



# 1 **Forecasting the Flame: Simulating Future Wildfire Regimes**

## 2 **in the Northeast Mediterranean**

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7 **Abstract.** Despite a global decline in total burned area, high-impact wildfire events continue to pose  
8 growing threats to ecosystems and human communities. As climate change amplifies hydroclimatic  
9 extremes, cycles of precipitation-driven fuel build-up followed by persistent drought are increasing the  
10 likelihood of severe wildfires. Moving beyond estimates of total burned area, this study aims to answer  
11 “where, and how often, will future landscapes burn?” by quantifying wildfire hazard through fire probability  
12 and fire return intervals for the northern segment of the Eastern Mediterranean Basin (34–46°N, 24–50°E),  
13 a region where such extremes are expected to fundamentally alter fire regimes. Potential changes in fire  
14 activity were investigated for the period 1961–2100 using the process-based dynamic vegetation model  
15 LPJ-GUESS coupled with SIMFIRE–BLAZE wildfire modules. Terrestrial vegetation was represented using  
16 regionally parameterized Plant Functional Types, and simulations were forced with ERA5-Land reanalysis  
17 for the historical period (1961–2025) and an ensemble of five CMIP6 climate projections under a high-  
18 emissions scenario (SSP5-8.5) for exploratory future analysis (2015–2100). Benchmarking against MODIS  
19 MCD64A1 observations revealed that while the model successfully reproduced domain-scale burned area  
20 magnitudes and interannual variability, weak spatial agreement highlighted the strong influence of localized  
21 anthropogenic ignition and suppression processes not represented in the natural-potential experimental  
22 design. Future projections indicated that changes in fire probability and return intervals are unlikely to be  
23 spatially uniform. Instead, simulation results highlight a fundamental reorganization of fire regimes driven  
24 by the interplay between hydroclimatic change, vegetation dynamics, and landscape structure. By  
25 combining temporally explicit reanalysis data with ensemble climate projections, this study distinguishes  
26 between the role of observed hydroclimatic extremes in shaping historical fire activity and the importance



27 of long-term climate trajectories in constraining future risk. The findings suggest that climate change may  
28 not simply increase overall wildfire activity, but rather systematically redistribute fire risk across the region,  
29 with urgent implications for anticipating emerging hotspots and adapting fire management strategies.

## 30 **1. Introduction**

31 As the effects of climate change intensify, large and severe wildfire episodes with significant socio-  
32 economic and ecological impacts continue to dominate global headlines. In January 2025 alone, the fatal  
33 Palisades and Eaton Fires devastated close to 38,000 ha of natural habitat and human settlements in the  
34 United States (CAL FIRE, 2025; WWA, 2025a), while during the subsequent summer months widespread  
35 wildfire activity across Portugal, Spain, Greece, Cyprus, and Türkiye continued to claim lives (Keeping et  
36 al., 2025; WWA, 2025b). Regardless of fire suppression efforts or the fire-adapted traits of many  
37 Mediterranean taxa, projected increases in the frequency and severity of disturbances under climate  
38 change, combined with the rapid expansion of the wildland–urban interface (WUI), are expected to  
39 exacerbate future wildfire hazard and uncertainty (Gonzalez and Ghermandi, 2024; Wasserman and  
40 Mueller, 2023). As a result, anticipating potential fire episodes and constructing plausible “wildfire  
41 trajectories” for densely populated regions with seasonal wildfire activity have become growing priorities  
42 from scientific, policy, and humanitarian perspectives.

43 While excess heat, fuel abundance, prolonged drying, and strong airflow are required for a high-severity  
44 wildfire (Newman Thacker, 2025), two overarching drivers – often operating in tandem – set the stage for  
45 megafires: ignitions, which are predominantly human-caused (Ekberzade et al., 2025; Ellis et al., 2025;  
46 Gelabert et al., 2025), and climate change. Although the former can be identified through forensic analyses,  
47 climate change has been robustly linked to the intensification of wildfire activity by expanding the amplitude  
48 of climatic variability (François et al., 2025; Wood, 2023) and amplifying hydroclimatic extremes (Sutanto  
49 et al., 2025; Richardson et al., 2022). This relationship has been particularly evident during recent fire  
50 seasons, including the extreme wildfire outbreaks in southern Europe in 2021 (San Miguel-Ayanz et al.,  
51 2022; Duane et al., 2021), and in Cyprus, Greece and Türkiye in 2025 (WWA, 2025b).

52 Much as human behavior is complex and human ignitions remain difficult to predict, analyses of climate  
53 variability and burned area (BA) based on large-scale remote sensing and observational datasets can



54 provide valuable insights into regions exhibiting persistent fire activity. Such analyses can identify active  
55 pyro-catchments, characterized by spatial persistence in BA (Ekberzade et al., 2025), as well as potential  
56 wildfire hotspots associated with temporal persistence. Process-based dynamic global vegetation models  
57 (DGVMs) coupled with fire modules offer a complementary framework for exploring how these fire-prone  
58 regions may respond to future climate change. By explicitly linking climate drivers with vegetation dynamics,  
59 coupled DGVMs enable the investigation of how fuel accumulation and burn potential – and, consequently,  
60 regional fire regimes – may evolve over time under different climate scenarios (Nurrohman et al., 2024;  
61 Pellegrini et al., 2023). Together, these approaches provide critical guidance for policymakers seeking to  
62 implement preventive measures and for first responders planning targeted interventions in high-risk areas  
63 ahead of the fire season.

64 This study presents simulations from the process-based dynamic vegetation model LPJ-GUESS, coupled  
65 with fire and combustion modules and driven by high-resolution reanalysis data and bias-corrected global  
66 climate model (GCM) outputs. Model simulations are synthesized with observational records, including  
67 satellite-derived burned area and climate indices such as the Standardized Precipitation-Evapotranspiration  
68 Index (SPEI), to evaluate the model's capacity to reproduce historical fire dynamics and distinguish natural,  
69 climate-driven fire potential from anthropogenic influences over the historical period (1961–2025). Building  
70 on this evaluation, an ensemble of future projections under the high-emissions SSP5-8.5 scenario is used  
71 to explore ecosystem responses to strong warming and drying conditions through the end of the century  
72 (2015–2100). These simulations investigate whether such climate trajectories will simply intensify existing  
73 wildfire activity or drive a fundamental spatial reorganization of fire regimes across the region.

## 74 **2. Methodology**

### 75 **2.1 Study area**

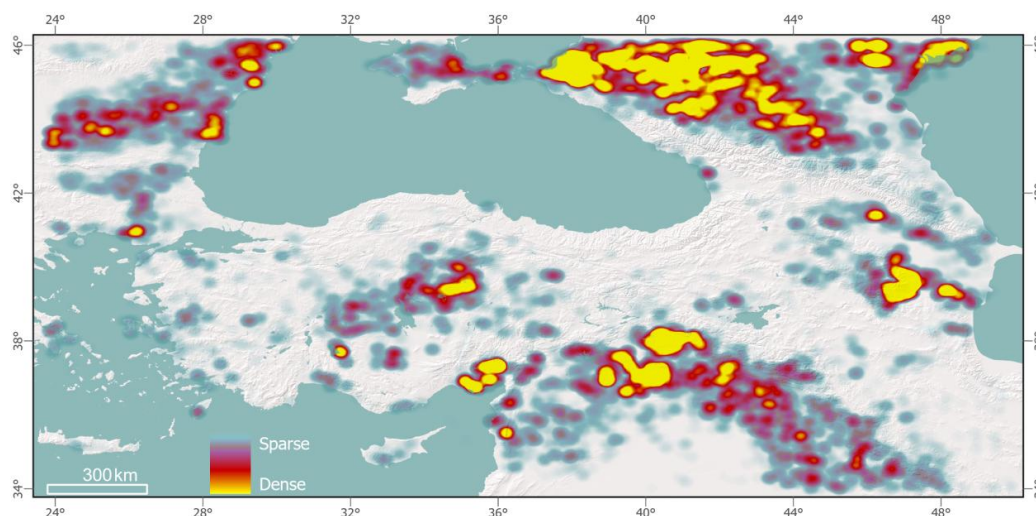
76 The study area is situated in the northern segment of the Eastern Mediterranean Basin. It centers on the  
77 Anatolian Peninsula, also covering its immediate surroundings between 34–46°N and 24–50°E. The  
78 Anatolian Peninsula is a high plateau with elevations increasing from the Aegean coast in the west towards  
79 the eastern highlands. Two mountain ranges in the north and the south block most of the maritime effect  
80 from both seas from entering inland, creating a semi-arid continental climate in the inner peninsula. The



81 coastal climates are mainly Mediterranean. In the northeast, there is a temperate rainforest belt that extends  
82 along the Black Sea coast towards the Caucasus Mountains. In the south, the Taurus Mountain Range  
83 continues to become the Zagros Mountains, where the East Anatolian deciduous forest ecoregion turns  
84 into montane steppes which continue for the greater part of this semi-arid mountain range.

85 The different climate and vegetation patterns of the study area create different fire histories. In certain  
86 places where vegetation forms dense canopies, the precipitation patterns may keep fire return intervals  
87 high (FRI  $\geq 50$  yr), such as in the southeastern Black Sea coast (northern Anatolia). In others, seasonality  
88 and aridity may encourage frequent burns. In zones where fire frequency is high (FRI is low), most woody  
89 taxa are not only adapted to, but also dependent on fire to survive (e.g., Mediterranean shrubs and certain  
90 pine species that are serotinous).

91 The region also bears a strong human imprint on the landscape. Large portions of Central Anatolia, the  
92 Pontic steppes, and the Caspian lowlands are dominated by croplands and heavily grazed rangelands.  
93 While agricultural expansion may amplify burned area in the observational record (through stubble burning,  
94 Fig. 1), grazing pressure and active fire suppression fragment natural fuel continuity and often reduce the  
95 spatial extent of large fires despite favorable climatic conditions. As a result, the observed fire regimes in



96 **Figure 1.** Wildfire hotspots within the study domain. The heatmap was created using MODIS MCD64A1  
97 dataset for burned area between 2000 and 2025 (Giglio et al., 2021). Bright yellow marks indicate tight  
98 burned area clusters, or wildfire hotspots.



99 many semi-arid ecosystems reflect not only climatic constraints but also intensive land management. This  
100 anthropogenic modulation is particularly relevant for steppe environments, where fuel continuity and  
101 biomass accumulation can fluctuate strongly between years. Consequently, in these landscapes, the  
102 climatic fire potential simulated by dynamic vegetation models may show acute differences in burned area  
103 from those recorded by satellite observations (Ekberzade et al., 2025).

## 104 **2.2 Dynamic vegetation and fire modeling framework**

105 Burned area (BA) and fire return interval (FRI) were simulated using the process-based dynamic vegetation  
106 model LPJ-GUESS v.4.1 (Smith et al., 2001). The model was coupled with the SIMFIRE (Knorr et al., 2014)  
107 and BLAZE (Rabin et al., 2017) fire modules. In this configuration, SIMFIRE estimates the probability of fire  
108 occurrence based on biome type, climate conditions, and vegetation abundance, the latter proxied by the  
109 fraction of absorbed photosynthetically active radiation (FAPAR). Within the LPJ-GUESS patch framework,  
110 these probabilities are used to generate stochastic ignition events, from which the realized burned area  
111 fraction emerges as the proportion of burned patches within each grid cell. BLAZE then simulates the  
112 mechanistic impacts of these fires, including combustion-related mortality, biomass consumption, and  
113 carbon fluxes, based on explicit fuel loads and local fire weather conditions.

114 Forced with seven climate variables (mean, minimum, and maximum temperatures, precipitation, relative  
115 humidity, solar radiation, and wind speed), soil properties, and atmospheric CO<sub>2</sub> concentrations, the model  
116 simulates each grid cell independently. All simulations in this study were conducted at a daily temporal  
117 resolution, producing annual outputs of burned area, fire probability, and vegetation state variables.  
118 Regional model parameterization, plant functional type (PFT) settings, and other calibration choices  
119 followed those described in Ekberzade et al. (2024). To isolate the role of climate and vegetation in shaping  
120 potential fire regimes, anthropogenic ignitions and fire suppression were excluded, assuming fires arise  
121 exclusively from natural ignitions.

