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Megafires in Mediterranean Europe: the compound role of fire weather and drought

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Large wildfires and megafires in Mediterranean Europe cause disproportionate social, ecological and economic impacts, yet the processes that allow some ignitions to grow into landscape-scale events remain poorly quantified. Here we analyse 11,403 summer wildfires across Mediterranean Europe during 2008–2022, classified into medium (30–100 ha), large (100–1000 ha), very large (1000–10,000 ha) and megafires (≥10,000 ha). Combining official fire perimeters with a high-resolution environmental and drought dataset, we quantify how fast-reacting weather and slow-reacting fuel and drought indicators jointly control transitions between fire-size classes. Very large fires are preferentially associated with anomalously hot, windy conditions acting on stressed fuels and multi-month drought, whereas the transition to megafire size is closely associated with unusually warm nights and strong winds near ignition. Using Random Forest classifiers and logistic regression, we show that these transitions are predictable from a small set of interpretable variables, including nighttime land-surface temperature, wind speed, and 3-month standardized precipitation–evapotranspiration index. Model performance indicates that up to two-thirds of megafires are correctly identified out of sample. Our results highlight that megafires in Mediterranean Europe emerge from the alignment of preconditioned fuels with exceptional short-term fire weather and emphasize the need to jointly manage fuel continuity and anticipate periods of persistent hot, dry and windy conditions in a warming climate.

Concern about large fires and megafires in Mediterranean Europe has grown in response to recent events that exceed historical precedents in both spatial extent and severity of impacts, posing serious threats to human life and ecosystems and stretching suppression capacities to their limits. Analyses of recent extreme fire seasons have highlighted that a small number of very large fires, often concentrated in space and time, account for a disproportionate share of burned area and damages in Mediterranean countries; in addition, these episodes are clearly distinct from the usual interannual variability in fire numbers and area burned[1–3]. This has consolidated the notion that megafires are rare but high-impact events that pose substantial challenges to conventional fire management approaches[4–6].

In Mediterranean Europe, ignition sources are mostly of human origin: over 95% of wildfires are human ignited, whereas only about 5% are sparked by natural causes, such as lightning[7–9]. Fire weather, such as anomalously hot, dry, and windy episodes, enhances the likelihood that ignitions develop into large fires. These fire-spread dynamics are primarily controlled by fuel availability and dryness, vegetation structure, topography, and fire-weather conditions, which together determine whether ignitions successfully spread and exceed suppression capacity[1,10,11].

Once a fire is established and reaches a size on the order of hundreds of hectares, it become less clear what limits further escalation to very large fires and megafires. One possible explanation is that, by the time fires reach this size, favourable fire-weather conditions are already in place and remain relatively similar across size classes[12,13]. From that point onwards, fuel continuity, landscape structure, and the availability of sufficiently dry biomass might become the main factors governing whether a fire can expand into a megafire[1,14–16]. Moreover, in Mediterranean Europe, generally a highly managed region, the final burned area can also be modulated by fire-management and suppression capacities[17,18]. Conversely, it is possible that truly anomalous weather, for example, extreme warmth, unusually strong winds, persistent drought, is required to enable transitions across fire-size thresholds even when fuels are abundant[12,13,19]. The relative importance of fuel versus weather limitation remains unclear, and, for weather, it is also uncertain whether fast-reacting weather-driven dynamics or slow-reacting

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fuel–drought processes are most influential, particularly for transitions from ordinary fires to megafires[20,21].

In Mediterranean Europe, a growing body of research has linked changes in burned area to increasing aridity, fuel build-up and land-use change, as well as to shifts in the duration and intensity of fire-weather windows[10,16,22]. At synoptic scales, large Mediterranean wildfires are systematically associated with atmospheric blocking situations, confirming that persistent circulation anomalies are a key control on fire size and intensity[12]. Relatively recent work has formalised this idea using a fire-weather-type (FWT) framework: wildfires across the Mediterranean Basin (Southern France, Greece, Portugal, and Tunisia) preferentially occur under a limited set of heat-induced and wind-driven FWTs, where short-term extremes in temperature, humidity, and wind coincide with accumulated summer drought[13,23]. In parallel, the expansion of wildland–urban interfaces, rural land abandonment and fuel accumulation have been identified as key contributors to high fire risk and to the potential for extreme events[1,14,15,24].

