

Supplementary Material

Spatiotemporal Dynamics of Active Fire in China (2003-2024): Regional Patterns and Land Cover Associations

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1 Data

This study employs monthly ERA5 datasets including 2m temperature, total precipitation, and 10m wind speed with a spatial resolution of $0.25^\circ \times 0.25^\circ$ from 2003 to 2024.

2 Method

2.1 Fire data perturbation design

To evaluate the robustness of fire point trend analysis, this study implemented a systematic sensitivity analysis framework. Based on MODIS fire point data from 2003-2024, daytime and nighttime fire point time series were extracted for seven geographical regions (Northeast, North China, Northwest, Central China, East China, Southwest, South China) and at the national scale. To simulate potential systematic observation errors, a multi-level perturbation scheme was designed, applying random perturbations of $\pm 5\%$, $\pm 10\%$, and $\pm 15\%$ to the original fire count series. Reproducibility of results was ensured through fixed random seeds.

2.2 Trend analysis

Trend analysis employed the non-parametric Theil-Sen estimator to derive robust slope estimates resistant to outliers, complemented by Mann-Kendall significance testing to detect monotonic trends at the 95% confidence level ($p < 0.05$).

2.3 Regression analysis with climate control variables

The study employs multivariate regression models with climate control variables to isolate policy effects from meteorological influences. The core regression specification follows:

$$\text{Fire Count} = \beta_0 + \beta_1(\text{Policy}) + \beta_2(\text{Temperature}) + \beta_3(\text{Precipitation}) + \beta_4(\text{Wind speed}) + \varepsilon$$

Policy variable is a binary indicator (0 for pre-2016, 1 for post-2016). Climate variables are standardized to z-scores (mean=0, standard deviation=1) to ensure comparability across different meteorological dimensions.

The estimation procedure employs ordinary least squares (OLS) regression conducted separately for each geographical region, extracting comprehensive output metrics including policy coefficient estimates with associated p-values, climate variable coefficients for temperature, precipitation and wind speed, model fit statistics (R-squared and F-test p-values), to provide a complete assessment of intervention impacts while controlling for meteorological influences.

2.4 Climate anomalies

Climate anomalies were calculated as deviations from region-specific long-term means to isolate interannual variability from baseline climatic conditions. Temperature anomalies were computed in absolute terms (°C) relative to each region's mean temperature, while precipitation anomalies were expressed as percentage (%) deviations from regional norms to account for varying precipitation regimes across different climatic zones. Wind speed anomalies were calculated as absolute deviations (m/s) from regional averages.

2.5 Fire peak month identification

The fire peak month identification employs a multi-method consensus approach: it first applies three statistical criteria (1) months exceeding the 75th percentile in fire counts, (2) months with Z-scores >1 indicating significant deviations from the mean, and (3) months contributing $\geq 8\%$ of annual fire occurrences; then selects months identified by at least two methods as the final peak season, with the 75th percentile results serving as a fallback when consensus is not reached, ensuring robust identification of fire-prone periods across different geographical regions.

Text S1

Figures S1 showed a systematic sensitivity analysis. Based on annual daytime and nighttime total fire counts from MODIS during 2003-2024 for each geographical region. This analysis ensures that the identified trends in fire counts remain reliable even when accounting for potential systematic observation errors, thereby strengthening the credibility of subsequent analytical conclusions.

Figure S2 and Table S1 showed climate-controlled regression results. It enables the identification of policy impacts while accounting for concurrent meteorological variations, providing more reliable estimates of intervention effectiveness by isolating policy effects from environmental confounding factors.

Figures S3 to S5 simultaneously displayed mean annual anomalies for each climate factor against annual fire counts with statistically significant trends highlighted.

Figure S6 showed the fire peak month identification for each geographical region.

Figure S7 and Table S2 showed climate-controlled regression results during the identified peak fire months of each year.

Figures S8 to S10 displayed mean anomalies for each climate factor against fire counts in peak fire months with statistically significant trends highlighted.