## 122 **2.3 Experimental design**

123 To characterize both current fire dynamics and potential changes in wildfire regimes, simulations were  
124 conducted in two stages: historical simulations and future projections. All post-simulation analyses were  
125 conducted using R and Python programming languages, Climate Data and NetCDF Operators (CDO/NCO).



126 **2.3.1 Historical simulations and pattern evaluation (1961–2025)**

127 In the first step, LPJ-GUESS coupled with SIMFIRE–BLAZE was forced with high-resolution reanalysis data  
128 for the historical period (1961–2025), and bias-corrected global climate model (GCM) datasets. These  
129 simulations were designed to assess the model's ability to reproduce observed spatial patterns and  
130 temporal variability of BA across the study region. Simulated BA, both from reanalysis and bias-corrected  
131 GCM datasets, was compared against satellite-derived burned area products using geospatial and  
132 statistical analyses.

133 Emphasis was placed on the spatial distribution and temporal variability of BA, rather than exact  
134 magnitudes, as even small anthropogenic interventions – which are absent in the experimental design –  
135 can produce disproportionately large observed burned areas (Ekberzade et al., 2025; Li et al., 2024;  
136 Hantson et al., 2016). Particular attention was given to natural vegetation zones, where natural ignitions  
137 are expected to drive fire activity more than anthropogenic ignitions (although the latter can still occur).  
138 Comparisons were performed for long-term means and interannual variability in burned area, allowing the  
139 identification of persistent wildfire hotspots and regions where simulated and observed fire patterns  
140 converged.

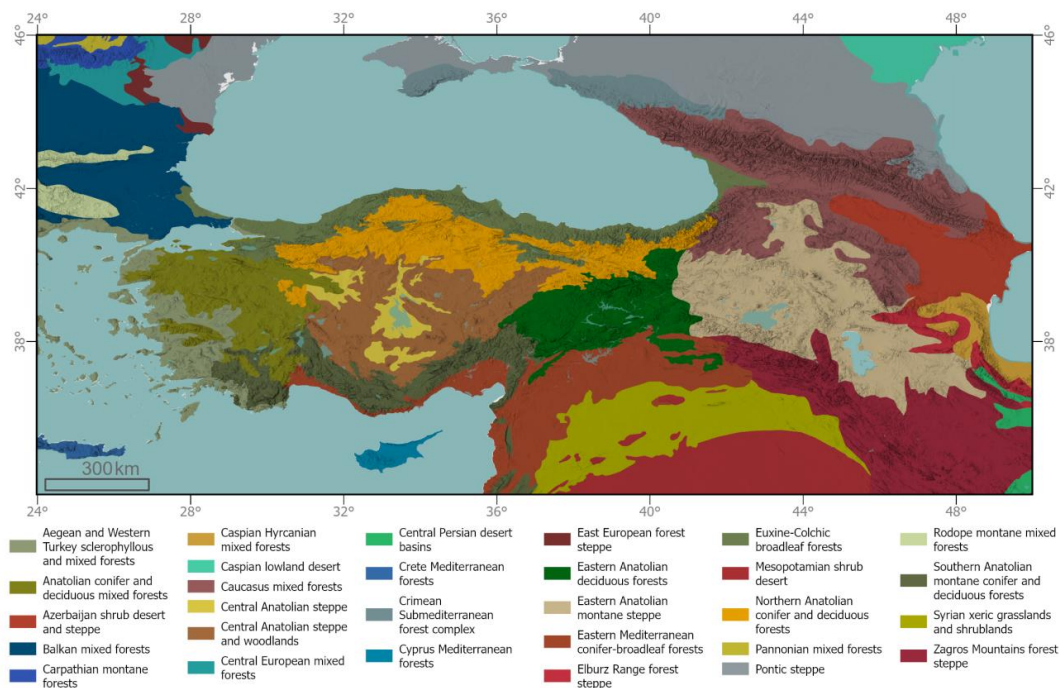
141 **2.3.2 Future projections (1961–2100)**

142 In the second step, an ensemble of simulations spanning 1961–2100 was conducted in which LPJ-GUESS  
143 was forced with bias-corrected, high-resolution global climate model (GCM) datasets. Bias correction was  
144 performed using the reference period 1995–2014, selected to represent contemporary climate conditions  
145 while overlapping with the observational period used for model evaluation. This ensures that the bias-  
146 corrected forcing reflects recent warming trends without relying on cooler late-20th-century climatologies.  
147 The SSP5-8.5 scenario was chosen as a high-end forcing pathway to explore the potential upper bound of  
148 climate-driven fire activity, intended as a stress test of ecosystem responses under strong warming and  
149 drying conditions rather than a deterministic prediction of future fire regimes. Simulation results were  
150 analyzed to examine potential changes in burned area, fuel availability (represented by FAPAR), and fire  
151 return intervals, with particular focus on fire-prone ecoregions and the emergence of new potential wildfire  
152 hotspots under strong warming and drying conditions.



153 **2.3.3 Spatial aggregation and ecoregion framework**

154 To evaluate model performance and characterize fire regime behavior across ecologically meaningful units,  
155 all analyses were conducted at the level of terrestrial ecoregions, since they delineate regions with relatively  
156 homogeneous climate, vegetation structure, fuel characteristics, and disturbance regimes, making them  
157 particularly suitable for fire-vegetation analyses. The Terrestrial Ecoregions of the World dataset by  
158 Dinerstein et al. (2017; data available from WWF, 2017) was selected as the primary spatial aggregation  
159 framework. A total of 29 of these ecoregions intersect the study area (Fig. 2). BA, vegetation, and fire  
160 regime metrics were aggregated annually within each ecoregion for both simulations and observations.  
161 Subsequent analyses focused on identifying ecoregions exhibiting persistent or recurrent fire activity (pyro-  
162 catchments), as well as those where fire occurrence is rare or episodic.



163 **Figure 2.** Ecoregions within the study area. The map is adapted from the dataset Terrestrial Ecoregions of  
164 the World (Dinerstein et al., 2017; data available from WWF, 2017), and shows the 29 ecoregions that were  
165 used as aggregation units in fire regime analyses. Note the diverse ecosystems in close proximity within  
166 the study domain.

167 **2.3.4 Model evaluation and statistical analysis**



168 Model performance was evaluated by comparing simulated BA from LPJ-GUESS–SIMFIRE–BLAZE  
169 against observed BA from the MODIS MCD64A1 dataset (Giglio et al., 2021). All datasets were aggregated  
170 to the 29 terrestrial ecoregions within the study domain to reduce scale mismatch between gridded model  
171 output and satellite observations. Annual BA was converted to square kilometers and normalized by  
172 ecoregion area to ensure comparability. Rather than pixel-level agreement, model evaluation focused on  
173 three complementary aspects of fire regime behavior: (1) spatial fire patterns across ecoregions, (2)  
174 interannual variability in burned area, and (3) persistence and dominance of high-fire years.

175 Spatial patterns were assessed by comparing long-term mean annual BA across ecoregions using  
176 Spearman rank correlation ( $\rho$ ). This approach evaluates the model's ability to correctly rank fire-prone  
177 versus fire-limited ecoregions, independent of absolute BA magnitude. Interannual variability was quantified  
178 by calculating the Spearman correlation between observed and simulated annual BA for each ecoregion.  
179 The distribution of these correlations was summarized using boxplots to evaluate overall model skill in  
180 capturing climate-driven fire activity.

181 To characterize recurrent fire activity and identify potential pyro-catchments, fire persistence was quantified  
182 for each ecoregion as the fraction of years in which BA exceeded the upper quartile of the local BA  
183 distribution. Ecoregions were ranked by this persistence metric to distinguish structurally fire-prone regions  
184 from those experiencing infrequent or episodic fires. Together, these analyses provide a regime-based  
185 evaluation of model performance across ecologically distinct fire environments, rather than a point-by-point  
186 comparison of burned area magnitudes.

187 Finally, the representation of extreme fire activity was evaluated by identifying, independently for  
188 observations and simulations, the year of maximum annual BA within each ecoregion and computing the  
189 absolute difference in peak-fire timing.

## 190 **2.4 Datasets**

### 191 **2.4.1 Climate datasets and bias correction**

192 For the historical analysis (1961–2025), LPJ-GUESS was forced with ERA5-Land reanalysis data. For the  
193 simulations including future projections (1961–2100), to ensure the robust representation of climate



194 variability and extreme events – which are critical drivers of wildfire dynamics in the SIMFIRE-BLAZE  
195 module – outputs from five GCMs (CMIP6, SSP5-8.5) were interpolated to  $0.1^\circ$  resolution, and bias-  
196 corrected against the 1995–2014 ERA5-Land reference period using Quantile Delta Mapping (QDM). QDM  
197 preserves the GCM-projected relative or absolute changes in all quantiles while effectively correcting  
198 systematic historical biases relative to the observational baseline (Supplementary Table S1 and Figs. S1–  
199 S7). ERA5-Land reanalysis data (aggregated to daily minimum, mean, maximum, and sum for precipitation)  
200 were utilized as the historical reference dataset. Prior to correction, all GCM calendars were standardized  
201 to a Gregorian leap-year calendar to ensure exact day-to-day temporal alignment with the reference  
202 observations.

203 The QDM algorithm was tailored to the specific physical boundaries of each meteorological variable. For  
204 precipitation, a multiplicative QDM approach was employed, applying a standard trace threshold of 0.1  
205 mm/day to stabilize correction factors and define discrete dry-day mass points, a necessary step for  
206 accurate soil hydrology modeling in LPJ-GUESS. Other lower-bounded variables, including surface wind  
207 speed, relative humidity, and solar radiation, were also corrected globally across the annual distribution.

208 Temperature variables ( $T_{min}$ ,  $T_{mean}$ ,  $T_{max}$ ) required specialized treatment to preserve the diurnal temperature  
209 range (DTR), which heavily dictates fuel moisture evaporation. Additive QDM was applied on a month-by-  
210 month basis. This monthly stratification prevented “all-seasons pooled ECDF” artifacts, wherein winter days  
211 and summer nights might otherwise be mapped across overlapping historical probability distributions,  
212 thereby artificially flattening the DTR. Because QDM corrects variables independently, minor statistical  
213 divergences can occasionally cause physical inversions (e.g.,  $T_{min} > T_{mean}$ ). To ensure thermodynamic  
214 stability within the LPJ-GUESS soil heat flux and snowpack modules, standard physical consistency rules  
215 were enforced pixel-by-pixel as a post-processing step, mathematically constraining daily temperatures  
216 such that  $T_{min} \leq T_{mean} \leq T_{max}$ . This comprehensive pipeline yielded physically consistent, CF-compliant  
217 forcing datasets that fully preserve the GCM climate change signals at the extreme tails of the distribution.

#### 218 **2.4.2 Soil**

219 LPJ-GUESS requires a soil dataset reflecting soil percolative properties. Using the R programming  
220 language and geospatial software, this dataset was constructed at 9 km resolution with data from the



221 National Soil Dataset for Türkiye and the Harmonized World Soil Database (HWSD v.2.0; FAO & IIASA,  
222 2023) for the neighboring regions.

### 223 **2.4.3 Drought Analysis**

224 Because LPJ-GUESS–SIMFIRE–BLAZE simulates natural fire potential strictly as a function of biophysical  
225 and climatic drivers, an independent assessment of regional hydroclimate was required to contextualize  
226 the simulation results. Specifically, to explain the timing of simulated wildfire episodes and to understand  
227 the spatial divergences between climate-driven simulations and human-influenced observations, trend  
228 analyses of the Standardized Precipitation Evapotranspiration Index (SPEI) at multiple temporal scales  
229 were conducted. This allowed for an assessment of how cumulative drying in preceding years influences  
230 vegetation conditions and, consequently, wildfire risk.