Large and megafires in Mediterranean Europe therefore account for a disproportionate share of burned area and impacts[3,25], yet the mechanisms that allow individual fires to escalate to landscape scale remain poorly constrained. Evidence from Portugal showed that extremely large fires (>2500 ha) tend to occur under the coincidence of exceptionally severe fire-weather conditions and high, continuous fuel loads, with the largest events becoming increasingly sensitive to weather extremes[26]. More recent research has linked megafires in southern Europe to heatwave conditions. In the EUMED5 countries (Portugal, Spain, France, Italy and Greece; 2008–2023), concurrent increases in heatwaves and megafires have been documented, showing that the fraction of fires igniting during heatwaves rises sharply with fire size, reaching about 40% for events larger than 10,000 ha. Notably, heatwave intensity is more strongly associated with megafire occurrence than heatwave duration[27]. Despite this growing evidence, most studies have focused on annual or seasonal burned area values, regional fire regimes, or the occurrence of large or extreme wildfire events at regional and national scales. In Mediterranean Europe, in particular, still lacks a comprehensive assessment of whether rare, large-scale fires are primarily constrained by fuel conditions, by episodic hot–dry–windy conditions, or by interactions between fast-reacting meteorological anomalies and slow-reacting fuel–drought preconditioning. Moreover, a systematic evaluation of which environmental variables most strongly influence the transitions between successive fire-size classes (e.g., from medium to large, and from large to megafires), and whether the drivers controlling these transitions are the same, remains largely unexplored.

Here, we address these gaps by adopting an event-based framework that explicitly targets fire-size escalation. We analyse how fast-reacting meteorological variables, acting at synoptic to daily timescales and evaluated within a ± 1-day window around the recorded ignition date (e.g., wind speed, air and land-surface temperature, relative humidity), together with slow-reacting indicators integrating conditions over weeks to months that characterize the state of the system at the time of fire occurrence (e.g., soil moisture, vegetation condition, multi-month drought indices), jointly influence transitions between successive fire-size classes, with a particular focus on megafires. By adopting an event-based framework, this approach allows us to assess whether the same environmental drivers govern fire escalation across size thresholds. To enable this novel event-based analysis of fire-size escalation, we took advantage of the recently developed MESOGEOS environmental–fire datacube[28], specifically designed for climate–fire research in the Euro-Mediterranean domain, together with high-resolution meteorological drought datasets[29] and official European Forest Fire Information System (EFFIS) wildfire perimeters (http://effis.jrc.ec.europa.eu).

Results

Megafires characteristics in Mediterranean Europe

We analysed 11,403 summer wildfires (June–September, JJAS) of at least 30 ha that occurred in the Euro-Mediterranean region between 2008 and 2022, collectively burning a total of approximately 4.5 million hectares (Fig. 1). Medium (30–100 ha, $n = 5139$; 45.1%) and large (100–1000 ha, $n = 5486$; 48.1%) events dominate the sample, together accounting for 93.2% of all events, yet accounting for only 42.4% of the total burned area. In contrast, very large fires (1000–10,000 ha, $n = 734$; 6.4%) and megafires (≥10,000 ha, $n = 44$; 0.4%) are comparatively rare, accounting for only 6.8% of events, yet disproportionately important in terms of area burned, jointly responsible for 57.6% of the total, with megafires alone contributing 17.7%.

Very large fires occur in all countries across the domain, whereas megafires are mostly concentrated in Portugal and north-western Spain, with additional hotspots on Sardinia (Italy) and in parts of Greece and western Turkey. The spatial clustering of fires of similar sizes (Fig. 1) likely reflects not only regional climate gradients but also the influence of past disturbances and land management practices. Indeed, recurrent fires, suppression history, and land-use changes can modify fuel structure and connectivity, which in turn affect fire spread and the likelihood that fires evolve into very large events or megafire. Although we do not explicitly analyse past fire history or management interventions here, these legacy effects provide important context for interpreting the observed spatial patterns and the

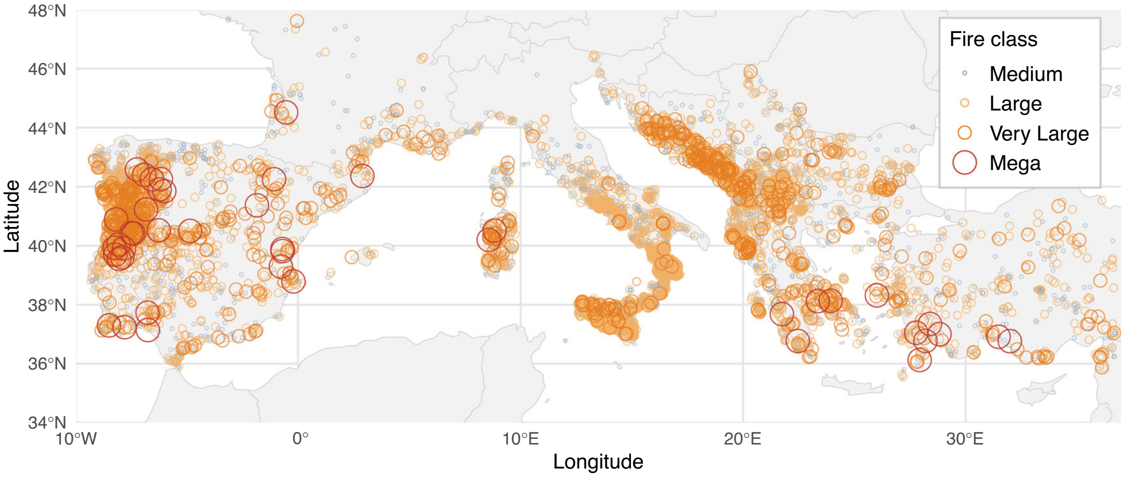

Fig. 1 | Spatial distribution of medium to mega wildfires in the Euro-Mediterranean region during summer (June–September) over the period 2008–2022. Location of wildfires ≥30 ha recorded within the Euro-Mediterranean analysis domain (34–48°N, 10°W–30°E). Fires are grouped by burned area into Medium (30–100 ha), Large (100–1000 ha), Very Large (1000–10,000 ha), and Mega (≥10,000 ha) events, with class totals indicated in parentheses.