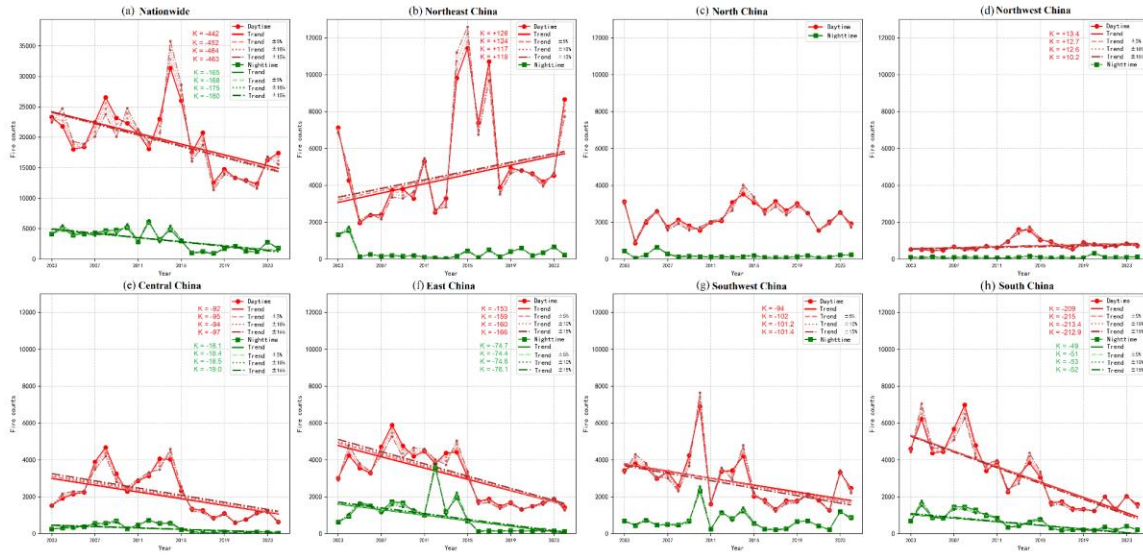


Figure S1. Sensitivity analysis for fire counts. To simulate potential systematic observation errors, a multi-level random perturbation $\pm 5\%$, $\pm 10\%$, and $\pm 15\%$ was applied to the original fire count series. Only Mann-Kendall test significant linear trend lines (dashed lines) are displayed, where slope (k) quantifies trend direction and magnitude.

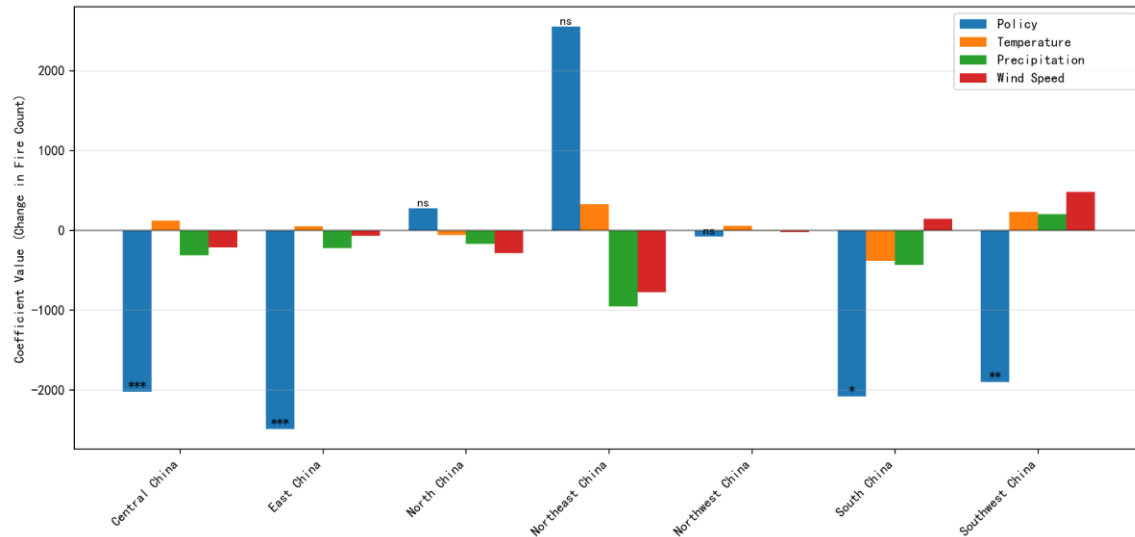


Figure S2. Multivariate regression coefficients including policy coefficient estimates with associated p-values, climate variable coefficients for temperature, precipitation and wind speed. Annual total fire counts, mean annual temperature and wind speed, annual total precipitation, analyzed separately for each geographical region.

