

Exceptionally high summer mean temperatures predict tundra fire activity, with stronger responses at greater previous-year leaf area index

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Abstract

Rapid Arctic warming may increase tundra fire activity, but the relative roles of climate, vegetation, and ignition remain uncertain. We analyzed annual fire carbon emissions, burned-area fraction, and environmental conditions in 0.25° tundra grid cells during 2001–2020. Relationships with nine environmental variables were evaluated using 20 equal-frequency bins and cross-validated linear and spline models. Interactions of summer temperature with precipitation, previous-year leaf area index (LAI), lightning density, and wind speed were assessed using year-and-spatial-block resampling. Fire activity was highest in Alaska and Russia and increased sharply in the warmest temperature bins across the tundra biome. Summer temperature and vapor pressure deficit showed the strongest cross-validated relationships with both fire responses. Previous-year LAI predicted both responses, whereas the Fire Weather Index predicted burned-area fraction. The temperature–fire relationship was stronger at greater previous-year LAI and higher lightning density but weaker under greater precipitation; no reproducible modification by mean summer wind speed was detected. Recurrent tundra-wide upper-tail temperatures largely overlapped spatially with fire hotspots. These findings identify summer temperature and atmospheric dryness as leading large-scale predictors of tundra fire activity and show that antecedent vegetation conditions strengthen the response to warmth. Increasingly frequent high-temperature conditions may therefore produce disproportionately large increases in tundra fire activity.

Introduction

Satellite observations indicate that fire-induced forest loss increased globally between 2001 and 2019 (Tyukavina et al. 2022), while global carbon emissions from forest fires increased by 60% between 2001 and 2023, driven primarily by rapidly rising emissions from extratropical forests (Jones et al. 2024). In contrast, global burned area decreased by approximately 25% between 1998 and 2015, primarily because of reductions in savanna and grassland fires associated with agricultural expansion and intensification, particularly in Africa (Andela et al. 2017). These contrasting trends emphasize that wildfire is not restricted to forest fire but encompasses fires occurring in shrublands, savannas, grasslands, croplands, and peatlands (Bowman et al. 2009; van der Werf et al. 2025b).

Wildfires release carbon dioxide (CO₂), methane (CH₄), and other radiatively and chemically active compounds during combustion (van der Werf et al. 2025a, b). They also consume living vegetation, litter, deadwood, peat, and soil organic matter, thereby altering vegetation structure, carbon storage, nutrient cycling, biodiversity, and surface energy exchange. These effects can be especially pronounced in Arctic and boreal ecosystems, where large quantities of carbon have accumulated in organic soils, peatlands, and permafrost over centuries to millennia. Severe fires may expose this legacy carbon to combustion and post-fire decomposition, potentially reinforcing global warming (Turetsky et al. 2015; Walker et al. 2019). Fire-induced removal of vegetation and insulating organic soil layers can also accelerate permafrost thaw and thermokarst development, producing ecosystem changes that persist long after fire (Iwahana et al. 2016; Jones et al. 2015).

Fire has occurred since shortly after terrestrial vegetation became established approximately 420 million years ago and is therefore a natural component of many terrestrial ecosystems (Bowman et al. 2009). Nevertheless, ongoing warming is increasing the frequency of hot, dry conditions conducive to fire at northern high latitudes. Shorter fire-return intervals can cause ecosystems to reburn before recovery is complete, reducing tree recruitment and stand density, altering species composition, and overwhelming boreal forest resilience when reburning coincides with drought (Whitman et al. 2019). In tundra, where fire-return intervals naturally range from decades to millennia, historical observations and sedimentary charcoal records reveal strong climate-fire relationships and threshold responses to summer temperature and precipitation (Hu et al. 2015). Climate-based projections consequently suggest that annual burned area in Alaskan tundra could approximately double by the end of the twenty-first century (Hu et al. 2015).

Contemporary satellite studies have begun to resolve the long-term and spatially heterogeneous behavior of tundra fire. Masrur et al. (2018) analyzed MODIS active-fire observations and MERRA climate fields across the circumpolar tundra during 2001–2015 and showed that warm, dry conditions from late spring through midsummer favored fire occurrence and intensity; reduced winter-spring precipitation and soil moisture were also associated with greater fire intensity in the following summer. Previous studies have also identified nonlinear climatic thresholds in northern fire regimes. Fire probability increased markedly above a mean July temperature of approximately 13.4°C in Alaska (Young et al. 2017), while annual burned area in the Siberian Arctic showed a near-exponential relationship with temperature-related fire conditions (Descals et al. 2022). For the broader Arctic region, Xing et al. (2023) found that burned area increased overall during 2001–2020 but varied markedly among regions, increasing significantly in parts of central Russia and decreasing in parts of western Russia. Relative humidity, vapor pressure deficit (VPD), and land-surface temperature had the greatest explanatory power, and the interaction between precipitation and land-surface temperature was especially important. However, their spatial trend analysis used 2.5° x 2.5° cells and included vegetation types beyond tundra.

Recent research has also demonstrated that broad Arctic-boreal patterns arise from distinct regional fire regimes. Scholten et al. (2024) used high-resolution VIIRS observations to characterize fire number, size, intensity, duration, and seasonality across Arctic and boreal regions, showing that climate, fuel properties, lightning, and human influence jointly structure spatial variability. Regional tundra studies provide complementary evidence. In Alaskan tundra, He et al. (2022) identified cloud-to-ground lightning as the strongest predictor of fire occurrence, while warmer and drier near-surface weather provided the conditions required for sustained burning. Climate-model projections further suggest that lightning frequency and lightning-induced fire risk will increase across Arctic permafrost regions under continued warming (Chen et al. 2021). Masrur et al. (2022) further showed that climate, topography, vegetation, and previous fire history regulate fire occurrence, size, and reburning in Alaskan tundra. In Canada, Landsat reconstruction identified 209 previously unrecorded tundra fires during 1986–2022 and increased the mapped burned area by approximately 30%, demonstrating that incomplete fire inventories remain an important source of uncertainty (Hethcoat et al. 2024).

Field and regional carbon studies illustrate why burned area alone cannot fully characterize the climatic importance of tundra fire. The 2007 Anaktuvuk River fire in Alaska released $2,016 \pm 435 \text{ g C m}^{-2}$, approximately 60% of which came from soil organic matter, and doubled the cumulative area known to have burned in that region since 1950 (Mack et al. 2011). In the Yukon-Kuskokwim River Delta, measurements and spatial upscaling showed that tundra fires produce both carbon emissions and radiative effects that can reinforce warming and future fire risk (Moubarak et al. 2023). Thus, fire extent, fuel type, organic-soil combustion, and burn severity jointly determine the carbon consequences of tundra fire.

Although 0.25° gridded fire products are now available, their native resolution has not generally been retained as a common analytical framework for circumpolar tundra-driver comparisons. GFED provides monthly burned area and emissions on a $0.25^\circ \times 0.25^\circ$ grid (Chen et al. 2023a, b; van der Werf et al. 2025a, b), but previous studies have typically analyzed fire detections or individual events, focused on particular regions, aggregated observations to coarser cells, or combined tundra with boreal forest. Consequently, few studies have simultaneously evaluated fire carbon emissions and burned-area fraction across the circumpolar tundra using spatially harmonized 0.25° grid-cell data and a common set of climatic, moisture, fuel, and ignition-related variables. This distinction is important for identifying tundra-specific fire drivers and avoiding the direct extrapolation of boreal-forest relationships to tundra because tundra and boreal forest are geographically contiguous but differ substantially in vegetation structure, fuel properties, human influence, and fire regimes.

In this study, we analyzed tundra fire activity from 2001 through 2020 using fire and environmental data harmonized to a $0.25^\circ \times 0.25^\circ$ latitude–longitude grid. The response variables were annual fire carbon emissions and annual burned-area fraction derived from the Global Fire Emissions Database. Tundra wildfire activity is concentrated primarily during the peak summer months of June–August (Masrur et al. 2018). Accordingly, candidate climatic predictors were summarized over the same period and included mean 2-m air temperature, relative humidity, vapor pressure deficit (VPD), precipitation, surface soil moisture, 10-m wind speed, and lightning density. Previous-year leaf area index (LAI) was included as an indicator of antecedent vegetation conditions.

We additionally evaluated two integrated indicators of fire-conducive conditions to test whether combinations of meteorological and fuel-moisture conditions explained tundra fire activity more effectively than individual environmental variables considered separately. The first was a study-specific meteorological factor inspired by the INteractive Fire and Emission algoRithm for Natural enviroNments (INFERNO), a reduced-complexity fire scheme developed for the UK Met Office Earth system modeling framework (Mangeon et al. 2016). The second was the Fire Weather Index (FWI), the final index of the Canadian Forest Fire Weather Index System, which integrates temperature, relative humidity, wind speed, precipitation, and antecedent fuel-moisture conditions into a numerical rating of potential fire intensity (Van Wagner 1987; Field 2020). By comparing individual environmental variables with these integrated indices, we sought to determine whether summer temperature was the strongest large-scale predictor of

tundra fire carbon emissions and burned area during 2001–2020, identify conditions that modified the temperature–fire relationship, and characterize regional and spatial heterogeneity.

Materials and methods

Study domain and analysis period

The analysis covered Northern Hemisphere tundra during 2001–2020. All fire and environmental data were harmonized to the native 0.25° latitude–longitude grid of the Global Fire Emissions Database version 5.1 (GFED5.1). Only grid cells at latitudes $\geq 0^\circ$ that intersected tundra polygons were retained. Fire carbon emissions and burned area were annual response variables, whereas the environmental predictors were summarized for summer (June–August; JJA). Lightning analyses were restricted to 2012–2020 because the configured lightning time series did not provide a complete 2001–2020 overlap. Analyses involving vegetation used previous-year JJA leaf area index (LAI), such that fire years 2001–2020 were paired with LAI from 2000–2019.