relative roles of weather, fuel preconditioning, and suppression capacity. Consistent with the strong size hierarchy shown in Fig. 1, previous work[25] shows that only a small fraction of the largest fires controls country-level extreme risk: their extreme value analysis yielded 10-year burned-area return period for a total of about 50,338 ha in Portugal, 33,242 ha in Greece, 25,165 ha in Spain and 8966 ha in Italy, underscoring how rare but very large events dominate the upper tail of the fire-size distribution.

Drivers of fire-size class transitions

Fast-reacting meteorological conditions show a clear intensification from medium to larger events: air temperature and land-surface temperature anomalies (AT, LSTd, LSTn) become progressively more positive, while relative humidity (RH) and precipitation (PR) anomalies become more negative and wind speed (WS) anomalies more positive, with most stepwise contrasts between medium to large fires and large to very large fires being highly significant (pairwise two-sided Wilcoxon rank–sum tests; panel titles in Fig. 2).

The transition from very large fires to megafires is characterised by an additional shift towards more extreme short-term fire weather, rather than by stronger drought or fuel anomalies. Megafires occur under significantly higher air and nighttime land-surface temperature anomalies (AT, LSTn), lower relative humidity (RH), stronger wind speed (WS), and more negative precipitation and soil-moisture (PR, SMI) anomalies than very large fires, whereas the two vegetation indices, Normalized Difference Vegetation Index and Leaf Area Index (NDVI, LAI), do not differ significantly between these two classes. Similarly, the drought indices SPEI (Standardized Precipitation–Evapotranspiration Index), namely SPEI-1 and SPEI-3, which represent drought-related moisture anomalies accumulated over one-month and three-month periods, respectively, are substantially more negative from medium to very large fires, but do not show further significant changes for megafires, while SPEI-6 shows no clear size dependence. This result is consistent with earlier findings that seasonal-scale (i.e., 3 months) droughts are coupled to year-to-year variations in summer burned areas in the Mediterranean region[30]. Together, these patterns suggest that antecedent drought and fuel conditions create favourable preconditioning for the development of very large fires, while the escalation to megafire size is mainly associated with exceptionally hot and windy weather in the immediate fire-weather window.

To further understand the underlying drivers of megafires, we used Random Forest classifiers with permutation feature importance (‘Methods’) to assess which variables best discriminate between fire-size classes (Fig. 3). For transitions from medium to large and very large fires, both fast and slow processes contribute air and land-surface temperatures (especially nighttime LST), together with multi-month drought (SPEI-3) and NDVI anomalies, consistently rank among the most important predictors. Although NDVI anomalies show only modest differences between size classes in univariate comparisons (Fig. 2), they emerge as important in the Random Forest analysis because their effect on fire size depends on interactions with other variables, particularly meteorological conditions. In other words, NDVI may have a subtle marginal effect, but it influences fire-size outcomes in the context of the other predictors, fast nuance that univariate analyses cannot reveal.

This pattern is consistent with fuel preconditioning processes, whereby sustained dry and warm conditions progressively reduce fuel moisture and increase flammability, thereby facilitating the transition from small to large fire events. Conversely, medium fire events may occur under comparatively less stressed fuel conditions. To sum up, this analysis indicates that very large fires tend to emerge under anomalously hot, dry and windy conditions acting on already stressed fuels. Transitions involving megafires ($n = 44$), however, are characterised by larger uncertainty because of the small sample size. Taken together across all transitions, the Random Forest analysis points to both slow-reacting indicators (e.g. SPEI-3 and NDVI) and fast-reacting meteorological variables (notably wind speed and nighttime LST) as playing a crucial role in enabling transitions towards larger fire sizes. As a robustness check, we repeated the analysis with an alternative Random Forest configuration and obtained very similar skill and variable-importance patterns (Fig. S1).

Key predictors of fire-size transitions

To complement the Random Forest analysis, which provides a robust ranking of predictors but not their direction of effect, we constructed out-of-sample Logistic Regression models to quantify how fast- and slow-reacting variables control transitions between fire-size classes (Fig. 4). A detailed description of the modelling framework is provided in the ‘Methods’.