231 Unlike simple precipitation metrics, SPEI accounts for the influence of temperature (through potential  
232 evapotranspiration), making it a critical tool for identifying climate-change-induced drying. SPEI datasets at  
233 1, 3, 6, 9, 12, 24, and 48-month resolutions were obtained from the ERA5 reanalysis (0.25° spatial  
234 resolution). The analysis period was extended to 1991–2025 – predating the burned area record – to  
235 capture the cumulative effects of antecedent drying on fuel characteristics and to detect long-term shifts in  
236 the regional moisture balance.

237 Monotonic trends were assessed using the non-parametric Mann–Kendall test, with magnitudes estimated  
238 via Sen’s slope. To account for serial correlation inherent in hydroclimatic time series, Hamed–Rao  
239 modification was applied, and a False Discovery Rate (FDR) correction was enforced to minimize false  
240 positives among significant grid cells. The results were visualized through spatial trend maps and Hovmöller  
241 diagrams to illustrate the latitudinal evolution of drought for the study area over time. Additionally, drought  
242 persistency was evaluated by mapping the frequency of severe ( $\text{SPEI} \leq -1.5$ ) and extreme drought ( $\text{SPEI}$   
243  $\leq -2.0$ ), and by calculating inter-index correlations with lags of 0, 6, and 12 months.

### 244 **2.4.4 Burned Area**

245 Burned area (BA), used for comparative analyses with simulation results, was quantified using the MODIS  
246 Collection 6.1 MCD64A1 product (Giglio et al., 2021). This dataset provides pixel-level burn detections at  
247 approximately 500 m resolution, identifying burned pixels based on changes in surface reflectance and



248 thermal anomalies. These detections were aggregated to the study's master grid in the WGS84 spatial  
249 reference (EPSG:4326) to align with LPJ-GUESS simulations. Grid cell areas were explicitly calculated  
250 using the ellipsoidal area function in the *terra* R package to account for the latitudinal variation in cell size  
251 inherent to geographic coordinate systems.

252 BA was temporally aggregated to monthly intervals by assigning pixels to their detection year and month.  
253 These monthly fields were summed annually, and the final outputs were exported in comma-separated  
254 values (CSV) format to facilitate spatial analysis in ArcGIS. To ensure consistency with parallel analyses  
255 using other datasets (e.g., FireCCI), quality assurance (QA) filtering was evaluated but not enforced beyond  
256 the default classification. Sensitivity testing showed that restricting analysis to higher-confidence detections  
257 produced negligible differences in regional BA totals, indicating that QA filtering does not materially alter  
258 large-scale BA estimates for the study area.

259 To assess observational uncertainty, MCD64A1 was cross-validated against the gridded FireCCI51  
260 (MODIS-derived for years 2002–2020; Lizundia-Loiola et al., 2020) and FireCCIS311 (Sentinel-derived for  
261 years 2019–2024; Chuvieco et al., 2024). While all three products exhibited identical interannual trends,  
262 FireCCI algorithms proved significantly more conservative in this region, consistently estimating lower total  
263 BA than MCD64A1 (Fig. A3). Given the likelihood of omission errors in conservative algorithms over  
264 discontinuous fuel beds, MCD64A1 was selected as the primary benchmark for model evaluation.

265 For aggregation of burned area by ecoregion, the Terrestrial Ecoregions of the World dataset by Dinerstein  
266 et al. (2017; data available from WWF, 2017) was used, cropped to the study domain in geospatial software  
267 and imported to RStudio for further analyses.

### 268 **3. Results**

269 Results are presented in three stages. First, the ability of LPJ-GUESS–SIMFIRE–BLAZE to reproduce  
270 historical fire regimes is evaluated against satellite observations (MCD64A1, 2001–2024), with emphasis  
271 on interannual variability, biome-specific biases, and fire persistence. This historical benchmarking uses  
272 both sets of simulations in its comparisons: those forced by phased historical reanalysis (ERA5-Land), and  
273 those forced by the Quantile Delta Mapping (QDM) bias-corrected GCM ensemble median.



274 Second, observed hydroclimatic trends are examined to establish the regional drought signal that drives  
275 fire activity in the northeastern Mediterranean. Finally, building on this evaluation, model projections are  
276 used to explore potential changes in burned area (BA), fuel characteristics, and fire return intervals under  
277 a high-emissions climate scenario (SSP5-8.5).

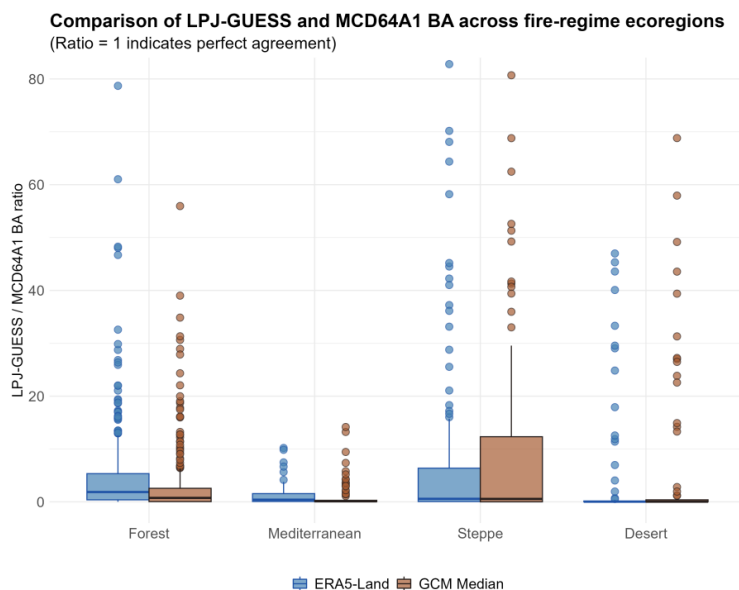
### 278 **3.1 Evaluation of Fire Regimes during the Satellite Era (2001–2025)**

#### 279 **3.1.1 Biome-specific magnitude and model performance**

280 LPJ-GUESS simulations, driven by both historical reanalysis and the GCM ensemble median, reveal  
281 systematic fire-regime-dependent divergences when compared to MODIS satellite observations. Despite  
282 the central tendency of the GCM ensemble results – maintaining an observation/simulation bias ratio close  
283 to 1.0 – these divergences point to the difference between simulated natural (climate-driven) fire potential  
284 and observed fire activity (including human interference), particularly in arid and semi-arid ecoregions (Fig.  
285 3). Mediterranean ecosystems exhibit the closest agreement between simulated and observed burned  
286 area, with median LPJ-GUESS/MODIS ratios near unity. In contrast, steppe and desert ecosystems display  
287 a much wider spread in simulated-to-observed ratios, a large interquartile range, and frequent  
288 overestimation despite an accurate median agreement. While the model/observation bias ratio for the forest  
289 ecoregions lies closer to 1.0 in the GCM ensemble results, both simulations still show moderate  
290 overestimation relative to MODIS observations. This pattern is consistent with the absence of explicit fire



291 suppression in the experimental design, allowing simulated fire activity to reflect potential flammability under  
292 climatic and vegetation controls alone.

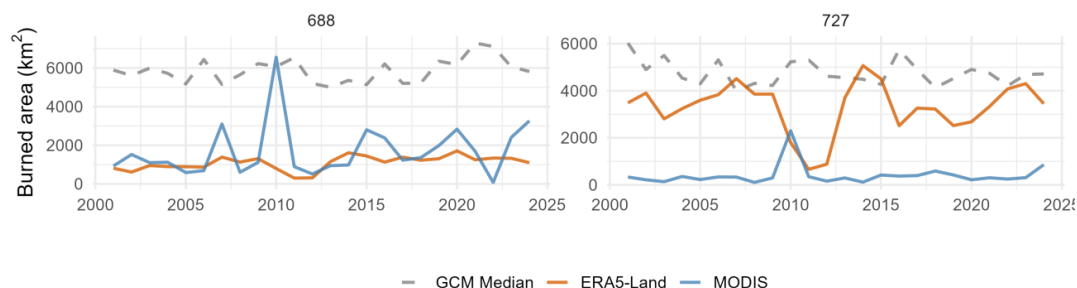


293 **Figure 3.** Distribution of simulated-to-observed burned area ratios grouped by biome. Mediterranean  
294 ecoregions show closer agreement with observations, while steppe ecosystems exhibit larger spread and  
295 systematic overestimation.

296 For the steppe ecosystems, the overestimations are particularly evident in ecoregions such as the Zagros  
297 Mountains forest steppe and the Eastern Anatolian montane steppe, where anthropogenic land use and  
298 landscape modification (e.g., agriculture, grazing, and fire management) strongly influence fire activity (Fig.  
299 4; for all ecoregions and the reference table: Fig. A1 and Table A1). In these ecoregions, simulated burned  
300 area remains consistently higher than MODIS observations, indicating that the model maintains persistent  
301 climate-driven fire potential while observed burned area reflects more constrained fire activity. Conversely,  
302 during years with strong climatic forcing, ensemble simulations and observations converge, as in 2010, a

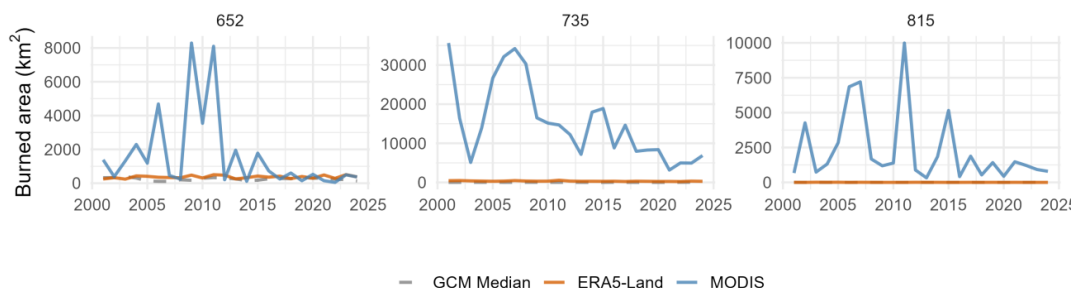


303 pronounced fire year for the Zagros and Eastern Anatolian regions, coinciding with documented regional  
 304 heatwave conditions and climate anomalies (Heidarlou et al., 2024).



305 **Figure 4.** Historical burned area trajectories across semi-arid ecoregions. Comparison of annual BA (km<sup>2</sup>)  
 306 simulated by LPJ-GUESS (ERA5-Land orange, GCM ensemble median grey) versus observed by MODIS  
 307 MCD64A1 (blue) for Zagros Mountains forest steppe [688] and Eastern Anatolian montane steppe [727]  
 308 ecoregions. Simulation results for the GCM ensemble median show a significant and steady overshoot,  
 309 except for 2010.

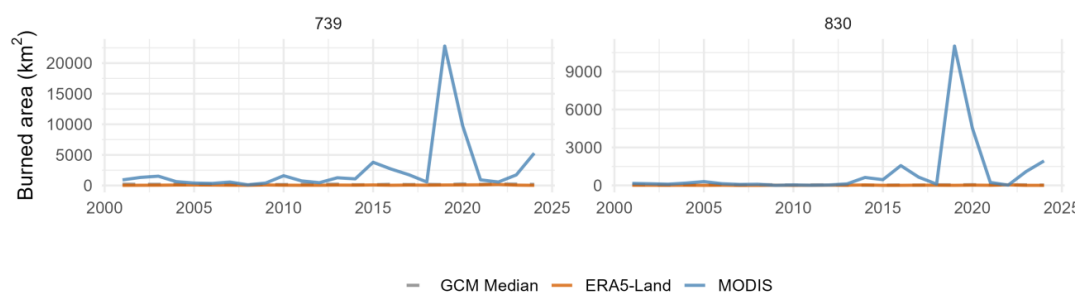
310 In contrast, several steppe and desert ecoregions display pronounced spikes in observed burned area that  
 311 are not reproduced by either the reanalysis-driven simulations or the GCM ensemble results. This pattern  
 312 is evident in Central Anatolian and Pontic steppe landscapes, as well as parts of the Caspian lowland desert  
 313 ecoregion, where MODIS observations show dynamic fluctuations in burned area while simulated burned  
 314 area values remain stable and low. The peaks in the satellite record coincide with agricultural regions where  
 315 post-harvest stubble burning is common, suggesting that these spikes reflect anthropogenic ignitions within  
 316 cropland mosaics rather than climate-driven wildfire activity.