Data sources

Fire emissions and burned area

Monthly carbon dioxide (CO₂) emissions were obtained from GFED5.1 gridded NetCDF files (van der Werf et al. 2025a, b). In the files analyzed, the CO₂ variable was reported as monthly grid-cell totals in grams of CO₂. Monthly values were summed over all 12 months, converted from CO₂ mass to carbon mass using the molecular-mass ratio 12/44, and divided by the physical area of each grid cell. The resulting annual field was expressed as fire carbon emissions (g C m⁻² yr⁻¹).

Monthly GFED5 burned area for 2001–2020 was obtained from the archived burned-area product (Chen et al. 2023a, b). The monthly total layer was converted to square kilometers when required and summed over the calendar year. Valid fill values in successfully read annual files were interpreted as zero burned area. Annual burned-area fraction was calculated as 100 times annual burned area divided by grid-cell area and is reported as % yr⁻¹. Values greater than 100% were retained because spatially distinct portions of a grid cell may burn in different months or the same area may burn repeatedly within a year.

Volcano locations and eruption histories were obtained from the Smithsonian Institution Global Volcanism Program database (Global Volcanism Program 2026). We retained volcanoes with confirmed eruptions that overlapped the 2001–2020 study period, including eruptions that began before 2001 but continued into the study period. The locations of these volcanoes were compared with the tundra fire hotspots.

Tundra mask and geographic regions

The tundra boundary was derived from the RESOLVE Ecoregions 2017 polygon data set (Dinerstein et al. 2017; RESOLVE 2017). Polygon attributes containing the term 'Tundra' were identified programmatically, rasterized onto the 0.25° GFED grid, and limited to the Northern Hemisphere.

For regional summaries, tundra was divided into Alaska (170°W–141°W), Canada (141°W–50°W), Greenland/Iceland, Fennoscandia (10°W–32°E), and Russia; an approximate Greenland coastline polygon and an Iceland bounding box were used to separate those islands from adjacent longitude sectors.

Meteorological and land-surface data

Monthly 2-m air temperature, 2-m dew-point temperature, volumetric soil water content in the first soil layer, and total precipitation were read from ERA5 monthly averaged single-level data (Hersbach et al. 2020, 2023). Monthly 10-m wind speed was read from a separate ERA5 file. The invariant ERA5 soil-type field was used to assign spatially varying saturated volumetric soil water content.

Fire Weather Index (FWI) was obtained from the MERRA-2-based Global Fire WEather Database (GFWED; Field 2020; NASA Goddard Institute for Space Studies 2025). Daily JJA records were averaged with equal daily weights; when the input contained one monthly record for each JJA month, the monthly means were weighted by the number of calendar days.

Previous-year vegetation was represented by GIMMS LAI4g v1.2 (Cao et al. 2023a, b), supplied as half-monthly GeoTIFF files. The two half-month fields in each month were averaged, after which June, July, and August were combined using 30-, 31-, and 31-day weights. The resulting LAI was paired with fire activity in the following year. To characterize the spatial distribution of vegetation independently of the lagged fire-response analysis, we also calculated mean JJA LAI for 2001–2020. For each year, the two half-monthly LAI fields within each month were averaged, and the June, July, and August values were combined using calendar-day weights of 30, 31, and 31 days, respectively. The resulting annual JJA LAI fields were then averaged across the 20-year study period for each 0.25° tundra grid cell. This contemporaneous 2001–2020 mean was used only for the spatial map in Fig. 7d; the statistical analyses of fire activity continued to use previous-year JJA LAI.

Lightning was represented by the World Wide Lightning Location Network Global Lightning Climatology (WGLC; Kaplan and Lau 2019). Monthly detection-efficiency-corrected lightning density was averaged over JJA with calendar-day weights and analyzed for 2012–2020.

Spatial harmonization and grid-cell area

Longitudes were transformed to -180° to 180° , coordinate vectors were sorted, and continuous fields were interpolated bilinearly to the 720×1440 GFED grid. Periodic longitude extensions were added at the dateline to avoid edge discontinuities. Saturated soil water content was interpolated with nearest-

neighbor interpolation to preserve categorical soil boundaries. The tundra mask was generated by polygon rasterization.

Grid-cell area was calculated on the WGS84 ellipsoid (semi-major axis 6,378,137 m; flattening 1/298.257223563) from the meridional and zonal length of 0.25° at each grid-cell center. Tundra area was the sum of all masked cell areas. Annual tundra-total carbon emission was the sum of grid-cell carbon mass, and mean emission density was annual total carbon mass divided by tundra area.

Derivation of summer environmental variables

ERA5 monthly fields were screened for physically implausible values, converted to the required units, and averaged over JJA with weights of 30, 31, and 31 days. At locations with a missing month, weights were renormalized over the available months. Air and dew-point temperatures were converted from kelvin to degrees Celsius. ERA5 monthly-averaged-by-day precipitation stored in meters was converted to mm day⁻¹ by multiplication by 1,000.

Saturation vapor pressure (e_s), actual vapor pressure (e_a), vapor-pressure deficit (VPD), and relative humidity (RH) were calculated monthly as

$$e_s = 6.1078 \exp[17.27 T / (T + 237.3)] \quad (1)$$

$$e_a = 6.1078 \exp[17.27 T_d / (T_d + 237.3)] \quad (2)$$

$$\text{VPD} = e_s - e_a, \text{RH} = 100 e_a / e_s \quad (3)$$

where T and T_d are air and dew-point temperature (°C), respectively, and vapor pressures are in hPa. Negative VPD values were treated as missing.

Surface soil moisture in the uppermost ERA5 soil layer (SM_1 ; 0–7 cm, m³ m⁻³) was used to represent near-surface moisture conditions. Relative soil moisture was calculated as $\theta = \min(1, \text{SM}_1 / \theta_{\text{sat}})$, where θ_{sat} is the soil-type-specific saturated volumetric water content. ERA5 soil-type classes 1–7 were assigned θ_{sat} values of 0.403, 0.439, 0.430, 0.520, 0.614, 0.766, and 0.766 m³ m⁻³, respectively, following the soil hydraulic parameters used in the ECMWF land-surface scheme (ECMWF 2017). The study-specific INFERNO-inspired meteorological factor (F_{met}) was calculated for each month before seasonal averaging:

$$F_{\text{met}} = f_T(T) f_{\text{RH}}(\text{RH}) \exp(-2R) (1 - \theta) \quad (4)$$

$$f_T(T) = 6.1078 \exp[17.27 T / (T + 237.3)] \quad (5)$$

$$f_{\text{RH}}(\text{RH}) = \min\{1, \max[0, (90 - \text{RH}) / (90 - 10)]\} \quad (6)$$

where R is precipitation (mm day^{-1}). The relative-humidity limitation f_{RH} decreased linearly from 1 at $\text{RH} \leq 10\%$ to 0 at $\text{RH} \geq 90\%$, consistent with the formulation reported for the updated JULES–INFERNO implementation (Velásquez-García et al. 2026). Because f_T is expressed in hPa and the remaining terms are dimensionless, F_{met} is expressed in hPa. The three monthly F_{met} fields were combined using JJA calendar-day weights. This study-specific formulation was inspired by INFERNO meteorological controls but did not include the complete PFT-specific fuel-load and ignition components of the full INFERNO model.

One-dimensional 20-bin response analysis

For each response variable, all valid 0.25° grid-cell–year observations were pooled. The explanatory variables were JJA temperature, VPD, surface soil moisture, precipitation, F_{met} , FWI, 10-m wind speed, previous-year JJA LAI, and JJA lightning density. Except for lightning (2012–2020), the response period was 2001–2020. Each explanatory variable was divided into 20 equal-frequency bins using pooled quantiles. The mean explanatory value, mean response, and standard error of the response were calculated for each populated bin. Therefore, each populated bin mean—not each raw grid-cell observation—was one equally weighted regression unit.

A linear model and a compact cubic regression-spline model were compared to determine whether each relationship was adequately represented by a constant linear response or instead exhibited nonlinear behavior, such as a threshold or an accelerated response at the upper end of the environmental gradient. After standardization, the linear design contained an intercept and z , whereas the spline design contained an intercept, z , z^2 , z^3 , and a truncated cubic basis $\max(z - k, 0)^3$, with knot k at the median of z . Prediction skill was measured using exact leave-one-bin-out cross-validated R^2 (LOOCV R^2), calculated from the prediction-error sum of squares (PRESS). The model with the larger LOOCV R^2 was selected; a negative value indicated performance worse than prediction using the overall mean.

Uncertainty was evaluated using 999 two-way cluster-bootstrap replicates (random seed 43). Years and $2^\circ \times 2^\circ$ spatial blocks were sampled independently with replacement, bin means were reconstructed, and both models were refitted in every replicate. Percentile 95% confidence intervals were obtained from the bootstrap distribution. For each model, one-sided bootstrap support was calculated as $[1 + \text{number of replicates with LOOCV } R^2 \leq 0] / [1 + \text{number of valid replicates}]$. Improvement of the spline over the linear model was assessed analogously using $\Delta R^2 = R^2_{\text{spline}} - R^2_{\text{linear}}$. These quantities describe the stability of positive predictive performance under clustered resampling; they are not conventional null-distribution p values. A support value ≤ 0.05 was used as an exploratory display criterion. Model selection and support assessment used the same binned data, and values were not adjusted for multiple comparisons; therefore, they should be interpreted as exploratory rather than confirmatory evidence.