Table S1. Ordinary least squares regression model fit statistics results

Region	R_Squared	Model_F_PValue
Central China	0.7091	0.0002
East China	0.8341	0.0000
North China	0.2743	0.2182
Northeast China	0.2946	0.1805
Northwest China	0.0307	0.9674
South China	0.7277	0.0001
Southwest China	0.5830	0.0035

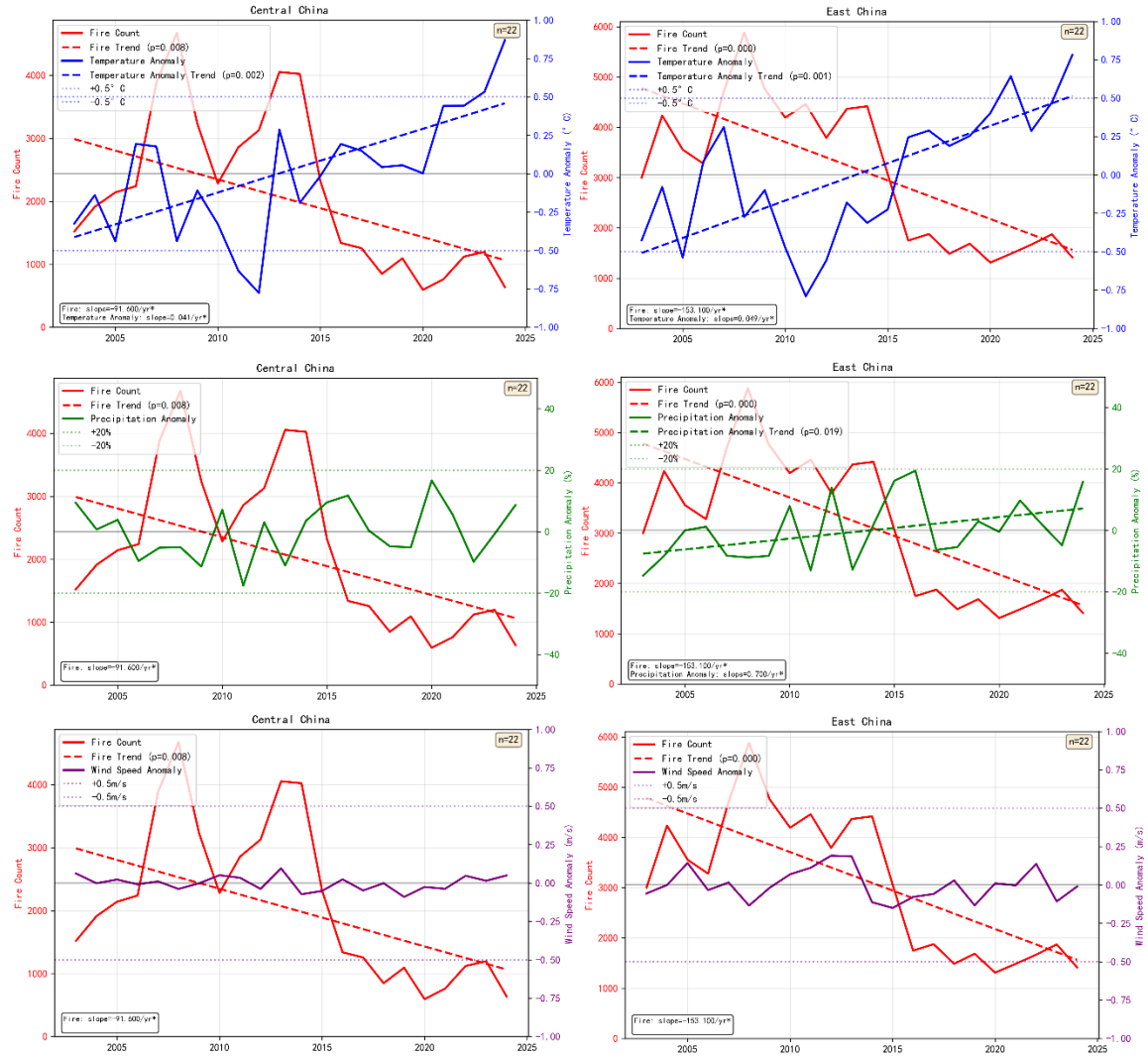


Figure S3. Annual fire counts (left axis) and mean annual climate anomalies (right axis) with statistically significant trends ($p < 0.05$) highlighted using dashed trend lines in Central China and East China from 2003 to 2024.