Across almost all transitions, the Logistic Regression confirm a clear imprint of fast fire-weather variables: LSTn and wind speed systematically display positive coefficients, indicating that warmer-than-usual nights and stronger winds around ignition substantially increase the odds that a fire will develop into a larger size class (as shown by the consistently positive standardized coefficients in Fig. 4). Short-term drought also plays a consistent role: SPEI-3 typically enters with negative coefficients, implying that drier-than-average multi-month conditions (i.e., negative SPEIs) favour transitions towards larger fires, especially when starting from medium or large events. In contrast, NDVI is never selected in the best filtered models, suggesting that for a given fire-weather configuration, its influence on size transitions is weaker and less systematic than that of LSTn, wind speed, and SPEI-3.

Importantly, these transitions are meaningfully predictable. The progressive increase in model performance across transitions (Fig. 4) indicates that larger fire events are increasingly governed by systematic meteorological and fuel preconditioning, while smaller fires are more influenced by stochastic ignition and suppression processes, resulting in weaker predictability. For each transition, the percentage of fires in the upper size class correctly identified by the best-performing model spans from 55% (medium to large) to 78% (medium to mega) with intermediate value for the other classes. Namely, in the transition from very-large to megafires, 67% of megafires were correctly predicted despite their extreme rarity. The analysis further indicates that LSTn emerges as the most robust and stable driver of megafire occurrence, with consistently positive and often sizeable coefficients across transitions to the mega class, although the associated confidence intervals are wide, and broad ROC ribbons reflect the inherent uncertainty due to sample scarcity. Overall, the logistic models indicate that megafires are most likely when fires spread under anomalously warm nighttime conditions, and upward transitions from lower to larger classes are generally sustained by high LSTn and strong winds, superimposed on antecedent drought conditions.

Given the prominence of nighttime land-surface temperature in both the Random Forest and logistic regression analyses, we tested whether our LSTn anomalies could be spuriously inflated by the radiative signal of the fires themselves rather than reflecting background environmental conditions. For each fire, we compared the 3-day mean LSTn around ignition (d–1, d, d + 1) with nighttime LST two days before ignition at the same fire pixels. The two metrics are tightly correlated (Pearson $r = 0.77$, $p < 0.001$) and differ on average by only 0.11 °C (3-day mean minus d–2), indicating that nighttime LST around ignition is very similar to pre-fire values and is unlikely to be dominated by direct fire radiance.

To test the robustness of these logistic regression results to the small number of Mega fires, we carried out a leave-one-mega-fire-out jackknife analysis (Method). Removing individual Megafire events led to only minor fluctuations in AUC for all three transitions, with AUC values remaining within 0.84–0.86 for the Medium→Mega transition, 0.80–0.82 for the Large→Mega transition, and 0.69–0.72 for the Very Large→Mega transition (Fig. S2). The estimated coefficients for nighttime land-surface temperature and wind speed remained consistently positive across all jackknife runs, with only limited variability in magnitude and no sign reversals. Taken together, these patterns suggest that our main results are robust and are not disproportionately influenced by any single megafire event.

Discussion

Our results showing a marked influence of nighttime land-surface temperature (LSTn) on the transition to very large fires and megafires align with