Temperature–driver interaction analysis

Joint response surfaces were constructed for temperature combined with lightning, precipitation, previous-year LAI, or 10-m wind speed. Each axis was divided into 20 equal-frequency bins, producing as many as 400 populated bin cells. For precipitation, LAI, and wind, common temperature-bin edges from the 2001–2020 temperature sample were used for both carbon emissions and burned area; lightning used its available 2012–2020 sample. The mean response in each populated two-dimensional bin was used as one regression unit.

Before model fitting, the binned response (Y), temperature (T), the second environmental driver (X), and the temperature-by-driver product ($T \times X$) were separately standardized to zero mean and unit standard deviation, yielding z_Y , z_T , z_X , and $z_{T \times X}$, respectively. The standardized response was then fitted as

$$z_Y = \beta_0 + \beta_T z_T + \beta_X z_X + \beta_{T \times X} z_{T \times X} + \varepsilon \quad (7)$$

Model performance was summarized by adjusted R^2 . Years and 2° spatial blocks were independently resampled in 999 bootstrap replicates (random seed 42), and the 20 × 20 bin means and regression coefficients were reconstructed for each replicate. Two-sided bootstrap support values and percentile 95% confidence intervals were calculated for the temperature, driver, and interaction coefficients. A support value < 0.05 was treated as exploratory evidence of a reproducible coefficient. Two-dimensional bin cells were equally weighted despite differences in the number of underlying grid-cell–year observations.

Regional summaries

For each of the five geographic sectors, pooled 2001–2020 grid-cell–year means of annual fire carbon emissions and burned-area fraction were calculated. Error bars were standard errors based on the number of valid grid-cell–year values, and the overall tundra mean was shown as a horizontal reference line. Because these descriptive standard errors combine spatial and temporal variation and treat neighboring grid cells as separate observations, they should not be interpreted as estimates of temporal variability alone. Spatial dependence was addressed explicitly only in the block-bootstrap analyses described above.

Annual area-weighted fire carbon emissions, burned-area fraction, and JJA mean temperature were calculated separately for each geographic sector. For each region, ordinary least-squares linear regressions used 20 annual observations to evaluate fire carbon emissions versus JJA mean temperature and burned-area fraction versus JJA mean temperature. Two-sided p values tested whether each slope differed from zero. Temporal autocorrelation was not modeled explicitly, and these regional regressions should therefore be interpreted as descriptive interannual relationships.

Highest-temperature-bin recurrence and fire maps

Annual JJA mean temperature maps were calculated for 2001–2020 and pooled across all valid tundra grid-cell–year observations. Twenty equal-frequency JJA temperature bins were defined from this

pooled distribution. The lower boundary of the twentieth bin, corresponding to the pooled 95th percentile, was used as a fixed upper-5% threshold for all years. For each 0.25° grid cell, we counted the number of years in which JJA mean temperature equaled or exceeded this threshold (range: 0–20 years). This tundra-wide threshold represents the upper tail of the pooled spatial and temporal distribution and is not a location-specific temperature anomaly; recurrence therefore reflects both spatial climate gradients and interannual variability. For each grid cell, we also mapped mean annual fire carbon emissions ($\text{g C m}^{-2} \text{ yr}^{-1}$) and mean annual burned-area fraction ($\% \text{ yr}^{-1}$) over 2001–2020.

Use of generative AI

ChatGPT 5.6 Sol (OpenAI) was used for English-language editing and to assist with editing and debugging the MATLAB code. All AI-assisted code modifications were reviewed, tested and validated by the authors. ChatGPT was not used to independently interpret the results or draw scientific conclusions. The authors take full responsibility for the accuracy of the code and the final manuscript.

Results

Regional variation in tundra fire activity

Annual tundra fire activity varied markedly among years and geographic regions during 2001–2020 (Fig. 1). Fire carbon emissions increased significantly with area-weighted June–August (JJA) mean temperature in Alaska ($R^2 = 0.50$, $p < 0.001$), Greenland/Iceland ($R^2 = 0.22$, $p = 0.039$), and Russia ($R^2 = 0.29$, $p = 0.014$). The relationship was strongest in Alaska. Annual burned-area fraction also increased significantly with summer temperature in Alaska ($R^2 = 0.49$, $p < 0.001$), Fennoscandia ($R^2 = 0.21$, $p = 0.041$), and Russia ($R^2 = 0.27$, $p = 0.018$). No significant regional temperature relationship was displayed for the other region–response combinations.

Mean fire activity differed strongly among the five tundra regions (Fig. 2). Alaska had the highest mean fire carbon emissions (approximately $5.6 \text{ g C m}^{-2} \text{ yr}^{-1}$), followed by Russia (approximately $5.0 \text{ g C m}^{-2} \text{ yr}^{-1}$); both values exceeded the tundra-wide mean of approximately $3.3 \text{ g C m}^{-2} \text{ yr}^{-1}$. Mean emissions were substantially lower in Canada (approximately $1.5 \text{ g C m}^{-2} \text{ yr}^{-1}$) and were close to zero in Greenland/Iceland and Fennoscandia. Mean annual burned-area fraction was highest in Russia and Alaska (both approximately $0.21\% \text{ yr}^{-1}$), compared with the tundra-wide mean of approximately $0.13\% \text{ yr}^{-1}$. Canada, Fennoscandia, and Greenland/Iceland had much lower mean burned-area fractions.

Environmental controls on fire carbon emissions

Fire carbon emissions showed strongly nonlinear responses to summer temperature and vapor pressure deficit (VPD) (Fig. 3a, b). A spline model was selected for both variables and explained most of the leave-one-bin-out variation (temperature: cross-validated $R^2 = 0.92$, one-sided bootstrap support = 0.001; VPD: cross-validated $R^2 = 0.95$, support = 0.002). Emissions remained low across cool and moderately warm

conditions but increased sharply in the warmest temperature bins. A comparable acceleration occurred at high VPD.

Previous-year leaf area index (LAI) also had a supported relationship with emissions; the linear model was selected (cross-validated $R^2 = 0.58$, one-sided bootstrap support = 0.001; Fig. 3h). Emissions generally increased with antecedent LAI, although the binned means peaked at intermediate-to-high LAI before declining slightly at the highest values. Soil moisture, precipitation, the study-specific INFERNO-inspired meteorological factor, Fire Weather Index (FWI), 10-m wind speed, and lightning density exhibited visible binned patterns, but their model support values did not meet the exploratory display criterion of ≤ 0.05 (Fig. 3c–g, i). Temperature and VPD therefore had the strongest cross-validated relationships with tundra fire carbon emissions among the variables evaluated.

Environmental controls on burned area

Annual burned-area fraction showed patterns broadly similar to those of fire carbon emissions (Fig. 4). Spline models were selected for summer temperature and VPD, with high predictive performance (temperature: cross-validated $R^2 = 0.97$, one-sided bootstrap support = 0.001; VPD: cross-validated $R^2 = 0.96$, support = 0.001). Burned-area fraction remained low through most of the environmental range and rose steeply in the warmest and driest atmospheric bins.

The linear model was selected for FWI (cross-validated $R^2 = 0.70$, one-sided bootstrap support = 0.001; Fig. 4f) and previous-year LAI (cross-validated $R^2 = 0.72$, support = 0.001; Fig. 4h). Burned-area fraction increased with both variables. In contrast, no model met the exploratory support criterion for soil moisture, precipitation, the study-specific INFERNO-inspired meteorological factor, wind speed, or lightning density (Fig. 4c–e, g, i), despite nonmonotonic binned responses to several variables.

Interactive effects of summer temperature and environmental drivers

Summer temperature had a consistently positive standardized coefficient in all four fire-carbon interaction models (Fig. 5; $\beta_T = 0.41$ – 0.58 , all two-sided bootstrap support values = 0.002). The temperature-by-lightning interaction was positive ($\beta_{T \times X} = 0.15$, 95% interval 0.07–0.32, support = 0.008), indicating a stronger temperature association at greater lightning density, although the lightning main-effect coefficient was not supported (support = 0.690). The temperature-by-precipitation interaction was negative ($\beta_{T \times X} = -0.16$, 95% interval -0.20 to -0.07 , support = 0.002), as was the precipitation main-effect coefficient ($\beta_X = -0.12$, support = 0.002), indicating a weaker positive temperature–emission relationship under wetter conditions.

The temperature-by-previous-year-LAI interaction was strongly positive ($\beta_{T \times X} = 0.39$, 95% interval 0.28–0.44, support = 0.002), whereas the LAI main-effect coefficient was not supported (support = 0.112). This model had the greatest explanatory power among the emission interaction models (adjusted $R^2 = 0.348$). Neither the wind-speed main-effect coefficient nor its interaction with temperature was supported

(support = 0.192 and 0.328, respectively). Adjusted R^2 values for the lightning, precipitation, and wind-speed models were 0.266, 0.203, and 0.211, respectively.

The interaction models for burned-area fraction produced closely corresponding results (Fig. 6). Temperature had a positive coefficient in every model ($\beta_T = 0.46\text{--}0.62$, all two-sided bootstrap support values = 0.002). Positive interactions occurred with lightning density ($\beta_{TxX} = 0.20$, 95% interval 0.08–0.39, support = 0.002) and previous-year LAI ($\beta_{TxX} = 0.41$, 95% interval 0.30–0.46, support = 0.002). In contrast, the temperature-by-precipitation interaction was negative ($\beta_{TxX} = -0.11$, 95% interval –0.16 to –0.01, support = 0.030). The wind-speed interaction was not supported (support = 0.224). None of the lightning, LAI, or wind-speed main-effect coefficients was supported, and the precipitation main-effect coefficient did not meet the 0.05 criterion (support = 0.064). The previous-year-LAI model again had the highest explanatory power (adjusted $R^2 = 0.404$), followed by the lightning, wind-speed, and precipitation models (0.313, 0.241, and 0.226, respectively).