317 **Figure 5.** Historical burned area trajectories across arid/semi-arid ecoregions. Comparison of annual BA  
 318 (km<sup>2</sup>) simulated by LPJ-GUESS (ERA5-Land orange, GCM ensemble median grey) versus observed by  
 319 MODIS MCD64A1 (blue) for Central Anatolian steppe and woodlands [652], Pontic steppe [735], and  
 320 Caspian lowland desert [727] ecoregions. MODIS observations show a continuous overshoot where  
 321 simulation results record minimal wildfire activity. These ecoregions coincide with cropland mosaics.



322 A similar divergence appears in the Syrian xeric grasslands and the Mesopotamian shrub desert  
 323 ecoregions. Here, MODIS observations exhibit an anomalous spike around 2019, while simulations remain  
 324 comparatively low. This increase coincides with the period of regional instability associated with the Syrian  
 325 civil war, suggesting that the satellite-detected burned area may result from conflict-related disturbances  
 326 rather than climate-driven wildfires.



327 **Figure 6.** Historical burned area trajectories across arid ecoregions. Comparison of annual BA (km<sup>2</sup>)  
 328 simulated by LPJ-GUESS (ERA5-Land orange, GCM ensemble median grey) versus observed by MODIS  
 329 MCD64A1 (blue) for Syrian xeric grasslands and shrublands [739] and Mesopotamian shrub desert [830]  
 330 ecoregions. The spike in 2019 in MODIS observations coincides with the 2019 Syrian civil war.

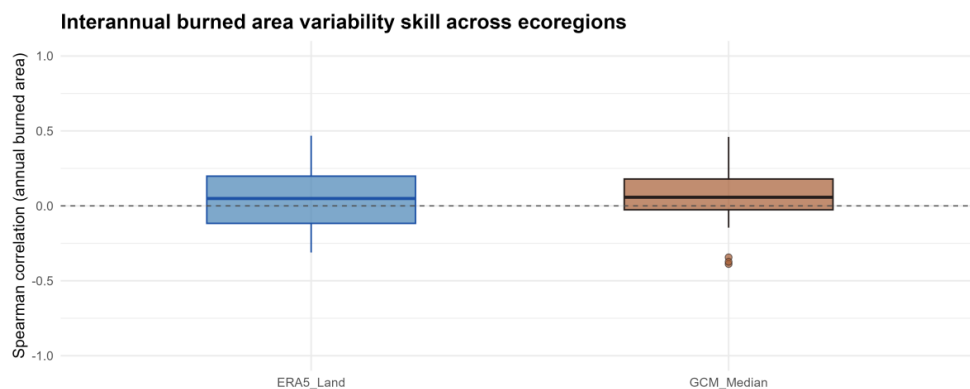
331 Consequently, these spatial heterogeneities contribute to weak overall agreement in long-term mean  
 332 annual burned area across the full domain (Spearman  $\rho = 0.17$  for ERA5,  $\rho = 0.15$  for the GCM median,  
 333 Fig. A2). However, comparisons of total annual burned area indicate that simulated magnitudes remain  
 334 broadly consistent with satellite-based estimates. In particular, the GCM ensemble median closely follows  
 335 the observed totals and occasionally approaches values derived from Sentinel-based burned area products  
 336 (Fig. A3). Taken together, these results indicate that while the model reproduces the overall magnitude and  
 337 biome-scale structure of burned area across the Eastern Mediterranean, local anthropogenic influences  
 338 strongly shape the spatial distribution of fire activity observed in satellite records.

### 339 3.1.2 Interannual variability and validation

340 Despite the spatial biases described above, the simulations demonstrate measurable skill in reproducing  
 341 the timing of fire activity. Interannual variability in burned area shows generally positive correlations with  
 342 satellite observations across ecoregions, indicating that the model captures portions of the year-to-year  
 343 variability in fire occurrence (Fig. 7). Both the ERA5-driven simulations and the GCM ensemble median  
 344 exhibit similar distributions of Spearman correlations, with median correlation values modest but positive,



345 indicating several regions displaying stronger agreement between simulated and observed annual burned  
346 area. This pattern suggests that large-scale climatic variability captured in the forcing datasets contributes  
347 to the timing of high-fire years in the simulations, even where the spatial magnitude of burned area differs  
348 from observations.

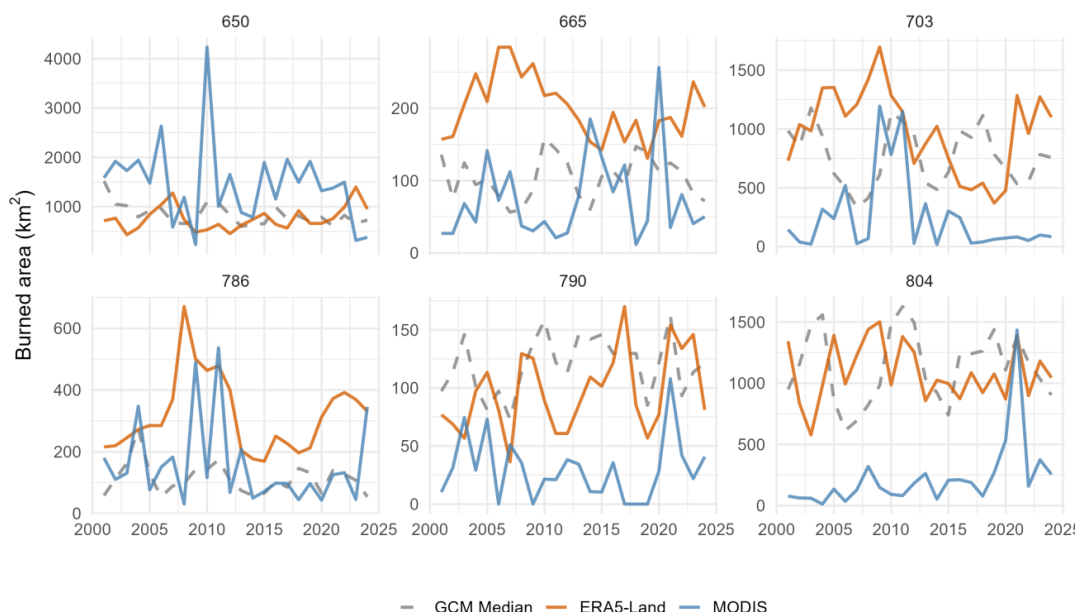


349 **Figure 7.** Interannual burned area variability across ecoregions. Spearman correlation coefficients  
350 quantifying the agreement between simulated and observed annual burned area time series across  
351 ecoregions.

### 352 3.1.3 Capture of extreme events and fire persistence

353 While interannual correlations remain modest across ecoregions, the simulations demonstrate stronger skill  
354 in identifying the timing of major fire episodes. Comparison of peak fire years between simulations and  
355 observations shows non-random agreement across ecoregions (Fig. A4). The median absolute difference  
356 in peak fire year is approximately 7 years, with 25% of ecoregions differing by fewer than 3 years. This  
357 temporal alignment is further illustrated in Figure 8, which compares annual burned area trajectories across  
358 a set of ecologically diverse forest ecoregions spanning Mediterranean, montane, and transitional systems.

359 In Mediterranean systems such as the Cyprus Mediterranean forests [790] and the Southern Anatolian  
360 montane conifer and deciduous forests [804], the model captures the timing of major fire episodes, including  
361 peaks in the late 2000s and around 2020, although simulated burned area generally exceeds observed  
362 values. In the Euxine-Colchic broadleaf forests [665], simulations driven by ERA5-Land, and occasionally  
363 by the GCM ensemble median, indicate consistently higher fire activity than observed in the satellite record.



364 **Figure 8.** Historical burned area trajectories across forest ecoregions. Comparison of annual BA (km<sup>2</sup>)  
 365 simulated by LPJ-GUESS (ERA5-Land orange, GCM ensemble median grey) versus observed by MODIS  
 366 MCD64A1 (blue) for six ecologically distinct regions. (Top Row) Caucasus mixed forests [650], Euxine-  
 367 Colchic broadleaf forests [665], and Northern Anatolian conifer and deciduous forests [703]. (Bottom Row)  
 368 Anatolian conifer and deciduous mixed forests [786], Cyprus Mediterranean forests [790], and Southern  
 369 Anatolian montane conifer and deciduous forests [804].

370 In montane and transitional regions such as the Anatolian conifer and deciduous mixed forests [786], the  
 371 model reproduces background levels of fire activity as well as periodic increases in burned area. The GCM  
 372 ensemble median generally follows the timing of observed burned area and, on occasion, the magnitude,  
 373 while the ERA5-Land simulation tends to produce larger burned areas but captures the overall temporal  
 374 trend. In the Southern Anatolian montane conifer and deciduous forests [804], the peak fire year of 2021 is  
 375 reproduced in both simulation datasets. Lower burned area levels observed during much of the remaining  
 376 period likely reflect the influence of fire suppression. A similar pattern is visible in the Cyprus Mediterranean  
 377 forests [790].

378 In addition to reproducing the timing of major fire episodes, the simulations capture the strong spatial  
 379 concentration of fire activity across the region. Analysis of observed burned area indicates that extreme fire  
 380 years are disproportionately associated with a limited subset of ecoregions, as illustrated by the Fire  
 381 Dominance Index (Fig. A5). Several regions exhibit consistently elevated frequencies of high-burned-area



382 years, effectively functioning as regional “pyro-catchments” where fire activity repeatedly concentrates. This  
383 persistence indicates that the model captures the landscape and climatic conditions associated with  
384 recurrent fire activity across the Eastern Mediterranean.

385 Overall, LPJ-GUESS historical simulations reproduce the climatic envelope and domain-scale magnitude  
386 of burned area across the Eastern Mediterranean, while spatial discrepancies primarily reflect the influence  
387 of anthropogenic land management and fire suppression, which are absent from the experimental design.