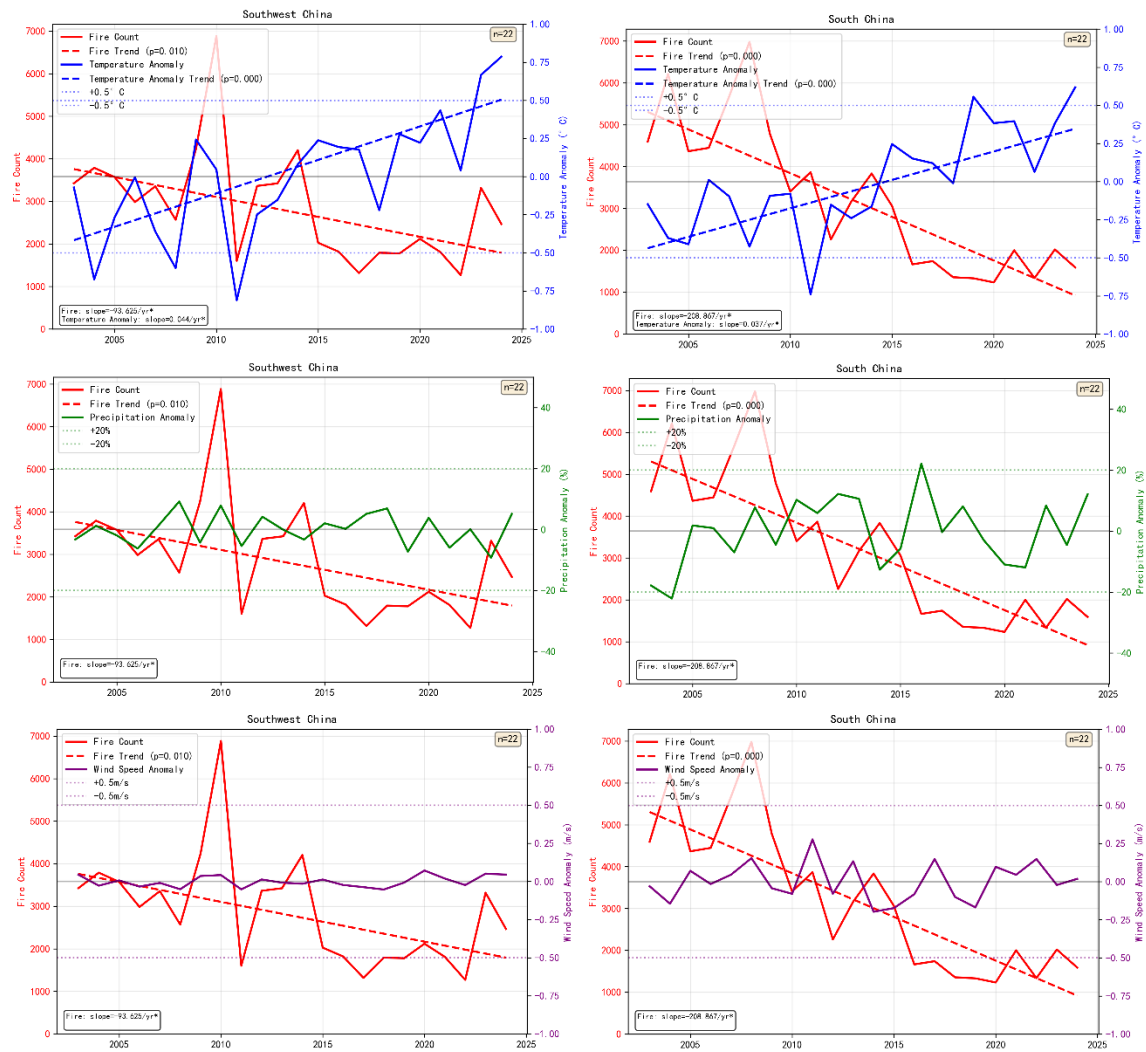


Figure S4. The same with Figure S3, for Southwest China and South China.