Spatial distributions

Recurrence above the tundra-wide upper-5% JJA mean-temperature threshold (12.8–19.7°C across the twentieth-bin observations) was spatially heterogeneous (Fig. 7a). Recurrent upper-tail conditions formed geographically restricted clusters rather than a continuous circumpolar band, with prominent concentrations in portions of Alaska, northern Canada, Fennoscandia, and northern Russia. Some grid cells exceeded the fixed threshold during most or all of the 20 study years, whereas extensive tundra areas never exceeded it. Because the threshold was derived from the pooled tundra-wide distribution, this map reflects both climatologically warmer tundra locations and interannual temperature variation.

Mean annual fire carbon emissions and burned-area fraction were likewise spatially concentrated (Fig. 7b, c). Emission and burned-area hotspots occurred in broadly similar locations, while much of the high Arctic had little recorded fire activity. Fire activity appeared to be concentrated along portions of the southern tundra margin near the boreal forest boundary, although adjacency was not tested quantitatively. The spatial distribution of recurrent tundra-wide upper-tail temperatures largely overlapped with that of the fire hotspots. These patterns were consistent with summer temperature as an important large-scale predictor, while regional regressions and interaction analyses indicated that moisture conditions, antecedent vegetation, and lightning modified the fire response.

When hotspots were defined as grid cells in the upper 10% of fire carbon emissions (Fig. 7b) or burned area (Fig. 7c) across the entire study area, the minimum distance between any hotspot and a volcano with a confirmed eruption during 2001–2020 was 39 km, indicating no direct spatial coincidence between the hotspots and volcanic centers.

Mean JJA LAI during 2001–2020 also showed pronounced spatial variation across the tundra biome (Fig. 7d). Relatively high LAI occurred primarily in the more vegetated southern and coastal portions of the tundra, including parts of Alaska, Fennoscandia, and northern Russia, whereas much of the Canadian

High Arctic, Greenland, and other northern tundra regions had low LAI. Some recurrently warm areas and fire hotspots occurred within or adjacent to areas of relatively high LAI, but the spatial correspondence was incomplete. Areas with high mean LAI did not consistently exhibit high fire carbon emissions or burned-area fractions.

Discussion

Summer temperature and atmospheric dryness as dominant controls

The clearest result of this study was the strong, nonlinear association of tundra fire activity with JJA mean temperature and VPD. For both fire carbon emissions and burned-area fraction, spline models substantially outperformed linear models and retained high predictive skill under leave-one-bin-out cross-validation. The response was not a gradual increase across the full climatic range. Instead, fire activity remained low through cool and moderately warm conditions and rose sharply in the warmest and driest atmospheric bins. This response is consistent with a threshold-like limitation: warming may have little observable association with fire while fuels remain too moist or ignitions fail to spread, whereas fire activity may rise rapidly once high temperature and atmospheric moisture demand jointly favor drying and combustion.

The sharp increase in fire activity observed in the warmest temperature bins is consistent with previously reported climatic thresholds in northern fire regimes. Young et al. (2017) identified a nonlinear increase in Alaskan fire probability above a mean July temperature of approximately 13.4°C, whereas Descals et al. (2022) found a near-exponential relationship between temperature-related fire conditions and annual burned area in the Siberian Arctic. Although the absolute temperature values are not directly comparable because our analysis used JJA mean temperature rather than July mean temperature, the agreement in response shape supports the interpretation that tundra fire activity may increase disproportionately once critical climatic conditions are exceeded.

The close correspondence between the emission and burned-area responses strengthens this interpretation. Temperature had cross-validated R^2 values of 0.92 for emissions and 0.97 for burned-area fraction, while VPD had corresponding values of 0.95 and 0.96. Thus, the statistical pattern was not confined to one fire metric. Higher burned-area fraction coincided with greater carbon release, consistent with warm and dry summers affecting both fire extent and carbon consequences. Nevertheless, emissions and burned area are not interchangeable: carbon emissions also depend on fuel loading, combustion completeness, and the types of organic material burned.

The apparent acceleration at the upper ends of the temperature and VPD gradients is particularly important for interpretation under continued Arctic warming. A linear extrapolation would distribute the response evenly across the climatic range and could underestimate changes near the warm tail. At the same time, the fitted relationships are empirical and should not be extrapolated far beyond the observed

2001–2020 range. The warmest bins represented climatic conditions that were uncommon during the historical period; however, continued global warming is expected to make such conditions more frequent, thereby increasing the likelihood of tundra fire. Although future tundra fire activity will also depend on vegetation change, fuel continuity, hydrological change and ignition frequency, the steep increase in fire activity at high summer temperatures warrants particular attention.

Regional heterogeneity in the temperature–fire relationship

Regional analyses showed that the biome-wide response did not occur uniformly. Alaska and Russia had the highest mean annual fire carbon emissions and burned fractions, and both regions exhibited significant positive relationships between summer temperature and the two fire metrics. The temperature relationship was strongest in Alaska, where it explained approximately half of the interannual variation in both emissions and burned area. Russia had weaker but significant relationships, suggesting that summer warmth was important but that additional controls accounted for a larger proportion of year-to-year variability.

The remaining regions differed between the two response variables. Greenland/Iceland showed a significant temperature relationship for carbon emissions but had very low mean fire activity, whereas Fennoscandia showed a significant relationship for burned area but not emissions. Canada showed no significant regional relationship in either panel despite occasional high-fire years. These contrasts indicate that statistical sensitivity to temperature does not necessarily correspond to a high regional fire burden. A low-fire region can show a detectable proportional response while contributing little to total tundra emissions, whereas a region with episodic large fires may have insufficiently consistent year-to-year behavior for a significant linear relationship. Differences in fuel type, landscape fragmentation, peat occurrence, snowmelt timing, human access, fire suppression, and ignition regimes may all contribute to the observed regional heterogeneity.

Fuel, moisture, and ignition modify temperature effects

The two-driver analyses demonstrate why temperature alone cannot fully explain tundra fire activity. Precipitation had negative interactions with temperature for both emissions and burned-area fraction. In the emission model, precipitation also had a supported negative main effect. These patterns indicate that wetter summer conditions were associated with lower fire activity and a weaker positive response to temperature. Temperature had its strongest association with fire under warm conditions that were not offset by precipitation. This interpretation is physically consistent with the need for fuels and surface organic layers to dry before ignition can produce sustained fire spread.

Previous-year LAI showed the opposite modifying pattern. Its interaction with temperature was strongly positive for both emissions and burned-area fraction, and the LAI models had the greatest explanatory power among the interaction models (adjusted $R^2 = 0.35$ and 0.40 , respectively). This pattern is consistent with antecedent vegetation abundance increasing the amount or continuity of combustible

material available when the following summer became warm. The unsupported LAI main-effect coefficient is not contradictory: higher LAI alone was not consistently associated with greater fire activity across all temperatures; rather, its association emerged primarily under warm conditions. LAI may also represent several linked processes, including productivity, vegetation structure, surface energy exchange, and longer-term moisture conditions, and should not be interpreted as a direct measure of burnable fuel mass.

Lightning density also had positive interactions with temperature for both fire responses, while its main-effect coefficients were unsupported. This pattern is consistent with lightning becoming more consequential under meteorological conditions favorable for ignition and spread. Additional lightning in cool or wet conditions may produce few sustained fires, whereas the same increase during warm, dry periods may elevate fire occurrence. The shorter lightning record (2012–2020) and the unsupported single-variable lightning model caution against treating ignition frequency as an independent dominant control. Instead, the results support a conditional ignition mechanism in which lightning and fire-conducive weather coincide.

Neither the wind-speed main-effect coefficient nor its interaction with temperature was supported. Wind can influence flame behavior and short-term spread at the event scale, but seasonal mean 10-m wind speed may not capture extreme winds during individual fires. The lack of a seasonal statistical relationship should therefore not be interpreted as evidence that wind is unimportant to fire behavior. It indicates only that the spatial and temporal aggregation used here did not produce a reproducible biome-wide wind pattern after temperature was considered.

Differences among fire indices and direct meteorological variables

FWI had a supported relationship with burned-area fraction but not with carbon emissions, whereas the study-specific INFERNO-inspired meteorological factor did not meet the support criterion for either response. The strong burned-area relationship with FWI indicates that this operational fire-weather metric captured conditions relevant to spatial fire spread. Its weaker correspondence with emissions may reflect additional controls on carbon consumed per unit area, including vegetation and soil organic matter. Conversely, the unsupported relationship for the INFERNO-inspired factor does not invalidate its component processes. Compressing temperature, humidity, precipitation, and soil moisture into a single multiplicative index can obscure nonlinear thresholds or regional limitations that were more clearly expressed by temperature and VPD individually.

Soil moisture and precipitation displayed nonmonotonic binned patterns when considered separately, but only precipitation had a supported interaction with temperature. Surface soil moisture represents a shallow layer and may not describe the moisture content of moss, litter, peat, and deeper organic horizons that contribute to tundra combustion. Seasonal means can also conceal short dry episodes that determine whether fuels become flammable. The interaction results therefore provide more

informative evidence than the single-variable curves: moisture conditions appear to matter chiefly by constraining the fire response to heat.