### 388 **3.2 Hydroclimatic Drivers of Fire Activity**

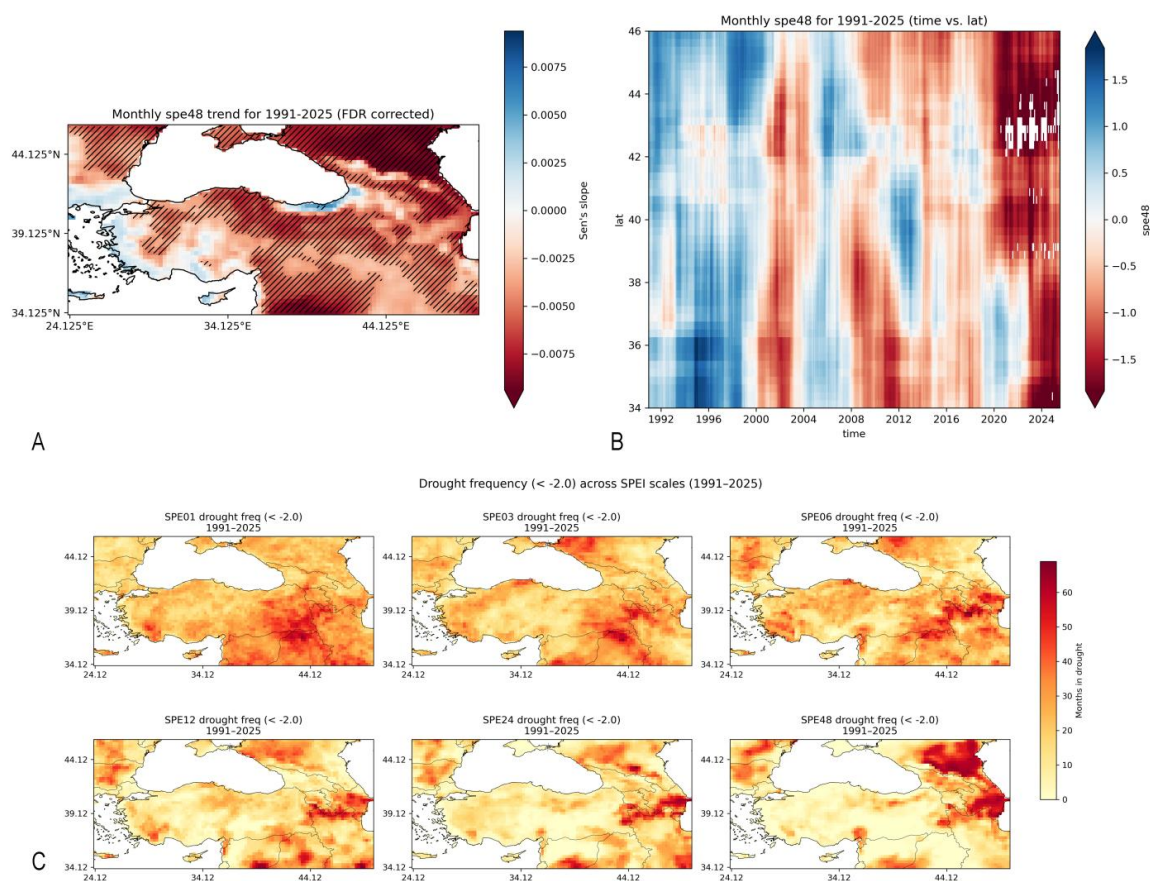
#### 389 **3.2.1 Regional drought trends**

390 Trend analysis of the ERA5-Land reanalysis data (1991–2025) revealed a strong and spatially coherent  
391 drought signal across the majority of the study region at all temporal scales. Negative SPEI trends emerged  
392 around 2008 and persisted through the remainder of the record, becoming stronger from 2015 onwards  
393 (Fig. 9b). This intensification was most pronounced at longer accumulation periods (e.g., SPEI-48),  
394 indicating a structural shift toward hydrologic deficit rather than merely seasonal variability (Fig. 9a). Parallel  
395 drying patterns were observed across all shorter temporal scales (SPEI-1 through SPEI-24; Figs. S9 and  
396 S10).

#### 397 **3.2.2 Coupling with fire activity**

398 The spatial distribution of this drying trend aligned closely with the region’s fire regime. Areas exhibiting  
399 statistically significant negative SPEI trends (Fig. 9a) generally coincided with zones of elevated burned  
400 area (BA) observed in the MCD64A1 record (2001–2024). Furthermore, the spatial persistence of severe  
401 drought conditions (SPEI < -2.0) between 1991 and 2025 was particularly evident in parts of the study area  
402 characterized by high clustering of BA (Fig. 9c).

403 Lagged correlation analyses between intermediate (SPEI-06 to SPEI-12) and longer-term drought indices  
404 (SPEI-24 to SPEI-48) further revealed similar spatial patterns of drought persistence (Figs. S8–S10).  
405 Together, these results indicate a persistent and intensifying drought signal across fire-prone portions of  
406 the study domain, providing the hydroclimatic backdrop against historical fire activity and establishing the  
407 baseline necessary to interpret the divergences between the simulations and observations.



408 **Figure 9.** Intensification of regional drought conditions (1991–2025). (a) Spatial distribution of the trend in  
 409 long-term drought (SPEI-48) using Sen's slope estimator. Hatched areas indicate statistically significant  
 410 trends ( $p < 0.05$ ), highlighting a broad drying signal across the northeastern Mediterranean. (b) Hovmöller  
 411 diagram (Time vs. Latitude) of monthly SPEI-48, illustrating the temporal shift from wetter conditions (blue)  
 412 to persistent, severe drying (red) beginning circa 2008 and intensifying after 2015. (c) Frequency of severe  
 413 drought months ( $SPEI \leq -2.0$ ) across varying accumulation periods (1–48 months). Note the spatial  
 414 concentration of high drought frequency in the southern and eastern sectors of the domain, coincident with  
 415 regions of high fire recurrence.

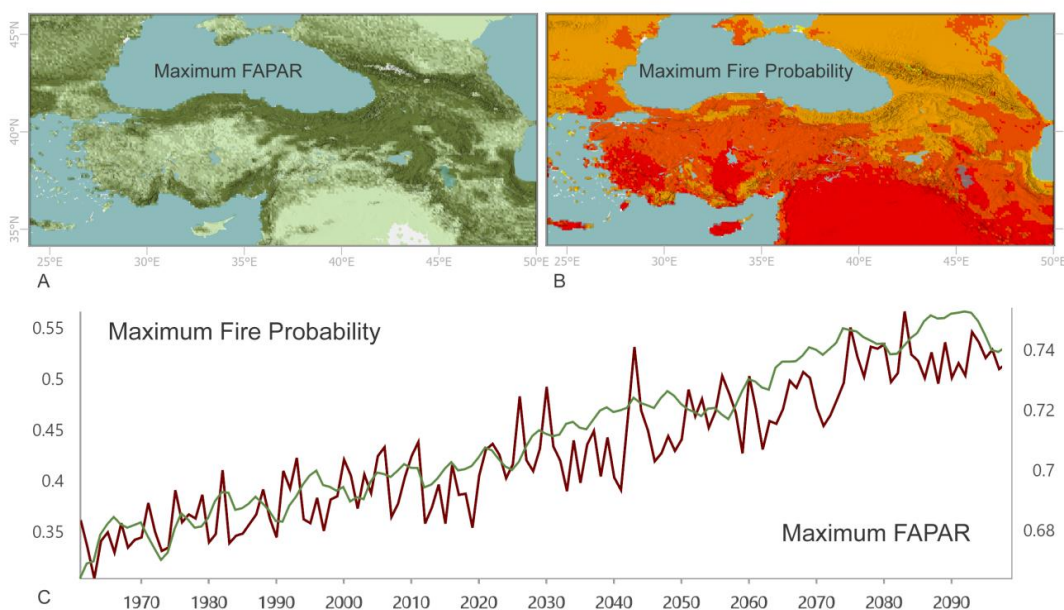
### 416 3.3 Long-term fire and vegetation trajectories (1961–2100)

417 To assess potential future risks relative to the historical trajectory, the simulation period from 1961 to 2100  
 418 was analyzed. This timespan encompasses the historical baseline (1961–2014) and the projected response  
 419 under the high-emissions SSP5-8.5 scenario (2015–2100). Overall, projected changes in vegetation  
 420 productivity and fire dynamics reveal a heterogeneous reorganization of fire regimes across the Eastern  
 421 Mediterranean region.



422 **3.3.1 Vegetation productivity and fire probability**

423 Simulated vegetation productivity, represented by the maximum annual fraction of absorbed  
 424 photosynthetically active radiation (FAPAR), shows a pronounced increase in the highland regions of the  
 425 study area by the end of the century (Fig. 10a). A strong increase with full vegetation connectivity can be  
 426 seen in northern Anatolia, along the Black Sea coast. In contrast, the largest increases in maximum fire  
 427 probability occur primarily in the interior arid and semi-arid regions, including south-central Anatolia and  
 428 northern Mesopotamia (Fig. 10b). These areas exhibit high projected fire probability maxima despite  
 429 relatively modest increases in FAPAR, indicating that climatic drivers of fire weather dominate over fuel  
 430 availability in these landscapes.



431 **Figure 10.** Projected shifts in vegetation and fire probability (1961–2100). (a) Spatial distribution of  
 432 cumulative maximum FAPAR (Fraction of Absorbed Photosynthetically Active Radiation) simulated under  
 433 SSP5-8.5, indicating regions of high fuel continuity. (b) Spatial distribution of cumulative maximum fire  
 434 probability, highlighting the high-risk zones in western and central Anatolia, Cyprus, and the Middle East.  
 435 (c) Regional time series of maximum FAPAR (green) and maximum fire probability (red). Note the  
 436 synchronous rise in both metrics towards 2100, suggesting that future fire regimes could be driven by  
 437 abundant fuel loads interacting with increased ignition probability, potentially leading to significantly shorter  
 438 fire return intervals.

439 In the northeastern highlands, where the Northern Anatolian Mountains transition into the Caucasus range,  
 440 maximum fire probability remains comparatively modest despite high vegetation productivity. A similar

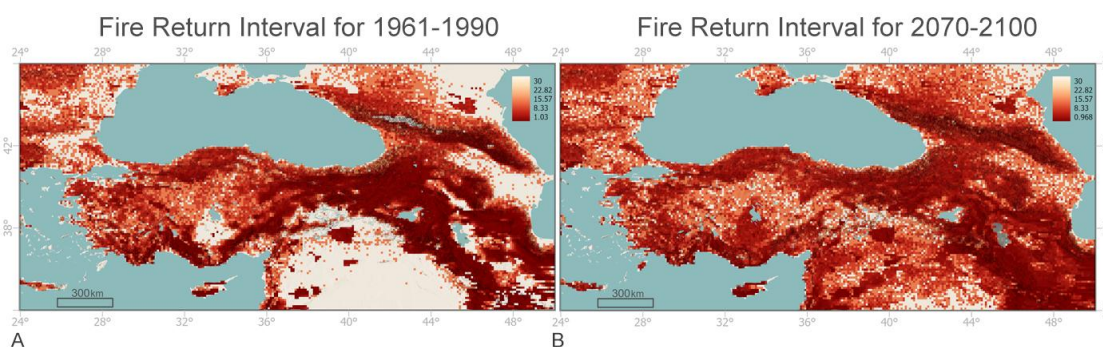


441 pattern is observed across parts of the Taurus Mountains, where FAPAR increases but fire probability  
442 remains spatially heterogeneous. These patterns suggest that topographic and climatic factors continue to  
443 limit the conditions necessary for large fire events in these high-elevation systems.

### 444 3.3.2 Changes in fire return intervals

445 Projected fire return intervals (FRI) indicate an overall increase in fire frequency across large parts of the  
446 region (Fig. 11). At the beginning of the simulation period, highland systems such as the eastern Anatolian  
447 highlands, the Caucasus, the Zagros Mountains, and the Taurus Mountains already exhibit relatively short  
448 FRI compared with the surrounding lowlands.

449 By the end of the century, substantial reductions in FRI emerge across several semi-arid regions. In  
450 particular, parts of southern Central Anatolia and the Zagros steppe regions transition from historically long  
451 fire return intervals (approximately 30 years) to much more frequent fire regimes, with projected intervals  
452 approaching one to two years. In contrast, high-elevation systems such as the Taurus Mountains exhibit  
453 comparatively stable FRI over the simulation period. These regions already experience relatively frequent  
454 fires in the historical period, and projected changes in fire frequency remain modest relative to those  
455 observed in the interior semi-arid zones.