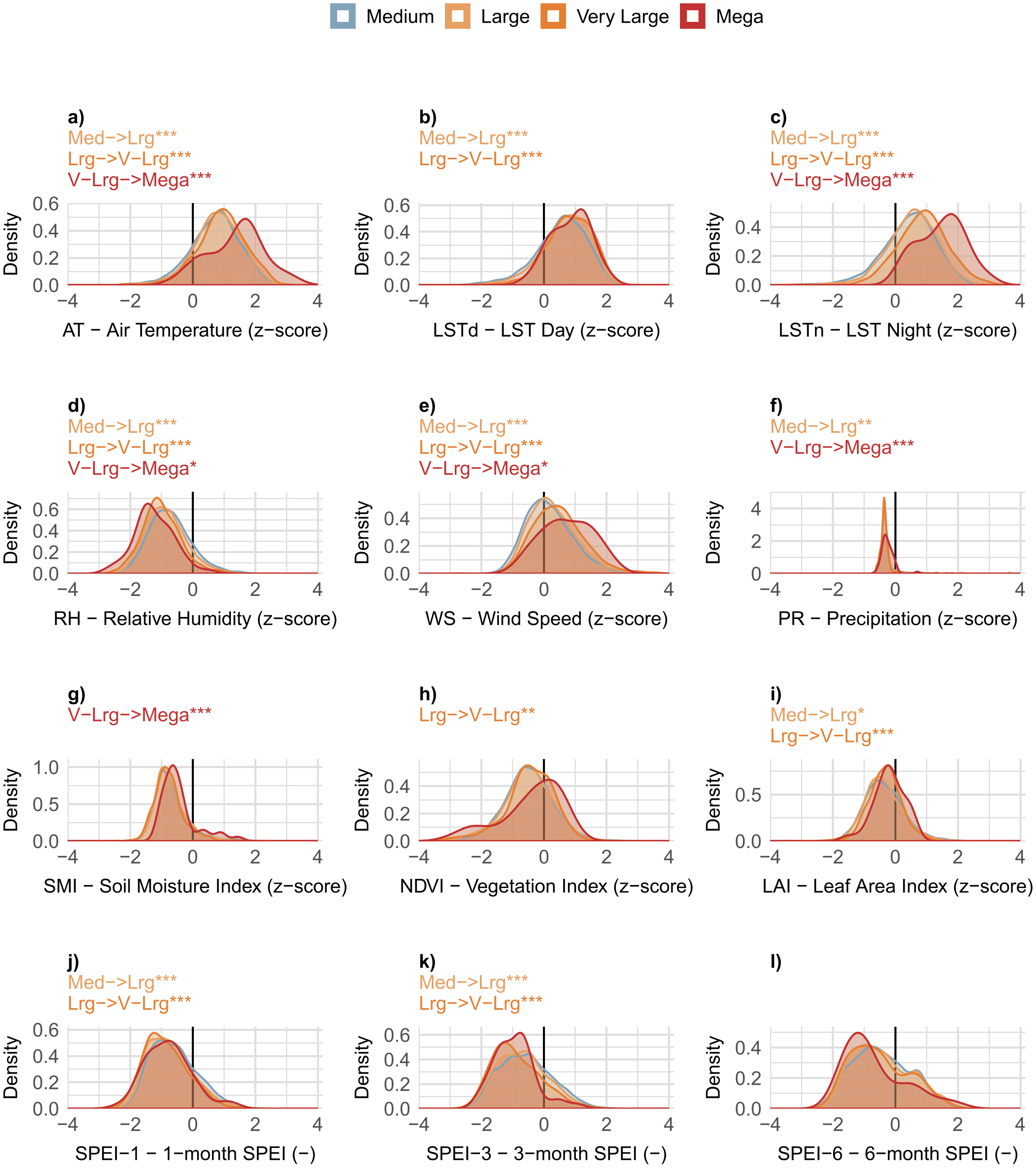

Fig. 2 | Anomalous weather conditions associated with different fire-size classes. Distributions of standardized anomalies (z-scores) of **a** air temperature (AT), **b** daytime land-surface temperature (LSTd), **c** nighttime land-surface temperature (LSTn), **d** relative humidity (RH), **e** wind speed (WS), **f** precipitation (PR), **g** soil moisture index (SMI), **h** NDVI, **i** leaf area index (LAI), and **j**–**l** SPEI at 1-, 3- and 6-month scales (SPEI-1, SPEI-3, SPEI-6) for medium, large, very large fires and megafires. Coloured curves indicate kernel density estimates for each size class, with zero corresponding to average conditions over the study period. Asterisks in the panel titles denote the significance of stepwise differences between consecutive size classes (Medium→Large, Large→Very Large, Very Large→Mega) based on pairwise two-sided Wilcoxon rank–sum tests (***$P < 0.001$, **$P < 0.01$, *$P < 0.05$).

emerging evidence that nocturnal conditions are no longer functioning as an effective limiting mechanism on fire spread[21,31]. Historically, cooler and moister nights allowed fuels to recover and provided operationally favourable periods for suppression, often determining whether a large fire could be contained. However, recent work shows that nighttime fire intensity has increased globally by over 7% between 2003 and 2020, coinciding with a 36% increase in flammable nighttime hours due to warmer and drier atmospheric conditions[31]. This reduction in nocturnal fire-spread limitation allows fires to continue spreading overnight, removing a long-recognised window for control and facilitating rapid and sustained growth once specific aridity thresholds are exceeded. Our finding that LSTn is a key predictor of fire escalation highlights its dual role as both a proxy for fuel