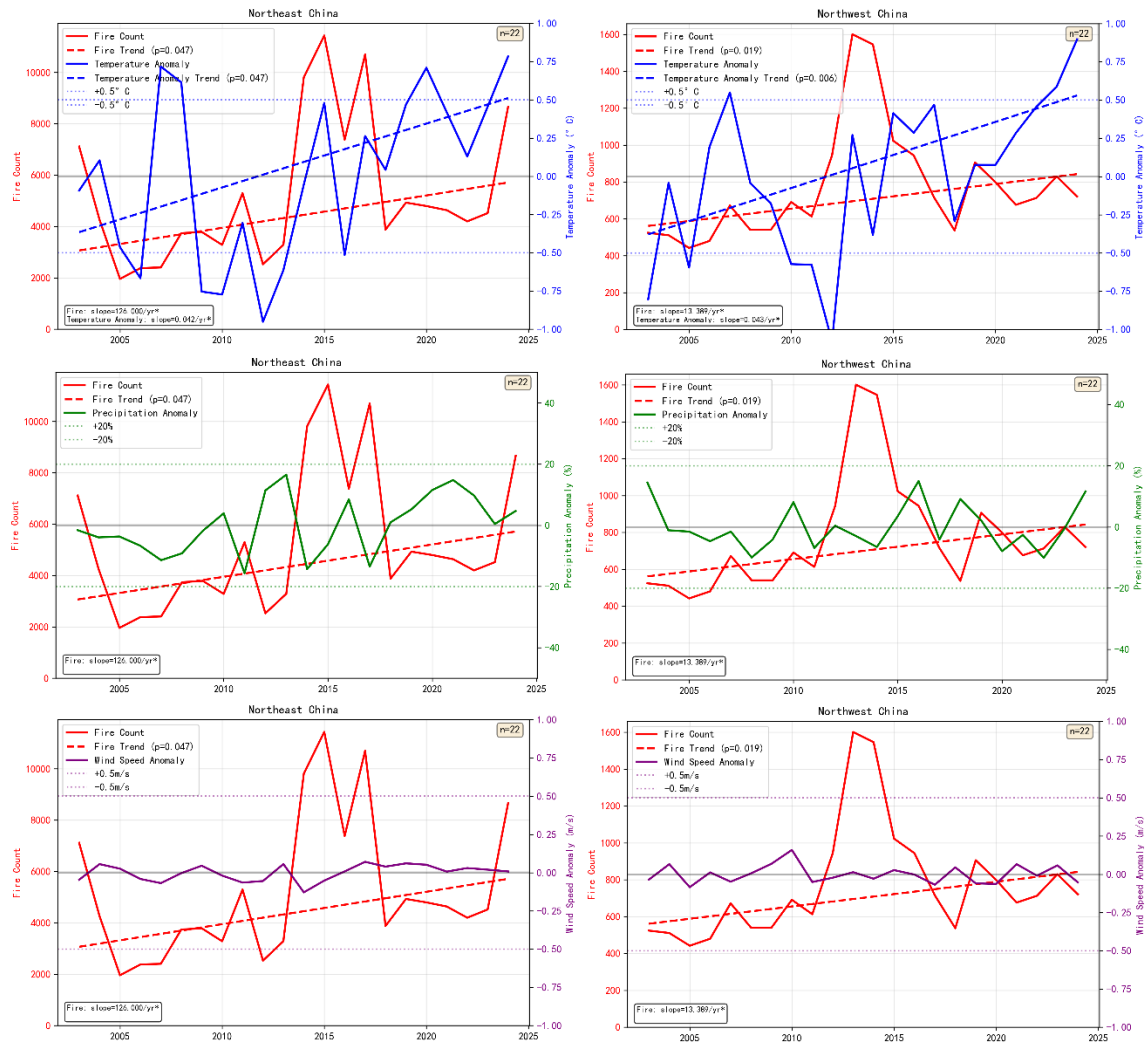


Figure S5. The same with Figure S3, for Northeast China and Northwest China.

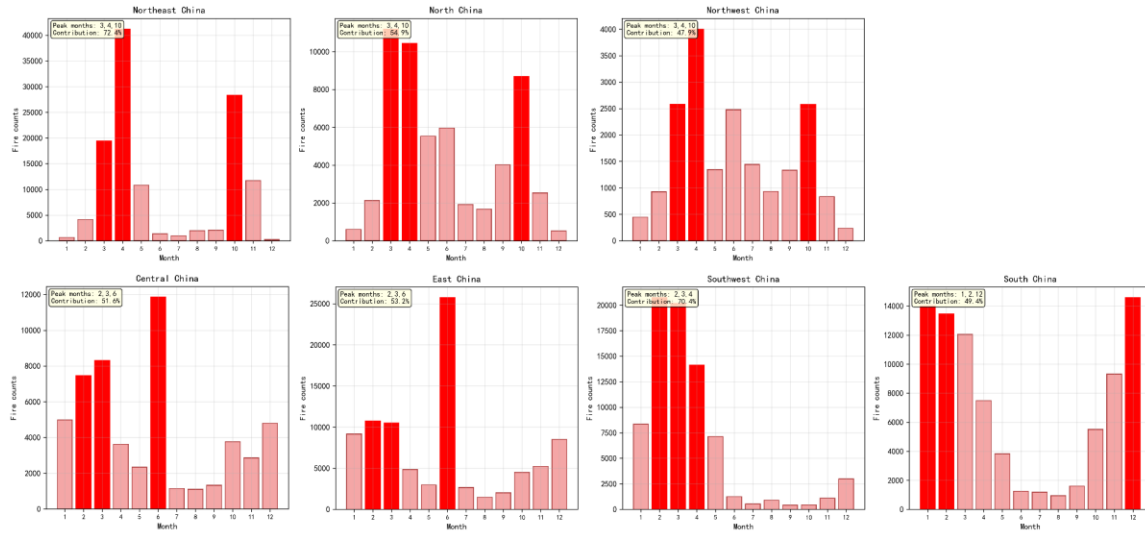


Figure S6. The fire peak month identification for each geographical region.