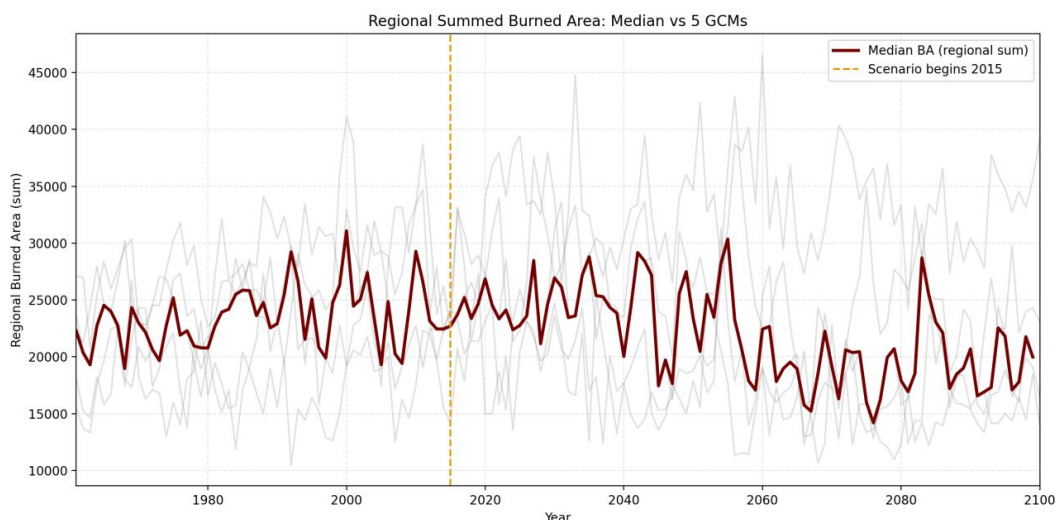


456 **Figure 11.** Projected intensification of fire cycles under SSP5-8.5. Comparison of the Fire Return Interval  
457 (FRI) in years between the historical baseline (1961–1990, left) and the end-of-century projection (2070–  
458 2100, right). Darker red colors indicate shorter return intervals (higher fire frequency). Note the significant  
459 shortening of intervals in the historically fuel-limited Central Anatolian and northern Mesopotamian regions,  
460 indicating a transition toward more frequent fire activity.

### 461 3.3.3 Regional burned area trajectories



462 Despite the projected increases in fire probability and fire frequency across parts of the region, the  
463 simulated median burned area across the Northeast Mediterranean remains relatively stable over the  
464 course of the simulation (Fig. 12). After a gradual rise during the late twentieth century, regional burned  
465 area exhibits a mild decline toward the end of the twenty-first century.



466 **Figure 12.** Future burned area trajectories under SSP5-8.5. Time series of regional summed annual BA  
467 (km<sup>2</sup>) from 1961 to 2100. Grey lines represent individual ensemble members from five bias-corrected  
468 GCMs; the dark red line represents the ensemble median. The vertical dashed line marks the start of the  
469 future scenario (2015). Despite high interannual variability, the projections indicate a sustained regime of  
470 elevated fire activity throughout the century without a monotonic surge in total area burned.

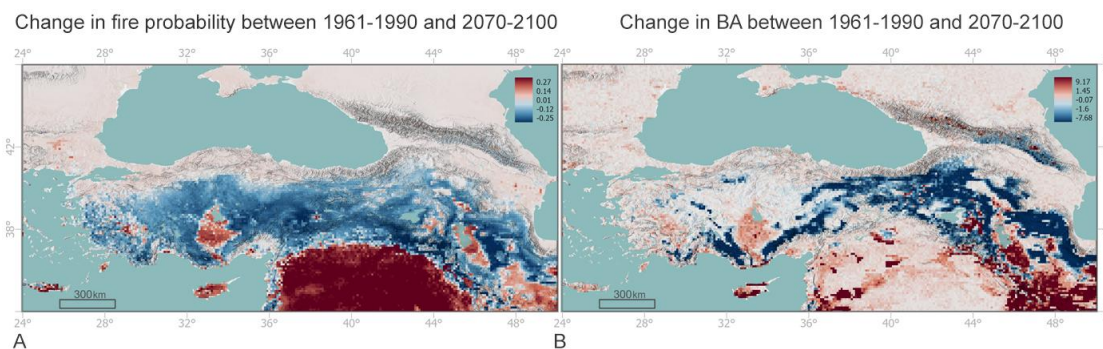
471 Uncertainty among climate model projections remains substantial, however. While the ensemble median  
472 indicates relatively stable burned area, individual GCM members show considerable spread, with some  
473 simulations projecting substantially higher burned area toward the end of the century, while others remain  
474 closer to the ensemble median. These results indicate that regional burned area trends are strongly  
475 influenced by spatial heterogeneity in fire regime responses across the study region.

### 476 3.3.4 Spatial redistribution of fire activity

477 Spatial patterns of projected fire regime change further highlight this regional heterogeneity (Fig. 13).  
478 Interior semi-arid regions, particularly Central Anatolia and northern Mesopotamia, exhibit strong increases  
479 in fire probability, with some locations showing increases exceeding 25%. However, these areas do not  
480 experience comparable increases in burned area, suggesting that more frequent but spatially limited fires



481 dominate these landscapes. In contrast, the Zagros steppe region shows concurrent increases in both fire  
482 probability and burned area, indicating an expansion of fire activity in this transitional landscape.



483 **Figure 13.** Projected spatial redistribution of fire activity (2070–2100 vs. 1961–1990). (a) Change in mean  
484 fire probability. (b) Change in BA (future minus historical) for the GCM ensemble median. Warm colors  
485 indicate an increase, highlighting the expansion of risk into southern lowlands.

486 Across parts of the Aegean region, fire probability decreases, whereas some Mediterranean island systems,  
487 including Cyprus, show localized increases. In the Taurus Mountains and parts of the eastern Anatolian  
488 highlands, simulated burned area declines despite increasing vegetation productivity and relatively stable  
489 fire return intervals. These patterns suggest that while fires remain frequent in these mountainous systems,  
490 their spatial extent may become more constrained.

491 Together, these simulation results indicate a spatial redistribution of fire regimes across the Eastern  
492 Mediterranean, with a potential increase in fire activity concentrated in semi-arid interior regions and parts  
493 of the Zagros steppe systems, while several montane forest regions experience more limited fire spread  
494 despite increasing vegetation productivity.

#### 495 **4. Discussion**

496 The simulations presented here suggest that future wildfire dynamics across the Northeast Mediterranean  
497 are likely to be shaped less by a uniform intensification of fire activity and more by a spatial redistribution  
498 of fire regimes. While rising temperatures and increasing atmospheric dryness elevate fire probability  
499 across much of the region, the resulting fire outcomes vary substantially depending on vegetation  
500 productivity, topography, and regional hydroclimatic conditions.



501 One of the most consistent signals emerging from the simulations is the growing importance of semi-arid  
502 interior landscapes, particularly Central Anatolia, northern Mesopotamia, and the Zagros steppe regions,  
503 as zones of increasing fire potential. In these regions, projected increases in fire probability occur despite  
504 relatively modest increases in vegetation productivity. This suggests that future fire regimes in these  
505 landscapes may become increasingly governed by climatic fire weather rather than fuel availability alone.  
506 The pronounced shortening of fire return intervals in parts of the Central Anatolian and the Zagros steppe  
507 ecoregions further indicates that historically infrequent fires may transition toward much more frequent  
508 disturbance regimes under continued warming and drying.

509 In contrast, several montane and northern forested regions exhibit a different trajectory. Along the southern  
510 Black Sea coast and across parts of northern Anatolia, simulated vegetation productivity increases  
511 substantially, reflecting enhanced growing conditions under warmer climates. However, these increases in  
512 fuel availability do not translate into proportional increases in fire probability or burned area. A similar pattern  
513 emerges across portions of the Taurus Mountains and the northeastern Anatolian highlands, where fire  
514 probability remains spatially heterogeneous despite increasing FAPAR. These results suggest that  
515 topographic complexity, cooler microclimates, and moisture availability may continue to constrain the  
516 spread of large fires in high-elevation systems, even as vegetation productivity increases.

517 Taken together, these patterns indicate that future fire regimes in the region may become more  
518 heterogeneous, with expanding fire activity in semi-arid transition zones and comparatively stable or  
519 spatially constrained fire regimes in several mountainous forest systems. This divergence between fire  
520 probability, fire frequency, and burned area highlights the importance of considering multiple fire regime  
521 metrics simultaneously when assessing future wildfire risk.

522 An additional notable feature of the projections is that regional burned area does not increase uniformly  
523 despite rising fire probability. The ensemble median suggests relatively stable or slightly declining burned  
524 area toward the end of the century, although individual climate model realizations exhibit substantial spread.  
525 This outcome likely reflects the spatial redistribution of fire activity across the region, where increases in  
526 fire frequency in some semi-arid landscapes are offset by reduced fire spread or more spatially limited fires  
527 in several forested mountain regions.



528 Overall, the simulations point toward a reorganization rather than a simple intensification of fire regimes  
529 across the Northeast Mediterranean, with important implications for ecosystem resilience, land  
530 management, and future wildfire risk.

#### 531 **4.1 The “Human Gap”: Interpreting model–observation divergences in managed landscapes**

532 Comparison between LPJ-GUESS–SIMFIRE–BLAZE simulations and satellite-derived burned area reveals  
533 a consistent pattern: the model captures the temporal variability of fire activity with notable skill, while  
534 systematic differences in spatial magnitude emerge across heavily managed landscapes. Rather than  
535 representing model failure, these divergences reflect the intentional design of the simulation framework.  
536 The simulations presented here isolate the biophysical controls on fire regimes by excluding anthropogenic  
537 ignition and suppression processes, which are highly complex and difficult to parameterize reliably.  
538 Consequently, the model represents a baseline estimate of the potential natural fire regime, whereas the  
539 satellite record reflects the contemporary anthropogenic fire regime shaped by land management,  
540 suppression infrastructure, and land-use fragmentation. The difference between these two signals therefore  
541 provides a useful diagnostic of the human imprint on regional fire dynamics.

542 This contrast is particularly visible in forested landscapes, where the model consistently produces higher  
543 burned area than satellite observations. In ecoregions such as the Northern Anatolian conifer forests and  
544 the Balkan mixed forests, the simulated overestimation of burned area likely reflects a suppression deficit,  
545 representing the magnitude of fire activity that current climatic conditions could support in the absence of  
546 effective fire suppression. In reality, the majority of these landscapes are heavily managed, and fire  
547 response systems across Türkiye and southeastern Europe routinely extinguish small ignitions before they  
548 can develop into large fires. While this management success masks the true climatic flammability of these  
549 ecosystems, the simulations indicate that these forests remain climatically capable of supporting  
550 substantially larger burn rates under favorable fire weather conditions (e.g., Caspian Hyrcanian mixed  
551 forests [649] and Euxine-Colchic broadleaf forests [665]). In this sense, the divergence between simulated  
552 and observed burned area may be interpreted as a latent “fire debt,” representing fire activity that is currently  
553 suppressed but could emerge if suppression capacity were overwhelmed during extreme fire seasons.



554 A complementary warning signal appears in steppe and agricultural transition zones such as the Central  
555 Anatolian Steppe [725]. In these landscapes, the model tends to underestimate observed burned area in  
556 historical simulations, primarily because LPJ-GUESS represents continuous potential vegetation, whereas  
557 the real landscape is fragmented by croplands and infrastructure. Human land use therefore dampens the  
558 spread of climate-driven fires while simultaneously elevating anthropogenic fire occurrence. However, this  
559 relationship shifts in the future simulation results, where LPJ-GUESS projects a transition toward more  
560 frequent, climate-driven fire activity in these regions. Given the current agricultural dominance of these  
561 landscapes, this projected shift from fragmented, human-modulated fire regimes toward shorter fire return  
562 intervals and more continuous burning represents a substantial and potentially disruptive change in system  
563 behavior.

564 Taken together, these contrasting patterns indicate that human land management currently acts as both a  
565 suppressor and redistributor of fire activity across the region, but its ability to buffer against climate-driven  
566 fire regimes may become increasingly constrained under future hydroclimatic conditions.

#### 567 **4.2 Hydroclimatic forcing and the role of extreme fire weather**

568 Understanding the divergence between historical simulations requires examining the underlying climate  
569 forcing datasets. In several forested ecoregions, simulations forced by historical reanalysis (ERA5-Land)  
570 produce substantially higher peak fire activity than simulations forced by the bias-corrected GCM ensemble  
571 median (e.g., Rhodope montane mixed forests [678], Carpathian montane forests [692], and Anatolian  
572 conifer and deciduous mixed forests [786]). This difference illustrates the sensitivity of the model to acute  
573 hydroclimatic extremes.