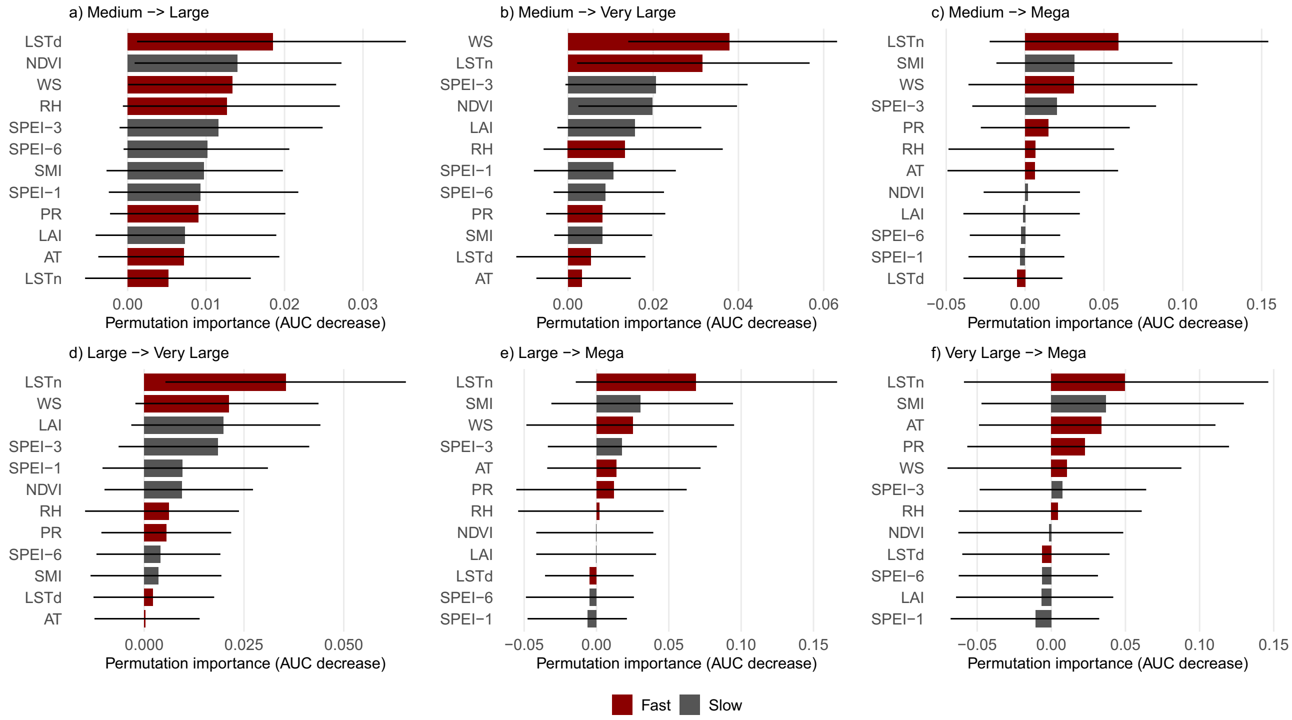

Fig. 3 | Random Forest permutation feature importance for transitions between fire-size classes. Panels (**a**–**f**) show the top predictors distinguishing between each pair of size classes: **a** Medium → Large, **b** Medium → Very Large, **c** Medium → Mega, **d** Large → Very Large, **e** Large → Mega, and **f** Very Large → Mega. Predictors are ranked by their mean decrease in Area Under the Curve (AUC) when permuted in a Random Forest classifier (permutation feature importance). Bars show the mean AUC decrease, with horizontal lines indicating empirical 95% intervals obtained from 5 × 50 repeated cross-validation with down-sampling of the majority class. Variables are coloured by process type: fast-reacting fire-weather variables in red (temperature, humidity, wind, and precipitation) and slow-reacting fuel and drought indicators in grey (soil moisture, NDVI, LAI, and SPEI).

aridity and an indicator of lost nightly suppression opportunities, supporting the concept that megafires are increasingly driven by continuous day–night alignment of fire-weather conditions, with important implications for management and risk planning.

Our analysis reveals that large and very large fires typically develop when anomalously hot and windy weather coincides with stressed fuels and prolonged multi-month drought (SPEI-3), whereas the transition to megafires is most strongly associated with extreme nighttime warmth. This pattern is consistent with conceptual models in which the size of the largest fires is controlled by the duration and intensity of fire-weather episodes once fuel thresholds are crossed[10], and is supported by observations in other fire-prone regions where very large fires preferentially occur when long-term drought coincides with sub-seasonal fuel dryness and short-lived synoptic fire-weather events[32].

In Mediterranean Europe, extremely large fires in Portugal and other western regions occur when severe fire-weather episodes act on continuous, highly available fuels, with the largest events increasingly sensitive to weather extremes[26] and directly linked to heatwaves[27]. Together with European evidence and the documented role of positive land-surface temperature anomalies in increasing the probability of large, long-duration fires[33], this provides robust, pan-Mediterranean support that drought and fuel conditions primarily precondition fires, while escalation to megafires requires the superposition of these background conditions with exceptional short-term fire-weather extremes, particularly anomalously warm nights and strong winds near ignition.

Our study leverages a large, high-quality wildfire dataset comprising 11,403 events with well-resolved perimeters across Mediterranean Europe. Limitations include the relatively short high-quality record (2008–2022) and the small number of megafires ($n = 44$), resulting in larger confidence intervals for models involving the mega class, although LSTn still emerges as a robust discriminator. While the Random Forest framework provides a robust approach to identify dominant drivers of fire-size transitions, methodological uncertainties must be acknowledged. Although long-duration fires experience evolving meteorological conditions and potential fire–atmosphere feedbacks, focusing on the ±1-day window around ignition captures the critical initial conditions under which fires escape early suppression and acquire the potential to transition into large-scale events. The strong imbalance between fire-size classes, particularly for megafires, increases uncertainty despite the use of repeated cross-validation, down-sampling and class weighting. Additionally, correlated predictors can result in permutation-based importance metrics being shared among related variables rather than assigned uniquely. Therefore, we interpret Random Forest results primarily at the process level, focusing on consistent patterns across transitions rather than fine-scale ranking among closely related variables.