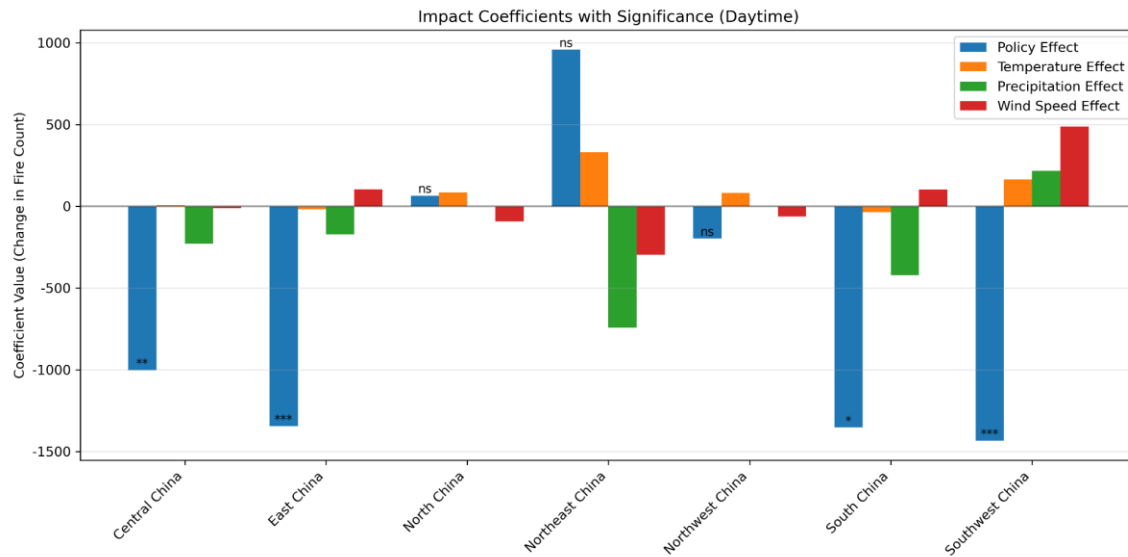


Figure S7. The same with Figure S2, using total fire counts, mean temperature and wind speed, total precipitation for identified peak fire months per year.

Table S2. Model fit statistics results

Region	R_Squared	Model_F_PValue
Central China	0.5991	0.0026
East China	0.6961	0.0003
North China	0.1338	0.6305
Northeast China	0.3359	0.1188
Northwest China	0.2274	0.3272