574 GCM simulations are designed primarily to capture long-term climate trajectories and large-scale circulation  
575 patterns. When multiple GCM outputs are combined into an ensemble median, the resulting signal  
576 inherently smooths interannual variability and suppresses extreme anomalies. While this approach provides  
577 a robust estimate of long-term climatic trends, it cannot reproduce the exact chronological sequence of  
578 weather events experienced by the landscape.

579 Historical reanalysis, by contrast, represents the chronological climate record that actually occurred during  
580 the satellite observation era. In addition to capturing drought severity, it preserves the temporal persistence



581 and sequencing of hydroclimatic conditions, including multi-year drought development and recovery  
582 phases. These dynamics introduce drought legacy effects, whereby antecedent moisture deficits influence  
583 vegetation productivity, fuel accumulation, and fuel dryness over timescales longer than a single season.

584 The strong response of LPJ-GUESS to ERA5-Land forcing therefore demonstrates the internal biophysical  
585 consistency of the model. When presented with verified hydroclimatic extremes, the model simulates  
586 correspondingly large natural fire potential. The fact that satellite observations often show comparatively  
587 low burned area during these same climatic peaks further reinforces the existence of a suppression-  
588 mediated fire regime, in which effective fire management prevents many fires from reaching their climatic  
589 potential.

#### 590 **4.3 Biophysical mechanisms governing natural fire regimes**

591 Removing anthropogenic influences from the simulations reveals the fundamental biophysical constraints  
592 that structure fire regimes across the region. Two contrasting mechanisms emerge: fuel-limited systems,  
593 where biomass availability controls fire activity, and climate-limited systems, where fuel is abundant but  
594 ignition and spread depend on climatic thresholds.

##### 595 **4.3.1 Fuel-limited hysteresis in closed forest systems**

596 One striking feature of the historical simulations is the behavior of the Caspian Hyrcanian mixed forests  
597 [649]. Following simulated peak fire years, the system exhibits a refractory period of several years under  
598 ERA5-Land forcing, during which fire activity drops to near zero. This lag is consistent with the time required  
599 for understory biomass and fuel continuity to recover after a disturbance event. In this closed-canopy  
600 deciduous system, fire activity is therefore not strictly climate-driven; instead, it is strongly fuel-limited. Once  
601 available biomass is consumed, the system temporarily loses the capacity to sustain fire spread until  
602 vegetation regrowth restores sufficient fuel connectivity. This dynamic contrasts with nearby pine-  
603 dominated systems, where rapidly accumulating needle litter maintains a continuously flammable fuel bed  
604 capable of responding quickly to drought events.

##### 605 **4.3.2 The “hotter and greener” paradox**



606 A second mechanism emerging from the simulations is the apparent paradox of increasing vegetation  
607 productivity under a warming climate. Classical drought theory often predicts that increasing aridity will  
608 reduce fuel availability and therefore suppress fire activity. However, the simulations show simultaneous  
609 increases in maximum FAPAR and fire probability across several northern and montane regions. This  
610 pattern likely reflects the combined influence of CO<sub>2</sub> fertilization and shifts in vegetation composition.  
611 Elevated atmospheric CO<sub>2</sub> improves plant water-use efficiency, allowing vegetation productivity to remain  
612 stable or even increase despite declining moisture availability. At the same time, warming temperatures  
613 may facilitate the expansion of drought-adapted species into previously cooler environments, maintaining  
614 canopy density and fuel continuity even under drying conditions. The result is a “hotter and greener”  
615 landscape in which the structural prerequisites for fire (fuel abundance) are maintained, while climatic  
616 constraints on ignition and spread weaken. This mechanism may be particularly important along the  
617 transitional zones of northern Anatolia, where rising productivity coincides with increasing fire probability.

#### 618 **4.4 Spatial redistribution of future fire regimes and implications for fire management**

619 Although the regional burned area signal remains relatively stable, the projected redistribution of fire activity  
620 has important implications for fire management. Current fire management strategies in the Northeast  
621 Mediterranean prioritize the wildland–urban interface and coastal landscapes where human ignitions  
622 dominate. However, the simulations indicate that future fire risk may increasingly emerge from semi-arid  
623 interior regions and transitional landscapes, particularly Central Anatolia and northern Mesopotamia. These  
624 regions, historically dominated by anthropogenic ignitions and fragmented landscapes, exhibit the strongest  
625 projected increases in fire probability and the most pronounced shortening of fire return intervals towards  
626 the end of the century.

627 Another emerging concern is the potential for simultaneous fire activity across large, topographically  
628 heterogeneous mountain belts. Currently, the majority of the highland regions in the study area show low  
629 fire probability – a contrast that helps explain why the regional median burned area remains relatively stable  
630 despite sharp increases in fire probability across semi-arid ecoregions in the south. However, if intensifying  
631 and prolonged warming and drying remove these climatic limitations on ignition across wide areas, multiple  
632 fires could occur concurrently across diverse ecoregions. Such scenarios could severely challenge existing



633 suppression systems by exceeding the logistical capacity of firefighting infrastructure, particularly during  
634 extreme, prolonged heatwave events.

635 Changes in fire frequency may also influence long-term vegetation dynamics. A potential increase in the  
636 frequency of wildfires in the lowlands may favor the expansion of fire-adapted shrublands and conifer  
637 species, potentially creating “fire ladders” that facilitate the upslope spread of high-intensity fires into  
638 ecosystems historically less adapted to frequent disturbance. Over longer timescales, such feedbacks  
639 could alter the composition and resilience of several Mediterranean and Anatolian forest systems.

## 640 **5. Conclusion**

641 This study demonstrates that future wildfire dynamics across the Northeast Mediterranean are unlikely to  
642 be characterized by a uniform increase in burned area. Instead, the simulations indicate a spatial  
643 redistribution of fire regimes, driven by the interaction between hydroclimatic change, vegetation  
644 productivity, and landscape structure. While fire probability increases across large parts of the region,  
645 particularly in semi-arid interior zones, this does not consistently translate into greater burned area. Rather,  
646 shifts in fire frequency, fuel continuity, and topographic constraints lead to divergent regional responses.

647 By isolating the natural fire potential using LPJ-GUESS–SIMFIRE–BLAZE, this study also highlights the  
648 extent to which contemporary fire regimes are shaped by human land management. The contrast between  
649 simulated and observed burned area reveals a dual role of human influence: effective fire suppression  
650 masks latent climatic flammability in forested systems, while land-use fragmentation constrains fire spread  
651 in agricultural landscapes. However, future projections suggest that these buffering effects may become  
652 increasingly limited under intensifying hydroclimatic stress and more frequent drought conditions.

653 Furthermore, the dual forcing approach in this study helps clarify the distinct roles of historical reanalysis  
654 versus bias-corrected climate model ensembles in anticipating fire regimes. Temporally explicit historical  
655 baselines reveal the critical role of observed drought sequences and legacy effects in priming ecosystems  
656 for elevated fire potential. Conversely, while the GCM ensemble median inherently smooths these acute  
657 historical extremes, it remains an indispensable tool for projecting centennial trajectories and forewarning  
658 of potential systemic, long-term shifts in future risk. Together, these complementary approaches enable a  
659 more robust interpretation of both existing mechanisms and future fire dynamics.



660 Ultimately, these findings suggest that the primary impact of climate change on wildfire in Northeast  
661 Mediterranean may not be a simple increase in fire activity, but a fundamental reorganization of where and  
662 how fires occur. This has urgent implications for fire management, as emerging risk zones and the  
663 increasing simultaneity of fire-conducive conditions across broad geographies threaten to challenge  
664 existing suppression strategies. Anticipating future wildfire risk therefore requires moving beyond  
665 expectations of uniform intensification and toward a mechanistic understanding of how climate, vegetation,  
666 and human land use jointly redistribute fire regimes across space.

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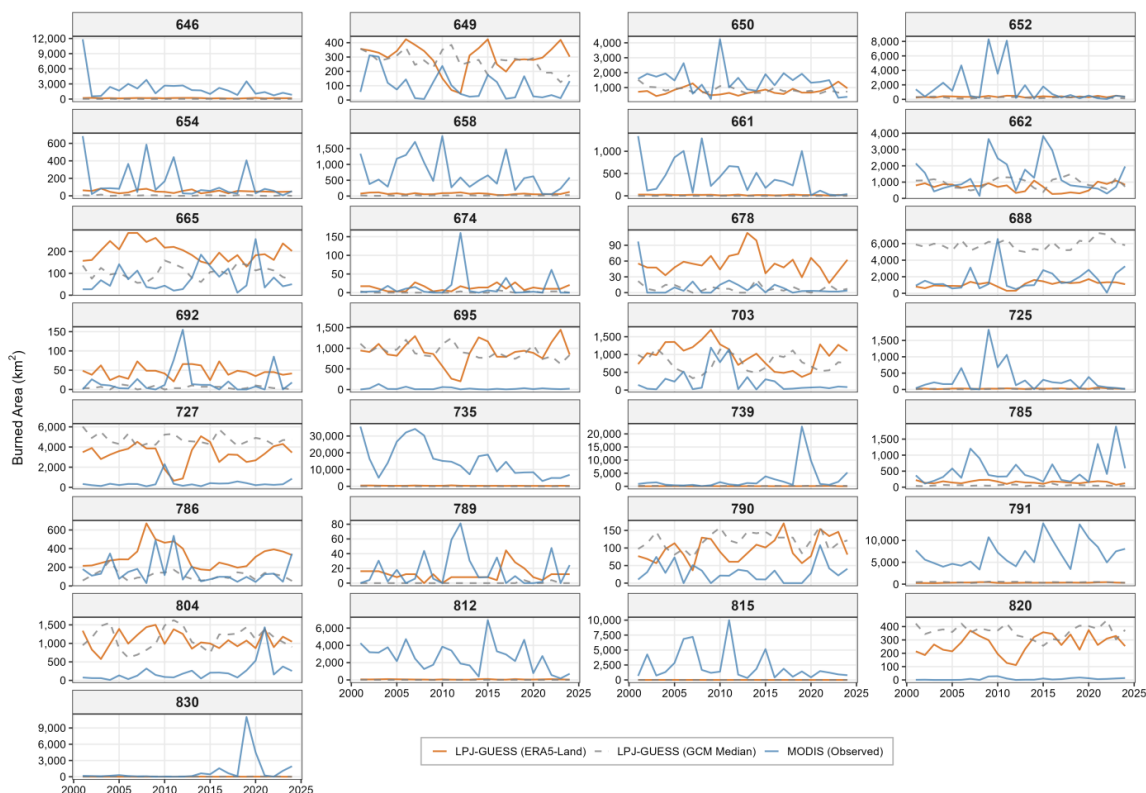
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671 APPENDIX

**Burned Area Trajectories: Reanalysis vs. GCM Ensembles vs. Observations**

Annual area burned across ecoregions (2001–2024)



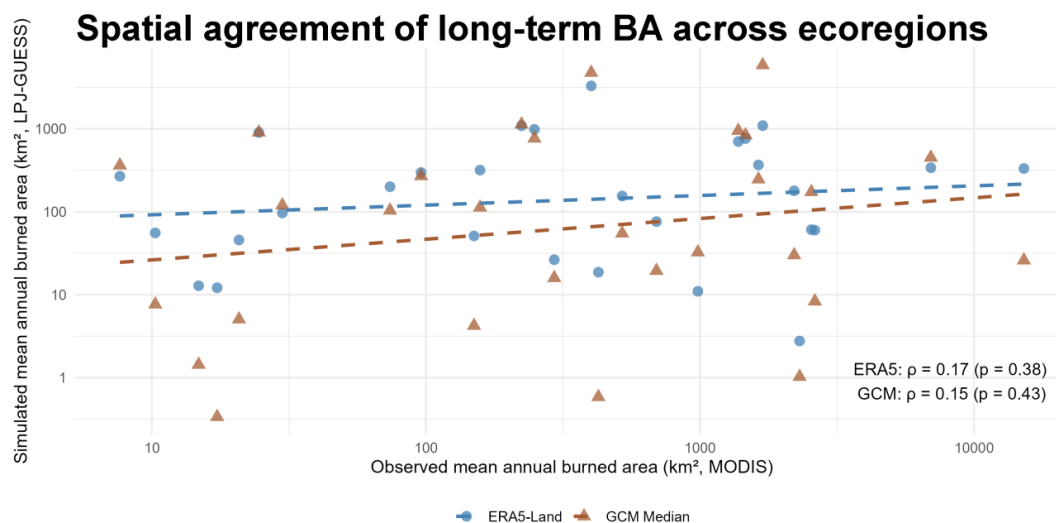
Data Sources: MODIS Collection 6 & LPJ-GUESS

672 **Figure A1.** Interannual burned area trajectories across all study ecoregions (2001–2024). Annual burned  
 673 area (km<sup>2</sup>) simulated by LPJ-GUESS driven by ERA5-Land (orange) and the GCM ensemble median  
 674 (grey), compared against MODIS MCD64A1 satellite observations (blue). The plots illustrate the model's  
 675 heterogenous performance across biomes. While Mediterranean ecoregions demonstrate strong temporal  
 676 alignment with observations, forested and steppe ecoregions exhibit systematic magnitude offsets. These  
 677 offsets are consistent with the complex bidirectional influence of anthropogenic fire suppression,  
 678 agricultural ignitions, and land-use fragmentation, which are intentionally excluded from the natural-  
 679 potential simulations.



