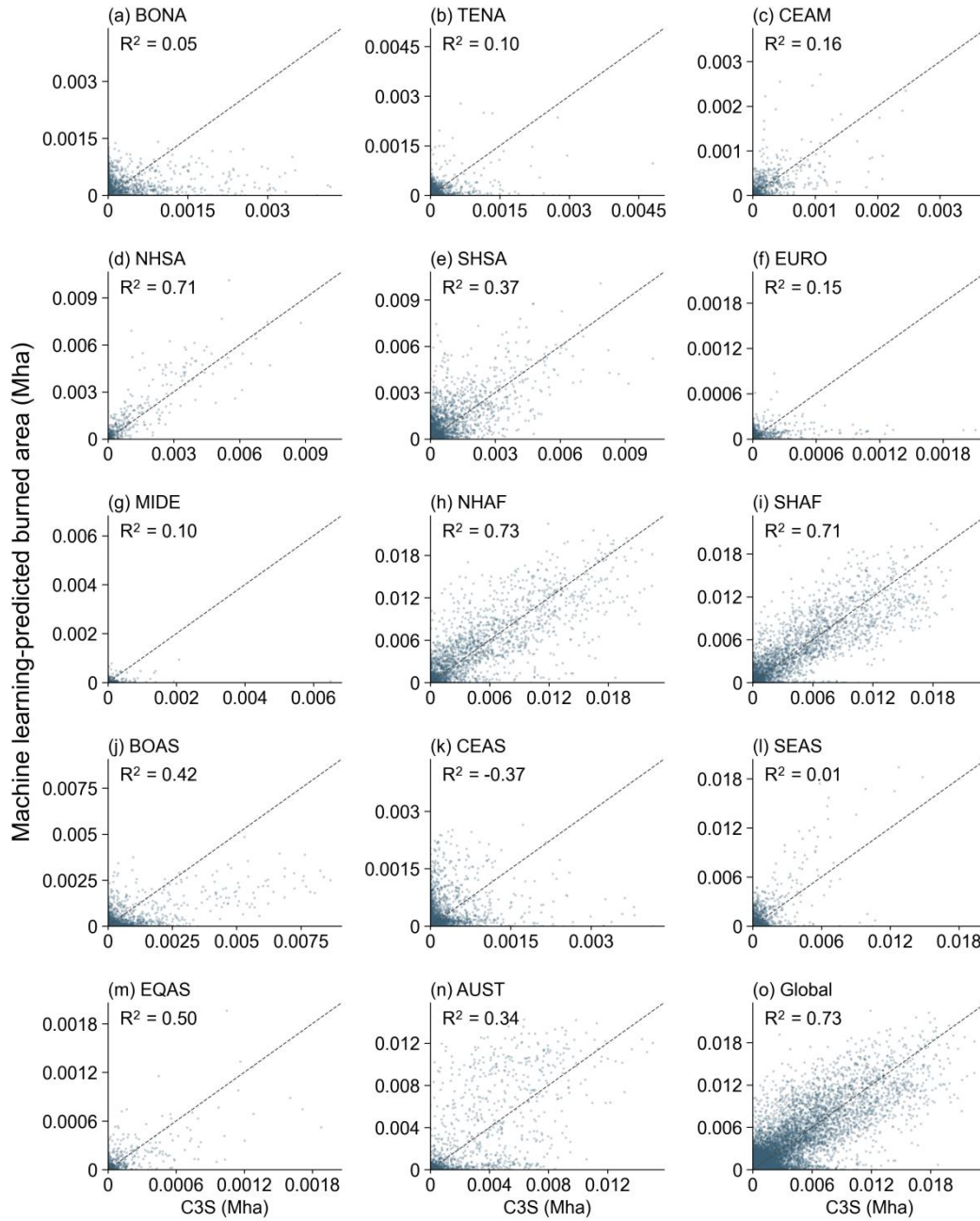


Figure S37. Spatial comparison of grid-cell burned area (BA) between machine-learning (ML) predictions and C3S observations. Each dot represents a $0.5^\circ \times 0.5^\circ$ grid cell where fire occurred during 2021–2023, with BA values averaged over that period. Dashed lines indicate the 1:1 relationship. R^2 represents the coefficient of determination between predicted and observed BA. The evaluation is restricted to 2021–2023, the period jointly covered by the ML predictions and the C3S product.