South China	0.6525	0.0008
Southwest China	0.6894	0.0003

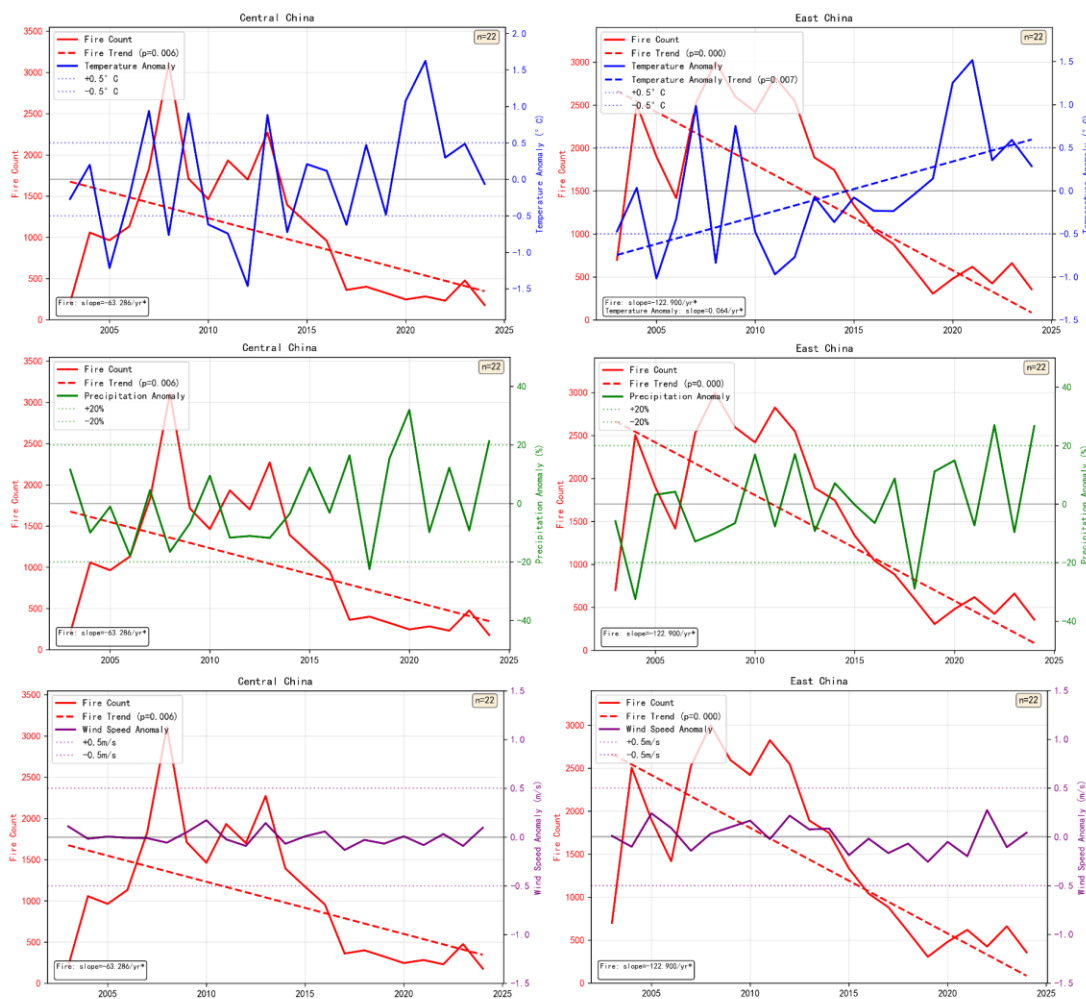


Figure S8. Fire counts (left axis) and mean climate anomalies (right axis) in identified peak fire months with statistically significant trends ($p < 0.05$) highlighted using dashed trend lines in Central China and East China from 2003 to 2024.

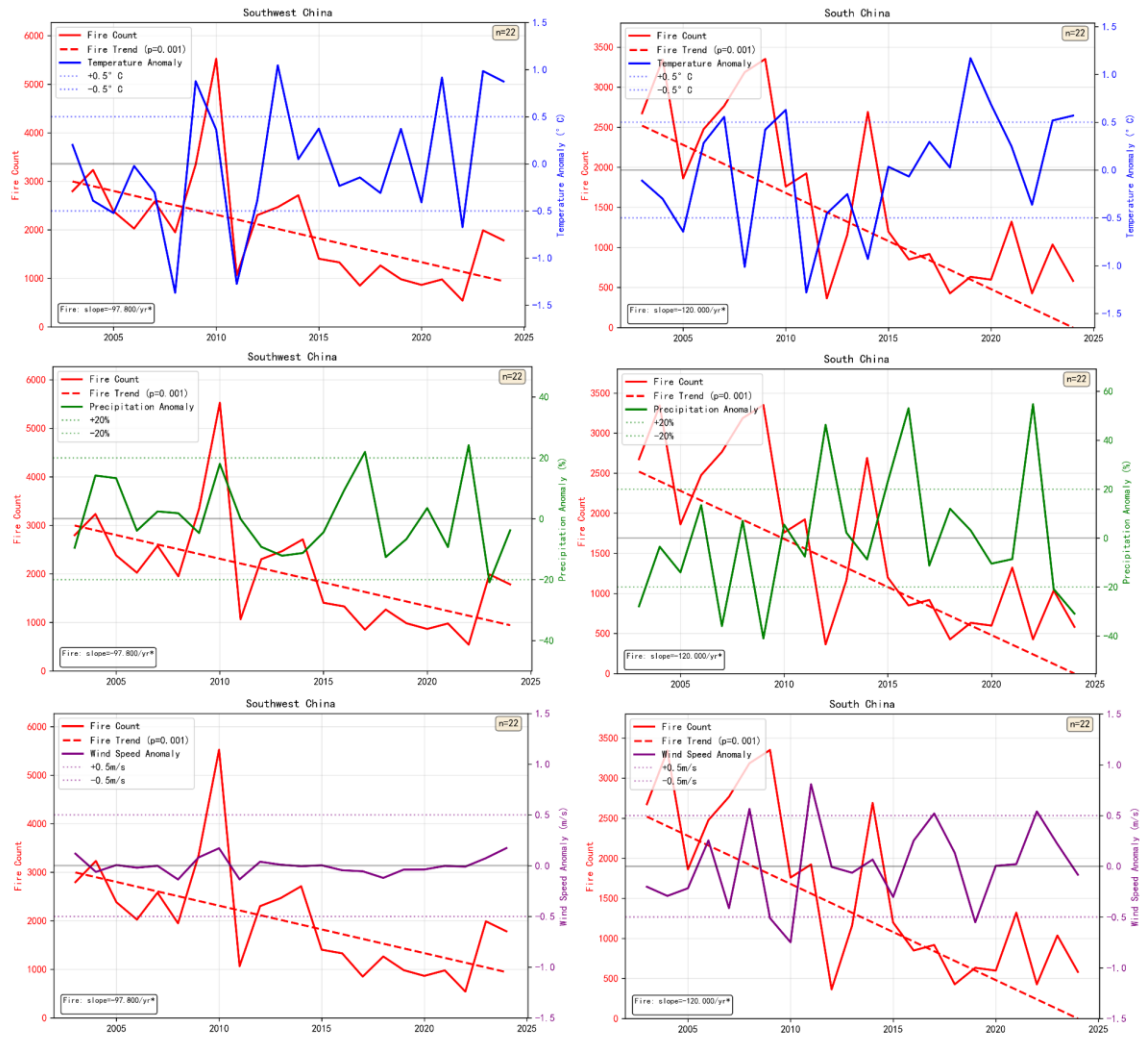


Figure S9. The same with Figure S8, for Southwest China and South China.