Spatial concentration of recurrent warmth and fire activity

The maps revealed that recurrent exceedance of the tundra-wide upper-5% temperature threshold was concentrated in discrete circum-Arctic clusters rather than distributed uniformly across tundra. Because a common threshold was used, the pattern reflects both spatial climate gradients and interannual variability and should not be interpreted as a map of location-specific temperature anomalies. Fire carbon emissions and burned-area fraction were also highly localized. Several recurrently warm areas overlapped fire hotspots, consistent with the statistical temperature relationships, but the correspondence was incomplete. Some frequently warm grid cells had limited fire activity, while some fire hotspots were not among the most recurrently warm locations. This mismatch is expected if temperature is an important but insufficient predictor: fire additionally requires available fuel, suitable moisture conditions, and an ignition source.

The spatial distribution of mean LAI provides additional context for the incomplete correspondence between recurrent warmth and fire activity. Areas with greater LAI may support more aboveground vegetation and potentially greater fuel availability or continuity, consistent with the positive interaction between summer temperature and previous-year LAI. Previous field-spectral studies in Alaskan tundra have shown that remotely sensed vegetation indices can reflect shrub cover, green phytomass, and plant productivity (Kushida et al. 2009, 2015). However, LAI represents photosynthetically active leaf area rather than combustible fuel mass and does not directly characterize litter, moss, peat, or soil organic matter. Moreover, the map shows the long-term mean spatial distribution of LAI and does not distinguish vegetation conditions preceding individual fire years. The spatial comparison should therefore be interpreted as contextual evidence rather than a direct test of whether vegetation caused the observed fire hotspots. Although post-fire vegetation dynamics were not examined in this study, increasing fire disturbance may alter tundra vegetation recovery and, in turn, future fuel availability. Linking fire history with post-fire LAI trajectories and field observations would help determine the magnitude and persistence of vegetation responses to fire.

The broad spatial similarity between carbon-emission and burned-area hotspots suggests that burned extent was a major determinant of regional carbon release during the study period. However, localized differences between the two maps may identify areas where carbon consumption per unit burned area was relatively high or low. Such differences could arise from variation in vegetation biomass, organic-soil depth, burn severity, and fire seasonality. Future analyses that explicitly calculate emissions per unit burned area and incorporate peat and soil-carbon characteristics would help distinguish changes in fire extent from changes in combustion intensity.

Limitations and implications

Several limitations should be considered. First, this was an observational analysis, and the reported associations and interactions do not establish causality. Second, the 20-bin procedure emphasized

mean responses across equal-frequency portions of each environmental gradient. It reduced the influence of the large number of raw observations but compressed within-bin variability and left only 20 regression units for univariate comparisons. Third, two-dimensional bin cells were equally weighted despite unequal raw sample sizes. Fourth, model selection and bootstrap support were evaluated using the same data for multiple variables and responses without multiple-comparison adjustment. The support values are not conventional null-distribution p values and should be interpreted as exploratory measures of stability. Finally, the 0.25° grid and seasonal averaging could not resolve individual fire events, short-lived weather extremes, fine-scale fuel mosaics, or local suppression activities.

Additional uncertainty arises from the input products and temporal coverage. Satellite- and model-derived fire emissions, burned area, meteorology, LAI, and lightning each have distinct retrieval and representation errors. Lightning was available for only nine years, limiting the characterization of rare high-fire seasons. The interaction models used standardized linear terms and therefore summarized the average direction of effect modification rather than the full nonlinear response surface. Finally, potentially important variables—including peat depth, soil carbon stocks, thaw state, snow-cover duration, fuel composition, and human ignitions—were not included.

Despite these limitations, consistency across regional regressions, cross-validated response curves, interaction models, and spatial maps provides convergent evidence that summer warmth and atmospheric drying are important large-scale predictors of tundra fire activity. Warming-related risk is unlikely to rise uniformly. The largest responses may occur where high temperature coincides with low precipitation, sufficient antecedent vegetation, and lightning. Process-based fire models and future projections should therefore represent these conditional controls rather than applying a uniform temperature sensitivity across the tundra biome.

Conclusion

Tundra fire activity during 2001–2020 was strongly associated with summer climate. Temperature and VPD showed the clearest nonlinear relationships with both fire carbon emissions and burned-area fraction, with rapid increases in the warmest and most atmospherically dry bins. The temperature–fire relationship was stronger at greater previous-year LAI, suggesting that antecedent vegetation conditions enhance the response of tundra fire activity to summer warmth. Higher lightning density also strengthened the relationship, whereas greater precipitation weakened it and JJA mean wind speed produced no reproducible modification. Spatial overlap between recurrent tundra-wide upper-tail temperatures and fire hotspots was substantial but incomplete. Among the variables examined, summer temperature and VPD showed the strongest cross-validated relationships with tundra fire activity. The response to summer temperature varied with previous-year LAI, precipitation, and lightning density, indicating that antecedent vegetation, moisture and ignition conditions may shape the magnitude of fire responses to warmth. The apparent acceleration in fire activity at the upper ends of the temperature gradients is particularly relevant under continued Arctic warming. Because a linear model assumes a constant response across the climatic range, linear extrapolation may underestimate changes near the

warm tail. Mean JJA LAI during 2001–2020 was spatially heterogeneous, with relatively high values occurring mainly in the more vegetated southern and coastal portions of the tundra. Some of these areas coincided with recurrent upper-tail temperatures and fire hotspots, although the correspondence was incomplete. This spatial pattern provides additional context for the influence of vegetation availability but does not demonstrate that high LAI alone causes greater fire activity. Although future tundra fire activity will also depend on vegetation change, fuel continuity, hydrological change and ignition frequency, the observed nonlinear response suggests that increasingly frequent high-temperature conditions could produce disproportionately large increases in fire activity, with important implications for tundra-fire feedbacks to the Arctic carbon cycle.

Declarations

Conflict of interest

The authors have no relevant financial or non-financial interests to disclose.

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Data Availability

All input datasets used in this study are publicly available. Monthly GFED5.1 fire-emissions data for 2001–2020 were obtained from the Global Fire Emissions Database (van der Werf et al. 2025a) and are archived in Zenodo (doi:10.5281/zenodo.16794692). Monthly GFED5 burned-area data for 2001–2020 were obtained from the dataset of Chen et al. (2023a), archived in Zenodo (doi:10.5281/zenodo.7668424).

ERA5 monthly averaged single-level data, including 2-m air temperature, 2-m dew-point temperature, total precipitation, volumetric soil water content in the first soil layer, and 10-m wind components, were obtained from the Copernicus Climate Data Store (Hersbach et al. 2023; doi:10.24381/cds.f17050d7). The invariant ERA5 soil-type field was used to assign soil-texture-specific saturated volumetric water content following the ECMWF land-surface parameterization (ECMWF 2017). Information on the ERA5 soil-type parameter is available at <https://codes.ecmwf.int/grib/param-db/43>.

Fire Weather Index data were obtained from the NASA Global Fire WEather Database (NASA Goddard Institute for Space Studies 2025), available at <https://data.giss.nasa.gov/impacts/gfwed/>.

Leaf area index data were obtained from GIMMS LAI4g version 1.2 (Cao et al. 2023b), archived in Zenodo (doi:10.5281/zenodo.8281930). Monthly lightning-stroke-density data were obtained from the

World Wide Lightning Location Network Global Lightning Climatology dataset (Kaplan and Lau 2019), archived in PANGAEA (doi:10.1594/PANGAEA.904253).

The tundra study domain was defined using the RESOLVE Ecoregions 2017 polygons (RESOLVE 2017), available at <https://ecoregions.appspot.com/>.

Volcano locations and confirmed eruption histories were obtained from the Smithsonian Institution Global Volcanism Program's Volcanoes of the World database (Global Volcanism Program 2026; doi:10.5479/si.GVP.VOTW5-2026.5.4).

The processed 0.25° datasets, derived spatial fields, statistical outputs, and MATLAB scripts supporting the findings of this study are available from the corresponding author upon reasonable request.