680 **Table A1:** Ecoregion classification. List of WWF terrestrial ecoregions within the study domain, their corresponding  
681 numeric ID used in analysis, and their broad biome classification (Forest, Mediterranean, Steppe, or Desert).

ID	Ecoregion Name	Vegetation Type
786	Anatolian conifer and deciduous mixed forests	Forest
678	Rodope montane mixed forests	Forest
703	Northern Anatolian conifer and deciduous forests	Forest
650	Caucasus mixed forests	Forest
662	Eastern Anatolian deciduous forests	Forest
665	Euxine-Colchic broadleaf forests	Forest
649	Caspian Hyrcanian mixed forests	Forest
646	Balkan mixed forests	Forest
674	Pannonian mixed forests	Forest
658	Crimean Submediterranean forest complex	Forest
692	Carpathian montane forests	Forest
654	Central European mixed forests	Forest
804	Southern Anatolian montane conifer and deciduous forests	Forest
785	Aegean and Western Turkey sclerophyllous/mixed forests	Mediterranean
790	Cyprus Mediterranean forests	Mediterranean
791	Eastern Mediterranean conifer-broadleaf forests	Mediterranean
789	Crete Mediterranean forests	Mediterranean
661	East European forest steppe	Steppe
725	Central Anatolian steppe	Steppe
688	Zagros Mountains forest steppe	Steppe
727	Eastern Anatolian montane steppe	Steppe
652	Central Anatolian steppe and woodlands	Steppe
735	Pontic steppe	Steppe
695	Elburz Range forest steppe	Steppe
820	Central Persian desert basins	Desert
815	Caspian lowland desert	Desert
830	Mesopotamian shrub desert	Desert
739	Syrian xeric grasslands and shrublands	Desert
812	Azerbaijan shrub desert and steppe	Desert



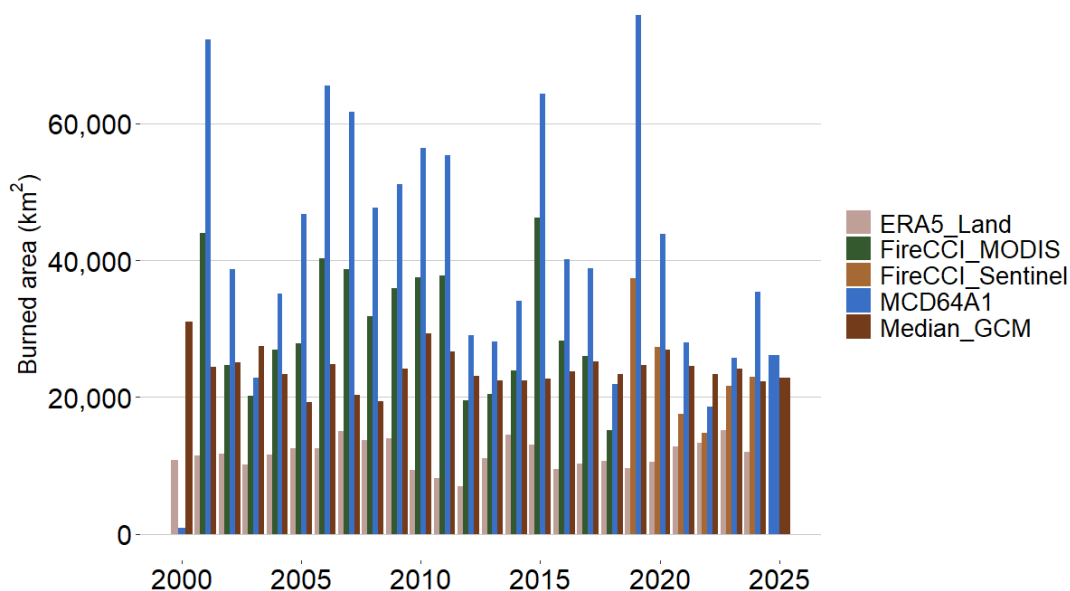
682 **Figure A2.** Spatial agreement of long-term burned area. Comparison of mean annual burned area (km<sup>2</sup>) simulated  
683 by LPJ-GUESS–SIMFIRE–BLAZE versus observed by MODIS MCD64A1 across all ecoregions within the study  
684 area. The blue dashed line represents linear trend for ERA5-Land simulations and the orange dashed line represents  
685 linear trend for the GCM ensemble median. Weak spatial correlations (Spearman rho = 0.17 for ERA5-Land  
686 simulation and rho = 0.15 for the GCM ensemble median) highlight the model's limitation in reproducing spatial  
687 magnitude heterogeneity driven by local anthropogenic factors, despite capturing temporal variability.

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## Domain-scale comparison of annual burned area

Sentinel-based bias factor: 0.69



704 **Figure A3.** Intercomparison of observational burned area products and simulation results. Annual burned  
705 area (BA) totals for the study domain derived from MCD64A1 (blue), FireCCI (orange/green) products,  
706 and ERA5-Land (beige) and GCM ensemble median simulation results (dark red). While absolute  
707 magnitudes differ – with MCD64A1 consistently detecting more BA than the more conservative FireCCI  
708 algorithms – the interannual variability remains highly consistent across all sensor platforms, confirming  
709 the robustness of the high-fire years identified in this study.

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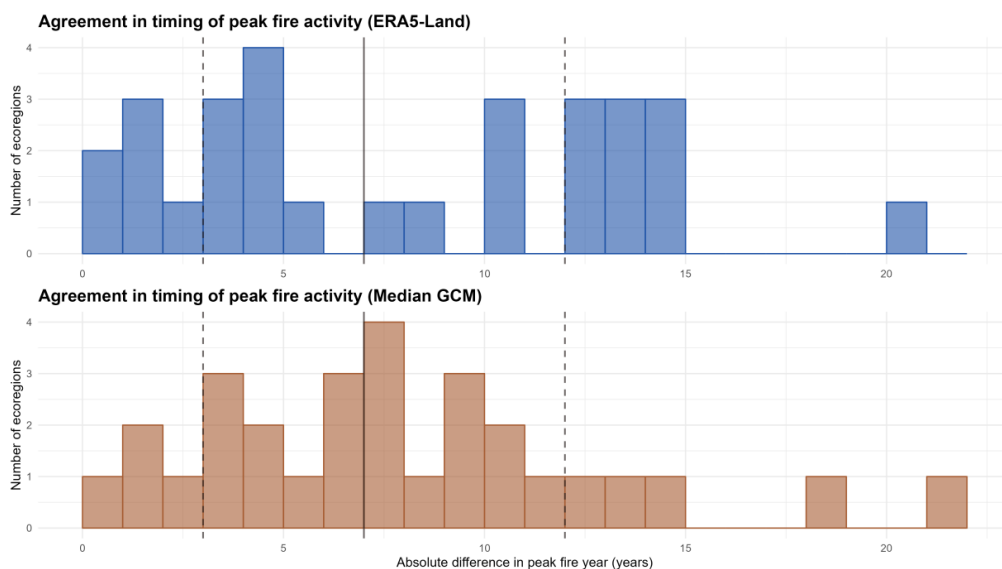
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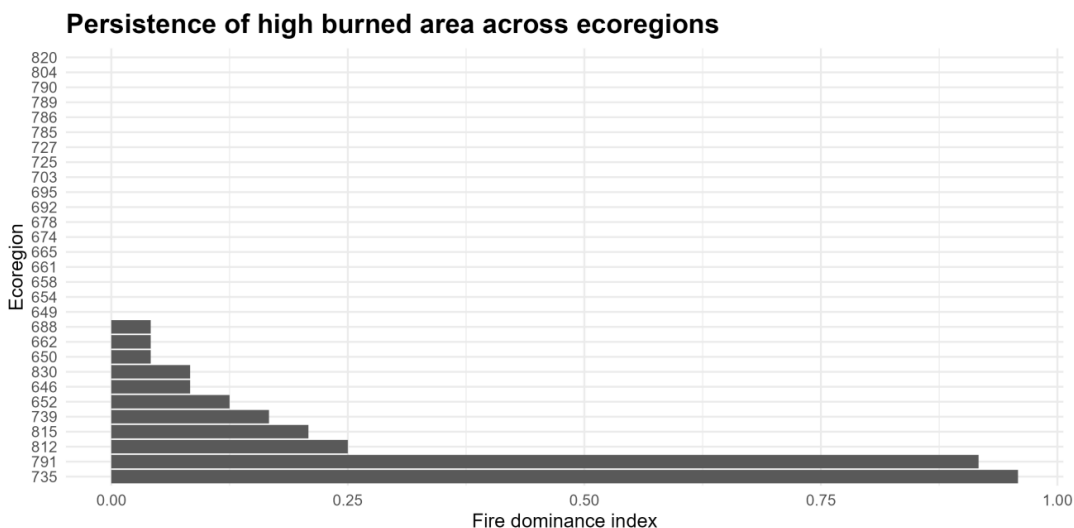
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720 **Figure A4.** Agreement in timing of peak fire activity. Histogram of the absolute difference (in years)  
 721 between the observed and simulated peak fire year across all ecoregions from the simulation results of  
 722 ERA5-Land and the GCM ensemble median. The solid vertical line represents the median difference (7  
 723 years). Dashed lines indicate the 25th percentile (difference  $\leq$  3 years) and 75th percentile, illustrating  
 724 that for a significant subset of ecoregions, the model successfully captures the broad temporal placement  
 725 of major fire episodes.



726 **Figure A5.** Persistence of high burned-area years across ecoregions. Ecoregions ranked by the Fire  
 727 Dominance Index, defined as the fraction of years in which annual burned area exceeds the global 90th  
 728 percentile of the regional burned-area distribution. The results show that extreme fire activity is  
 729 concentrated in a limited subset of ecoregions, indicating persistent “pyro-catchments” that account for a  
 730 disproportionate share of regional burned area.



731 **Data Availability**

732 All datasets used in this manuscript for drought, ecoregions, and burned area analyses can be downloaded  
733 from their original sources. LPJ-GUESS simulation results are available in Zenodo (embargoed until  
734 publication, but available during peer review at: <https://tinyurl.com/ForecastingTheFlame>) at <https://doi.org/10.5281/zenodo.18200254>).

736 **Code Availability**

737 The R and Python codes generated and used during the study are part of an ongoing study, but are readily  
738 available from the corresponding author by request. LPJ-GUESS dynamic vegetation model's home page  
739 is: <https://web.nateko.lu.se/lpj-guess/>

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743 **Author Contributions**

744 B.E. designed the study and its methodology, curated the data, conceptualized the experimental design,  
745 conducted the formal analysis, validated the results, wrote the manuscript and visualized the data.

746 **Competing Interests**

747 The author declares no conflict of interest.

748 **Funding Declaration**

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