The limited role of NDVI, LAI, and SMI in discriminating very large fires and megafires suggests that fuel condition alone does not drive the largest fire-size transitions. In Mediterranean ecosystems, drought can increase fuel flammability by reducing live and dead fuel moisture without producing strong negative vegetation anomalies, particularly in fire-adapted forests and shrublands. While NDVI and LAI robustly describe vegetation presence and phenology, they saturate at moderate to high biomass levels and do not capture fuel continuity, vertical structure, or live-dead partitioning, that represents critical properties for sustaining extreme fire spread. Recent studies suggest that productivity-based metrics, such as gross primary production, can better capture variations in biomass and fuel accumulation not reflected in greenness indices, especially when followed by intense seasonal drying[34,35].

As Mediterranean summers continue to warm and heatwaves intensify, episodes of anomalously warm nights and strong winds are projected to become more frequent, expanding the environmental envelope conducive to megafires[6,36–38]. In the present study, we focus solely on weather, environmental, and drought indicators as drivers of wildfires, and we do not explicitly model changes in suppression, ignition patterns,

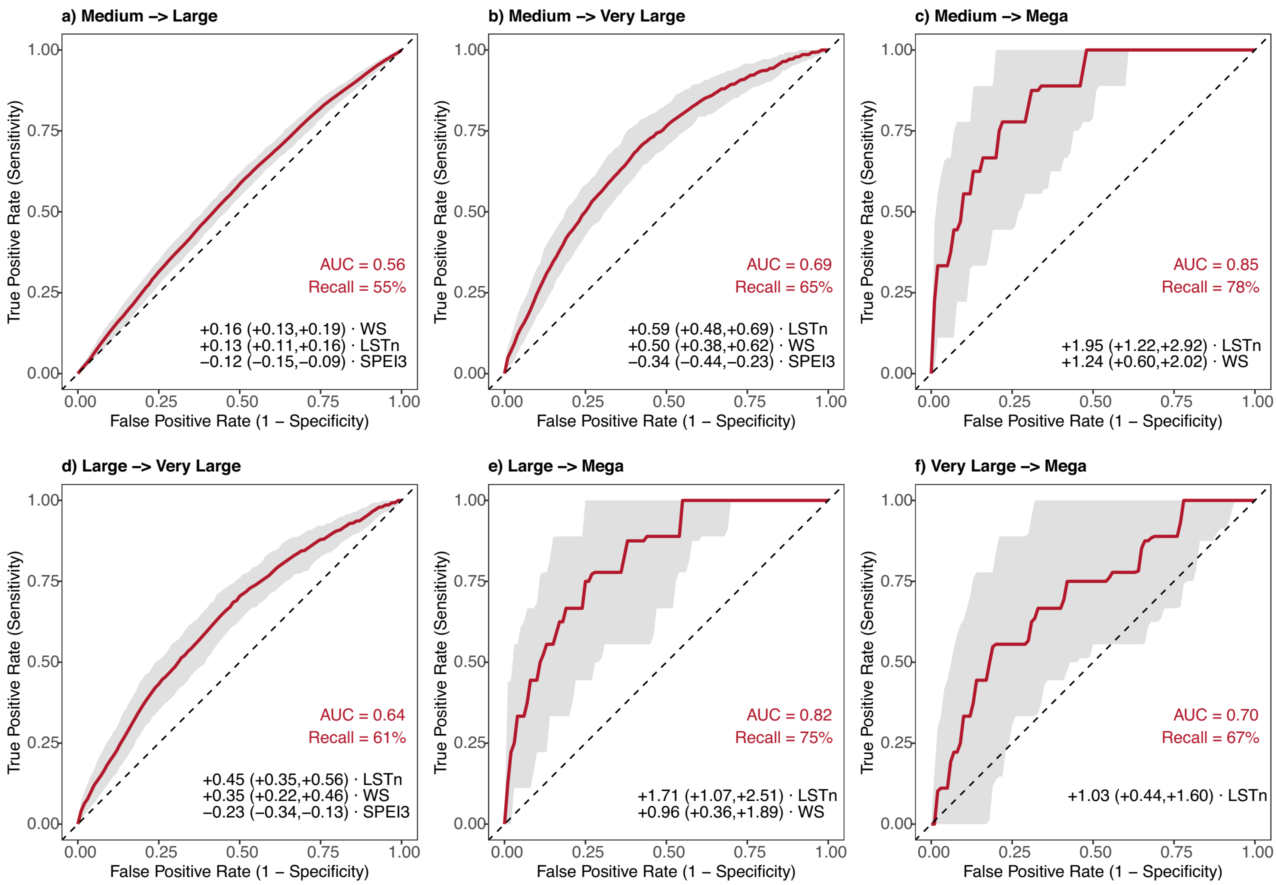

Fig. 4 | Key predictors of fire-size transitions from logistic regression models. Receiver operating characteristic (ROC) curves for the best logistic model selected for each transition between size classes: **a** Medium→Large, **b** Medium→Very Large, **c** Medium→Mega, **d** Large→Very Large, **e** Large→Mega, and **f** Very Large→Mega. Models use standardized anomalies of nighttime land-surface temperature (LSTn), wind speed (WS), NDVI, and SPEI-3 around the ignition day as predictors and are evaluated with 5×50 repeated cross-validation and down-sampling of the majority class ('Methods'). Solid lines show the median ROC across all resamples; shaded bands indicate the central 95% empirical range of true positive rate at each false positive rate. Insets report the cross-validated area under the curve (AUC) and recall at a fixed 0.5 probability threshold, together with the median logistic coefficient and its 95% empirical interval (2.5–97.5th percentiles across resamples) for each selected predictor. Positive coefficients for LSTn and WS, and negative coefficients for SPEI-3, where present, indicate that warmer nights, stronger winds, and drier multi-month conditions systematically increase the probability that fires evolve into larger size classes, including megafires.