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Figures

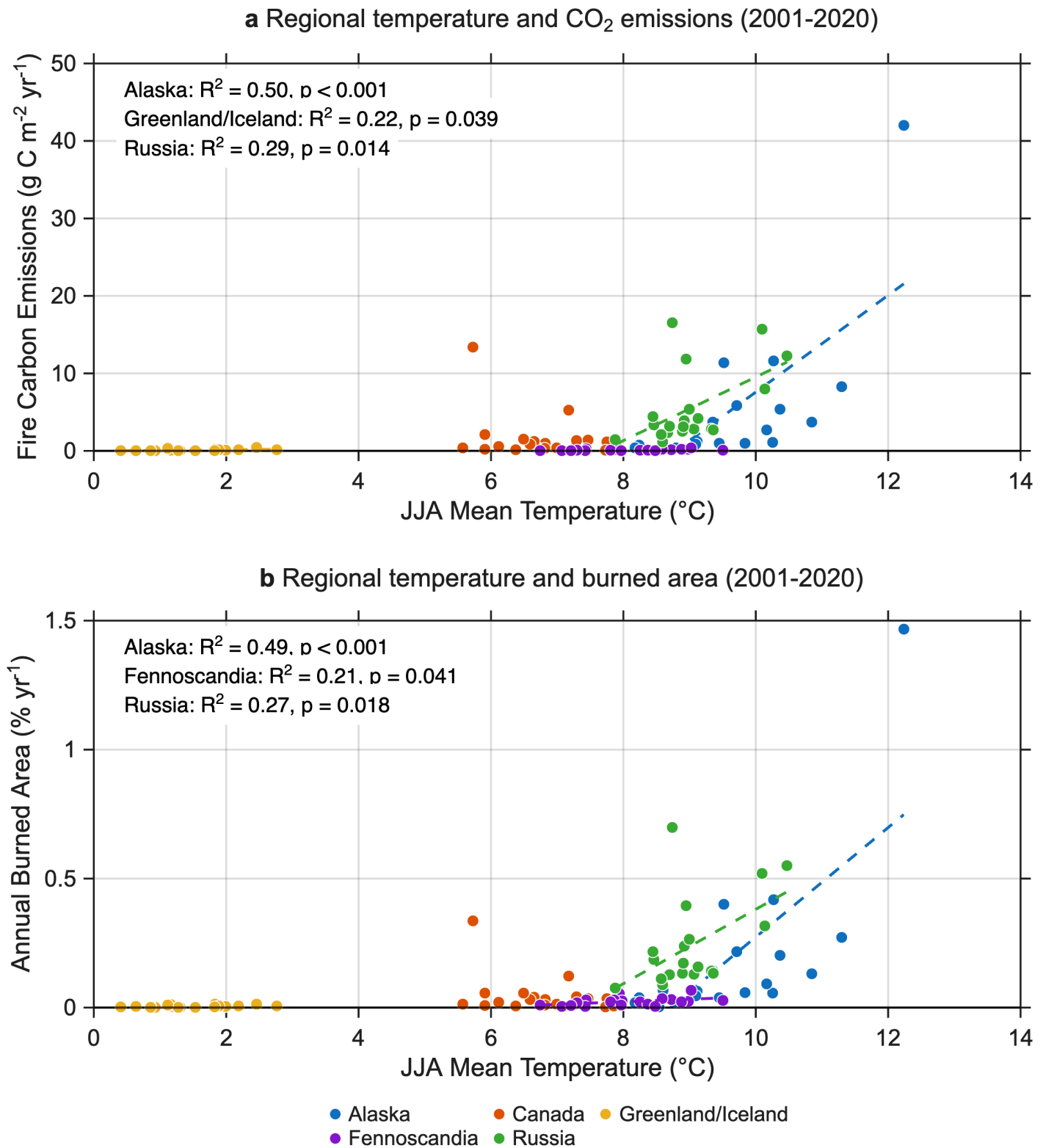


Figure 1

Regional relationships between summer temperature and tundra fire activity

Relationships between area-weighted June–August (JJA) mean temperature and annual tundra fire activity across five geographic regions during 2001–2020. (a) Fire carbon emissions ($\text{g C m}^{-2} \text{ yr}^{-1}$). (b) Annual burned-area fraction ($\% \text{ yr}^{-1}$). Each point represents the area-weighted value for one region in one

year; colors distinguish Alaska, Canada, Greenland/Iceland, Fennoscandia, and Russia. Fire carbon emissions were derived from GFED5.1 CO₂ emissions, converted to carbon using the molecular-mass ratio 12/44, and normalized by regional area. Dashed ordinary least-squares regression lines are shown only for regions in which the slope differed significantly from zero in a two-sided test ($p < 0.05$). Corresponding R^2 and p values are displayed in the relevant panel; nonsignificant regression lines and statistics are omitted.

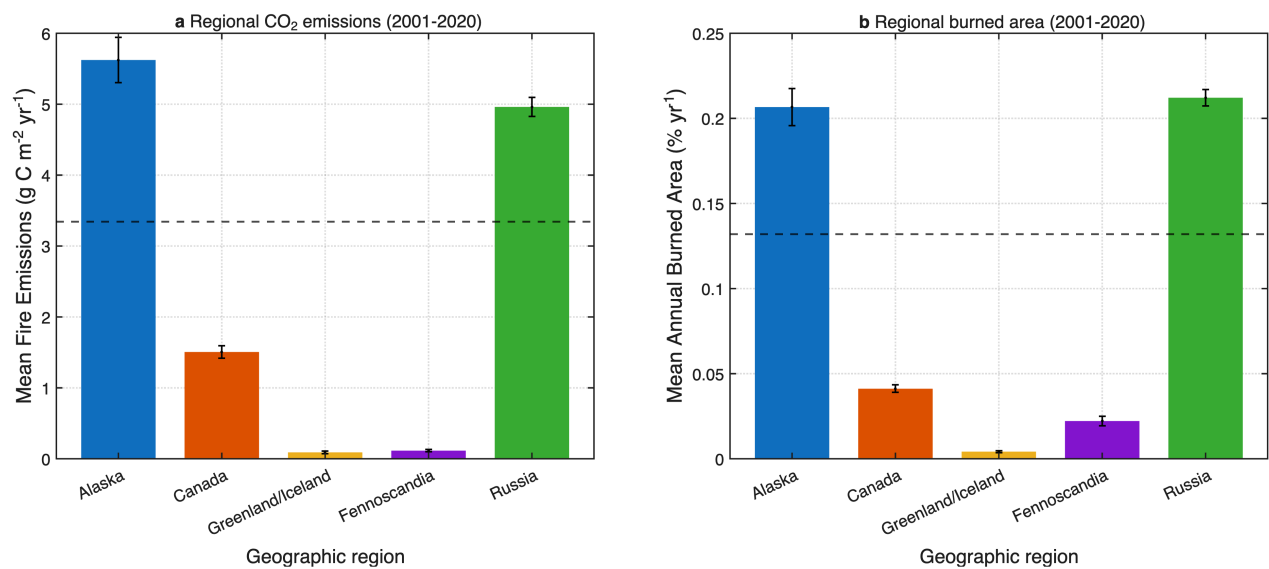


Figure 2

Regional variation in fire carbon emissions and burned-area fraction in tundra

Regional means of (a) fire carbon emissions and (b) annual burned-area fraction in tundra during 2001–2020. The five geographic regions are Alaska, Canada, Greenland/Iceland, Fennoscandia, and Russia. Bars and error bars represent means and standard errors of pooled grid-cell–year values, respectively. These error bars combine spatial and temporal variation and should not be interpreted as temporal variability alone. Horizontal dashed lines indicate the corresponding means across all tundra grid-cell–year observations.

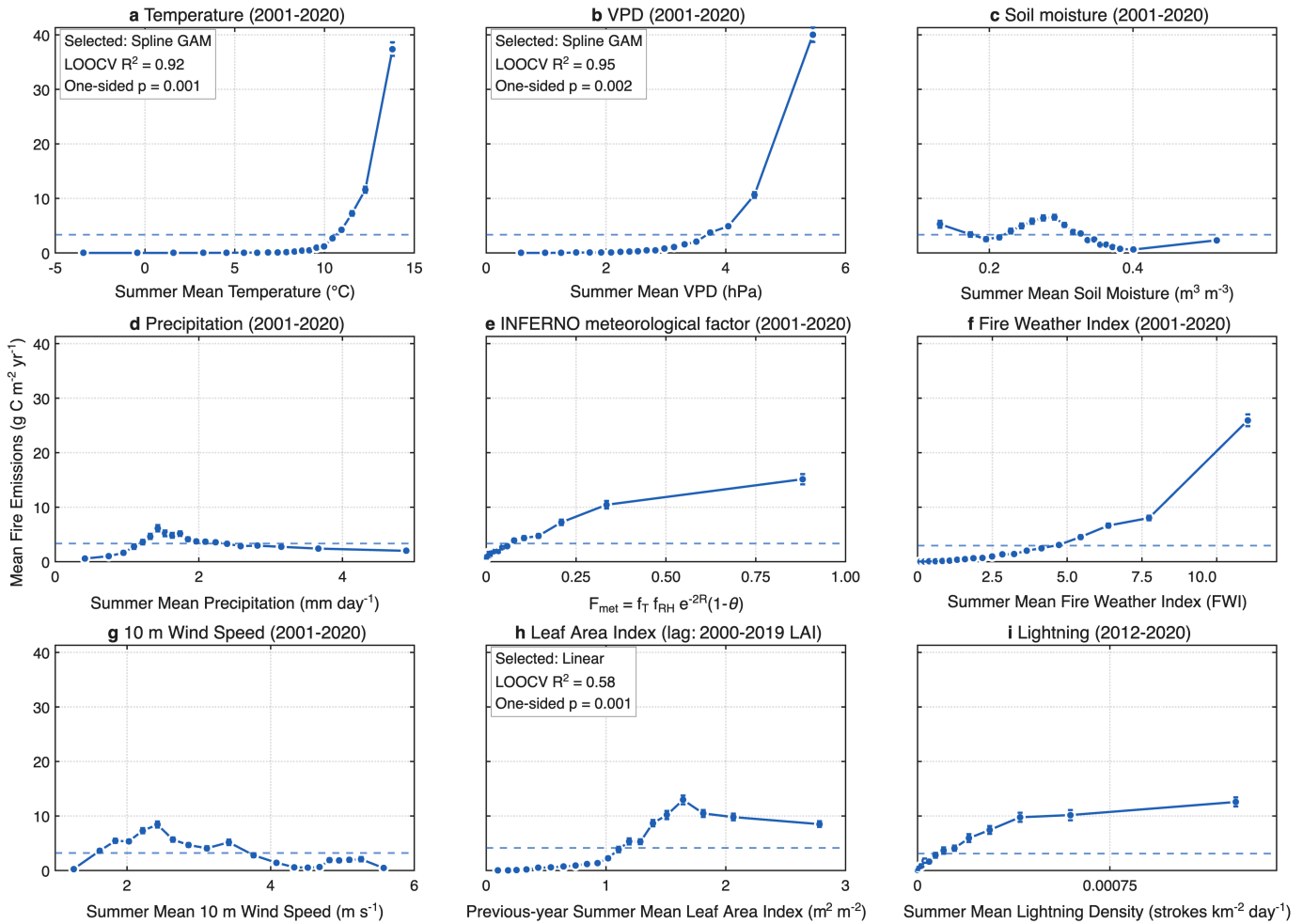


Figure 3

Relationships between fire carbon emissions and environmental variables in tundra

Relationships of mean annual fire carbon emissions to (a) JJA mean temperature, (b) vapor pressure deficit (VPD), (c) surface soil moisture, (d) precipitation, (e) the study-specific INFERNO-inspired meteorological factor (F_{met}), (f) Fire Weather Index (FWI), (g) 10-m wind speed, (h) previous-year leaf area index (LAI), and (i) lightning density. Each explanatory variable was divided into 20 equal-frequency bins; symbols and error bars represent the mean and standard error of fire carbon emissions in each bin. Horizontal dashed lines indicate the overall mean. Data cover 2001–2020, except lightning density (2012–2020). Previous-year LAI covers 2000–2019 and corresponds to fire years 2001–2020. Linear and spline models were compared using leave-one-bin-out cross-validation. The model with the larger cross-validated R^2 is displayed when its one-sided year-and-2°-spatial-block bootstrap support value is ≤ 0.05 .