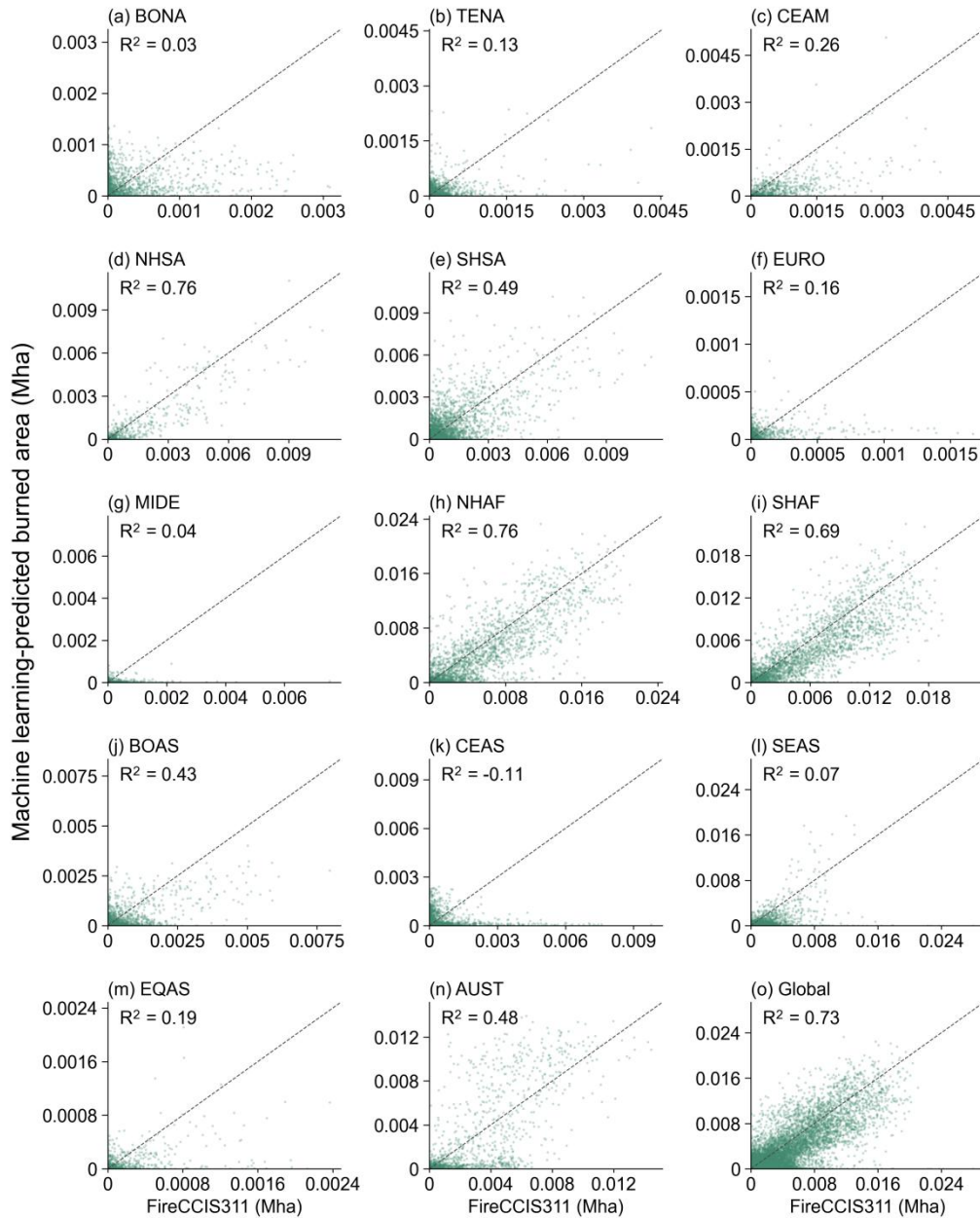


Figure S38. Spatial comparison of grid-cell burned area (BA) between machine-learning (ML) predictions and FireCCIS311 observations. Each dot represents a $0.5^\circ \times 0.5^\circ$ grid cell where fire occurred during 2021–2024, with BA values averaged over that period. Dashed lines indicate the 1:1 relationship. R^2 represents the coefficient of determination between predicted and observed BA. The evaluation is restricted to 2021–2024, the period jointly covered by the ML predictions and the FireCCIS311 product.

Table S1. DGVM forcing variables derived from ECMWF seasonal forecasts³ for July–December 2026.

Variable	Temporal resolution	Variable type
10-m u-components of wind	6 hourly	Instantaneous variable ^a
10-m v-components of wind	6 hourly	Instantaneous variable
2 m air temperature	6 hourly	Instantaneous variable
2 m dewpoint temperature	6 hourly	Instantaneous variable
Mean sea-level pressure	6 hourly	Instantaneous variable
Surface downward shortwave radiation	24 hourly	Accumulated variable ^b
Surface downward longwave radiation	24 hourly	Accumulated variable
Total precipitation	24 hourly	Accumulated variable
Snowfall, water equivalent	24 hourly	Accumulated variable

a: Instantaneous variables are forecast as model states at individual valid times.

b: Accumulated variables are forecast as time-integrated quantities up to each forecast endpoint.

Table S2. Explanatory variables used in machine learning models.

Variable	Description	Data source
Tmax	Daily maximum temperature (°C)	ERA5 ³
Tmin	Daily minimum temperature (°C)	
Precip	Monthly total rainfall (mm/month)	
Wind	Wind speed (m/s)	
VPD	Vapor pressure deficit (hPa)	Calculated from ERA5
FWI	Fire Weather Index	
Popd	Population density (individuals/km ²)	HYDE3.2 (2004-2020) ¹⁹ HYDE3.5 ^a (2021-2025) ²⁰
Forest	Fraction of specific land use type	LUH2 v2h (2004-2020) ^{21,22} ESA CCI Land Cover ^b (2022) ²³
Shrub		
Natural		
Grass		
Cropland		
LAI	Leaf Area Index	DGVMs output
BAF	Burned area fraction	FireCCI51 ^{11,12}

a: HYDE 3.5 population data were used for 2021–2025. Because population data for 2026 were unavailable, the 2025 values were carried forward to 2026.

b: Because annual land-cover data were unavailable for 2021–2026, land-use inputs were held constant at the 2022 ESA CCI Land Cover distribution throughout this period.

Table S3. Satellite-derived burned area products used for validation of machine learning-based burned area predictions.

Satellite product	Sensor	Spatial resolution	Temporal coverage
MODIS FireCCI Burned Area Grid Product, Version 5.1 (FireCCI51) ^{11,12}	MODIS (Terra)	0.25°	2001–2022
C3S Sentinel-3 OLCI burned-area product v1.1 (C3S) ¹³	Sentinel-3 OLCI	0.25°	2017–2023
Sentinel-3 SYN Burned Area Grid product (FireCCIS311) ¹⁴	Sentinel-3 OLCI SLSTR	0.25°	2019–2024

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