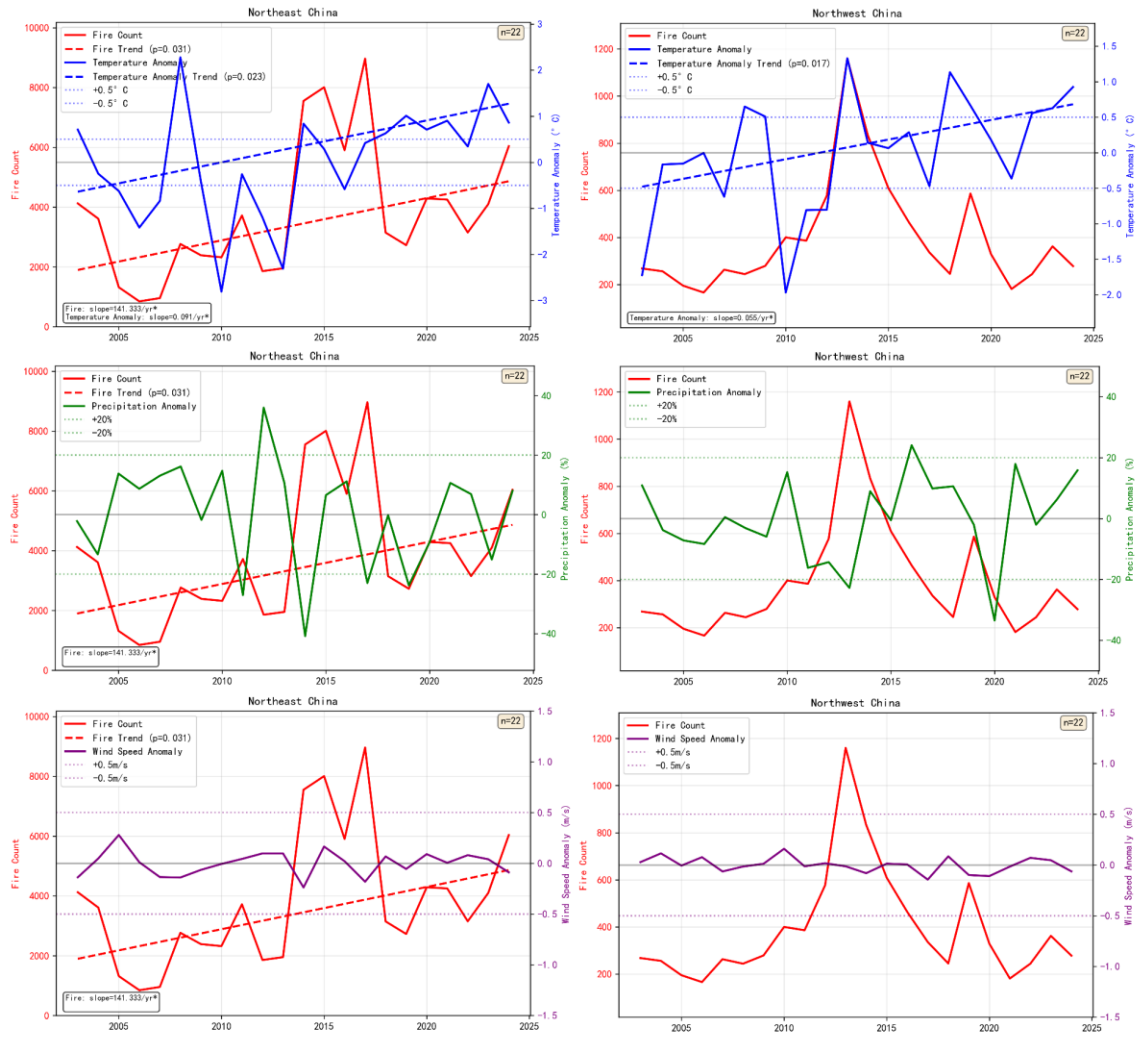


Figure S10. The same with Figure S8, for Northeast China and Northwest China.