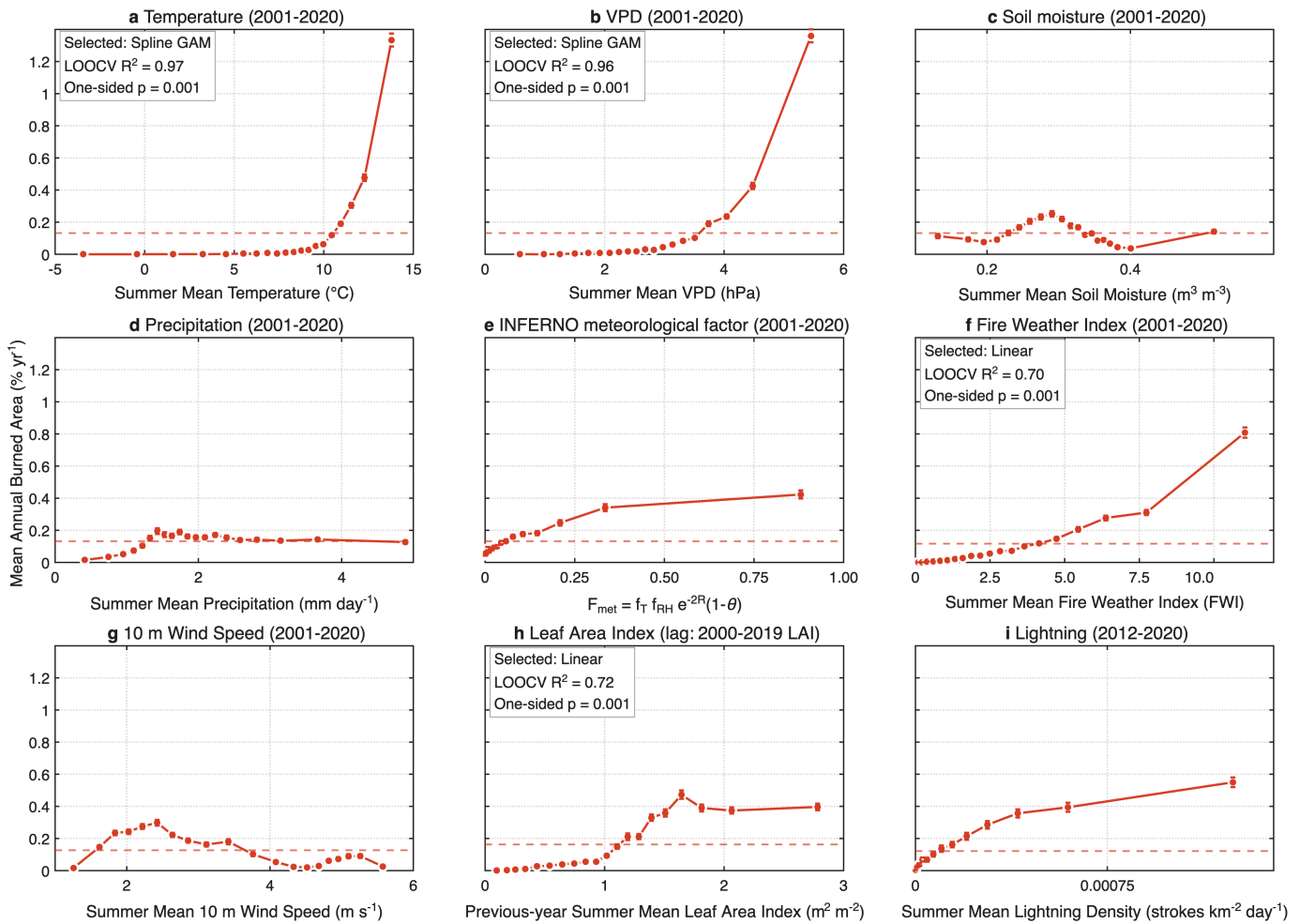


Figure 4

Relationships between burned-area fraction and environmental variables in tundra

Relationships of mean annual burned-area fraction to (a) JJA mean temperature, (b) VPD, (c) surface soil moisture, (d) precipitation, (e) F_{met} , (f) FWI, (g) 10-m wind speed, (h) previous-year LAI, and (i) lightning density. Each explanatory variable was divided into 20 equal-frequency bins. Symbols and error bars represent the mean and standard error of annual burned-area fraction in each bin. Horizontal dashed lines indicate the overall mean. Data cover 2001–2020, except lightning density (2012–2020). Previous-year LAI covers 2000–2019 and corresponds to fire years 2001–2020. Linear and spline relationships were compared using leave-one-bin-out cross-validation and year-and-2°-spatial-block resampling.

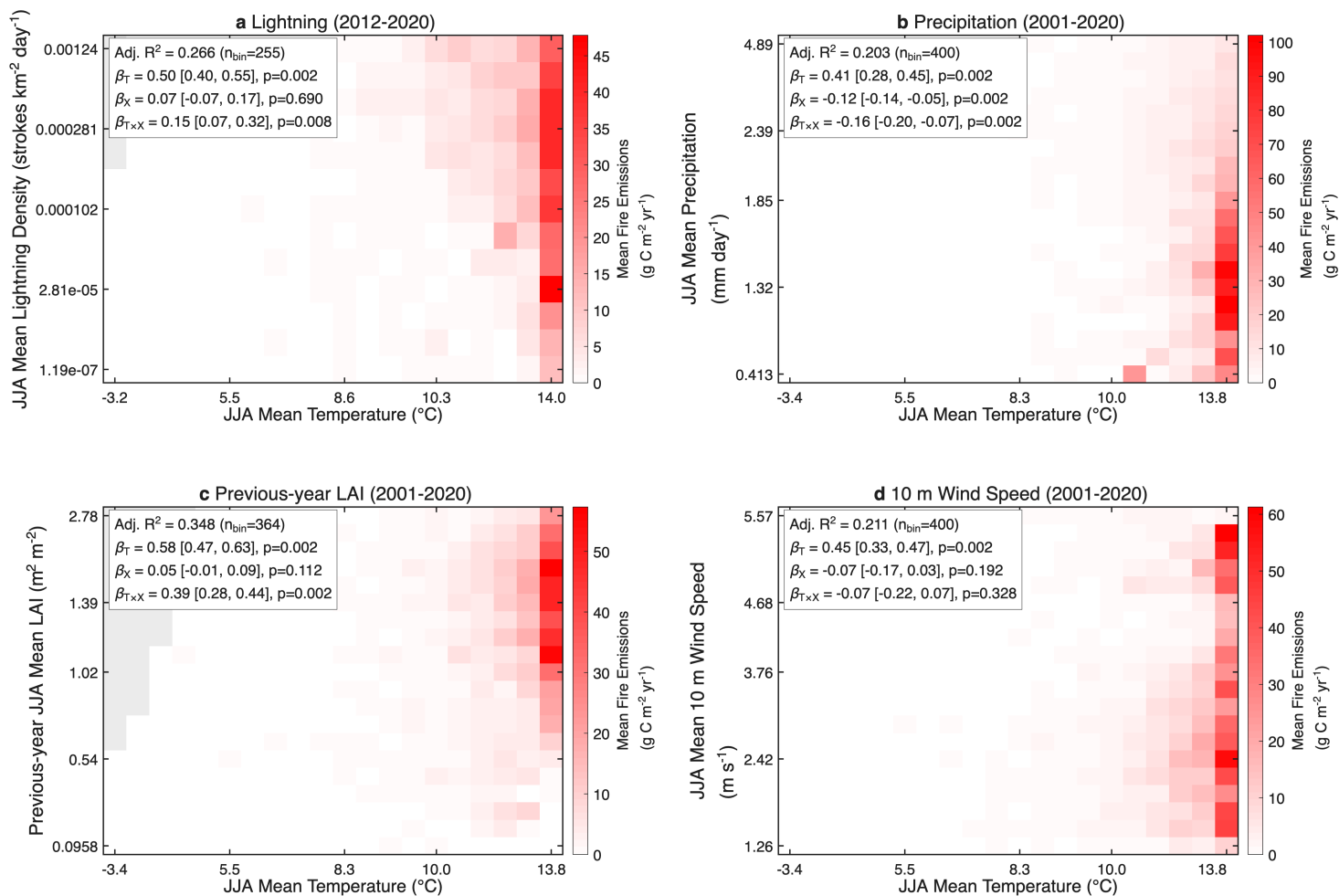


Figure 5

Interactive effects of summer temperature and environmental predictors on tundra fire carbon emissions

Two-dimensional relationships of mean annual fire carbon emissions with JJA mean temperature and (a) lightning density, (b) precipitation, (c) previous-year LAI, and (d) 10-m wind speed. Both variables were divided into 20 equal-count bins, producing a maximum of 400 populated bin combinations. Cell colors indicate mean fire carbon emissions. Lightning data cover 2012–2020; the other variables cover fire years 2001–2020, with previous-year LAI obtained for 2000–2019. The temperature-by-driver interaction was evaluated by resampling years and 2° spatial blocks 999 times.

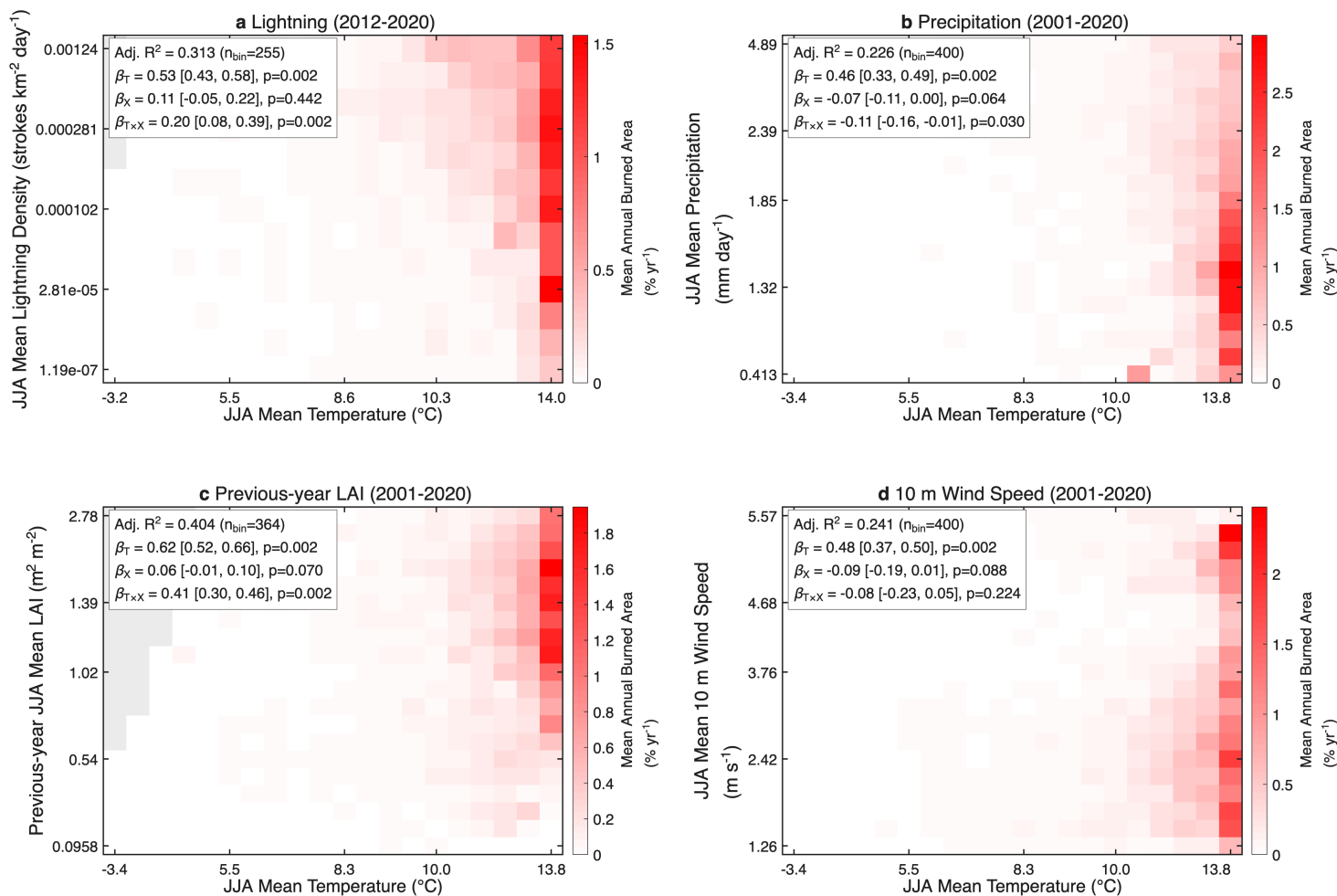


Figure 6

Interactive effects of summer temperature and environmental predictors on tundra burned-area fraction

Two-dimensional relationships of mean annual burned-area fraction with JJA mean temperature and (a) lightning density, (b) precipitation, (c) previous-year LAI, and (d) 10-m wind speed. Both variables were divided into 20 equal-frequency bins, and cell colors indicate mean annual burned-area fraction within each populated bin combination. Lightning data cover 2012–2020; the other variables cover 2001–2020. Temperature-by-driver interactions were evaluated using 999 year-and-2°-spatial-block bootstrap resamples.

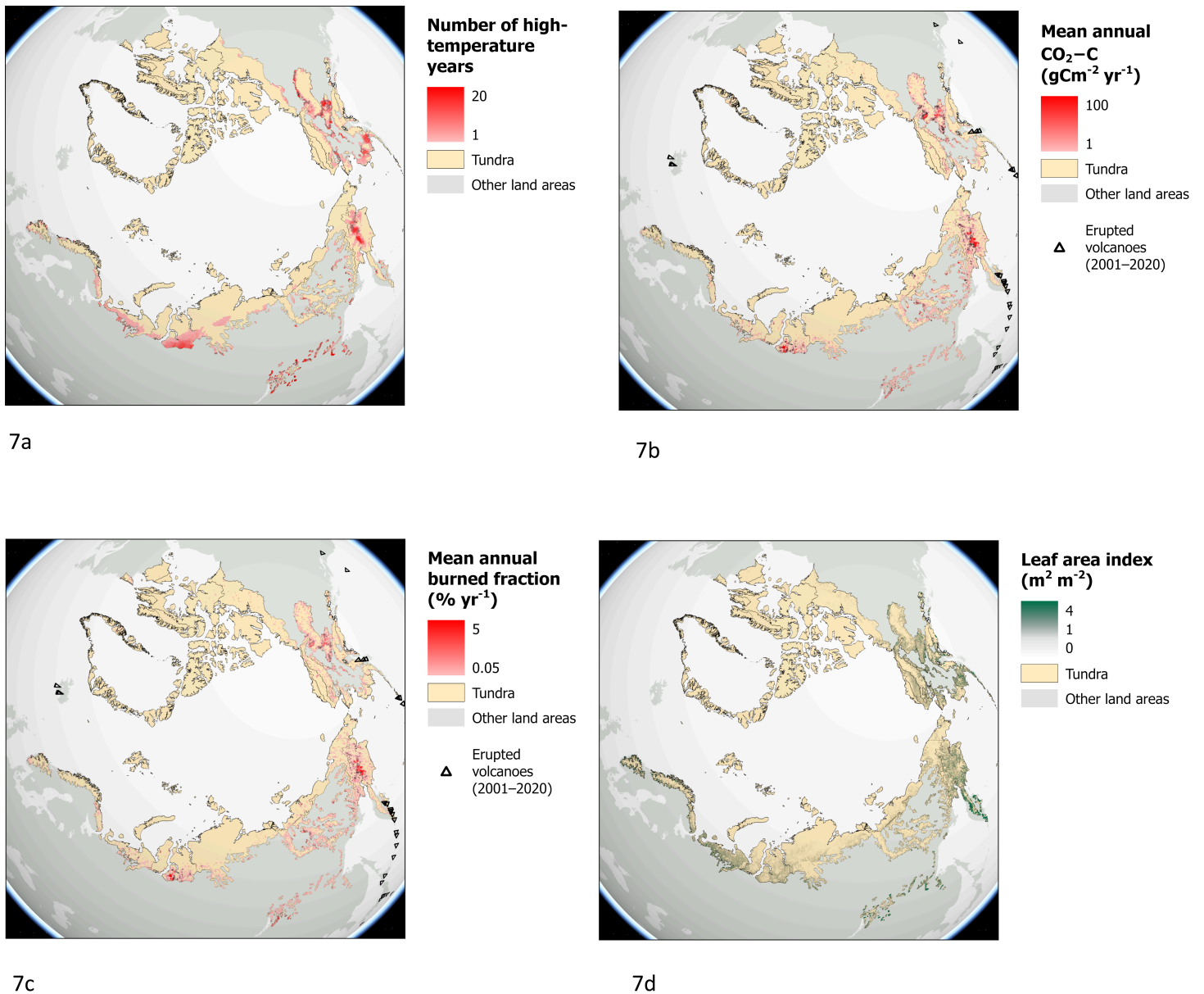


Figure 7

Spatial distributions of recurrent upper-tail temperature conditions, fire carbon emissions, burned area, and leaf area index

Spatial distributions of (a) the number of years in which each tundra grid cell exceeded the fixed tundra-wide upper-5% JJA mean-temperature threshold, (b) mean annual fire carbon emissions, (c) mean annual burned-area fraction during 2001–2020, and (d) mean JJA leaf area index (LAI) during 2001–2020. The temperature threshold was the lower boundary of the highest of 20 equal-frequency bins derived from all pooled tundra grid-cell–year observations. It therefore represents the upper tail of the pooled spatial and temporal distribution, not a location-specific temperature anomaly. Recurrence values range from 0 to 20 years. Fire carbon emissions are expressed as $\text{g C m}^{-2}\text{yr}^{-1}$, and burned-area fraction is expressed as $\%\text{yr}^{-1}$. Open black triangles in (b) and (c) indicate volcanoes that erupted during 2001–

2020. Beige areas represent tundra outside the displayed data ranges, and gray areas represent other land-cover regions.