or socio-economic exposure, implicitly assuming broadly comparable coping capacities across the region. Moreover, fire growth can be further amplified by the synchronicity of extreme fire-weather events, which may trigger simultaneous wildfires and strain suppression resources[6].

By adopting an event-based fire-size–escalation framework, this study advances existing Mediterranean fire–climate research by jointly quantifying the roles of fast-reacting fire-weather extremes and slow-reacting fuel–drought preconditioning, with particular emphasis on the rare but high-impact occurrence of megafires. In conclusion, our study reveals that megafire emergence in Mediterranean Europe is primarily driven by the alignment of extreme fast-reacting weather, with antecedent slow-reacting fuel preconditioning. Nighttime land-surface temperature (LSTn) is a key indicator of fire escalation, reflecting both fuel aridity and the loss of nightly suppression opportunities. While large fires develop under hot, windy, and drought conditions, the transition to megafires requires exceptional nighttime warmth, whereas fuel condition alone, as captured by NDVI or LAI, does not distinguish the largest fire-size transitions.

The strong role of weather in escalating fires across size classes, coupled with the uncontrollable nature of extreme meteorological events, poses a significant challenge for suppression. Nonetheless, effective management remains possible: extreme fire-weather episodes translate more readily into megafires where fuels are abundant, continuous, and dry. Prevention and landscape management strategies that reduce fuel abundance, connectivity, and continuity—through landscape planning, targeted fuel treatments, and broader fire prevention—are therefore critical to limit fire growth and mitigate megafire risk. Such adaptation measures will be essential to complement climate mitigation efforts as Mediterranean summers continue to warm and heatwaves intensify.

Despite remaining uncertainties due to data limitations and class imbalance, our findings offer guidance for designing risk frameworks, informing fire-management strategies, and supporting landscape planning under ongoing climate change. Future work should aim to extend this framework to longer records, incorporate explicit indicators of fire-management and suppression capacity, integrate spatial fuel patterns, and explore projected changes in nighttime heat, wind regimes, and fuel continuity to better predict megafire probability and inform effective mitigation strategies.

Methods

Fire data

Our analysis focuses on Mediterranean Europe (34–48° N, 10° W–30° E), a region characterized by complex topography, dense and highly flammable vegetation, and dry and hot summers, which together create an exceptionally fire-prone environment. Input data came from the European Forest Fire Information System (EFFIS), developed by the Joint Research Centre (Copernicus Emergency Management Service[39]). The EFFIS burned-area product provides spatially explicit wildfire perimeters derived from satellite imagery, based on MODIS data (250 m) in earlier years and enhanced since

2008 with higher-resolution Landsat (30 m) and, since 2018, Sentinel-2 (20 m) observations. Each record includes the date of detection (start date) and the burned area (in hectares).

We extracted all wildfires that (i) occurred within the Euro-Mediterranean domain (34–48° N, 10° W–30° E), (ii) burned ≥30 ha, and (iii) ignited during June–September (JJAS), the core fire season[1,13,18]. The ≥30 ha threshold was adopted because smaller fires are known to be under-detected or inconsistently mapped in EFFIS (https://forest-fire.emergency.copernicus.eu/applications/data-and-services). After removing records from countries lacking continuous EFFIS coverage from 2008 onward and discarding fires with incomplete environmental data, the final dataset retained wildfires from Portugal, Spain, France, Italy, Croatia, Bosnia and Herzegovina, Montenegro, Albania, Kosovo, Serbia, North Macedonia, Bulgaria, Greece, and western Türkiye (country attribution taken from the EFFIS perimeter "country" field), and comprised 11,403 individual wildfire events over 2008–2022. To aid interpretation and comparability, we classified fires into logarithmically spaced size classes. The term *megafire* has been formalized using a purely spatial "mega–giga–tera" hierarchy based on orders-of-magnitude size thresholds, which provides a familiar language for increasingly large, size-based fire categories[2]. The lower bound of 30 ha corresponds to the minimum fire size that is consistently and reliably mapped in the EFFIS perimeter database over our study period, ensuring both conceptual consistency with the mega–giga–tera hierarchy and robustness given our data constraints. Following this logic, we fixed our upper class at >10,000 ha, consistent with their definition of megafires, and then defined progressively smaller, order-of-magnitude bins tailored to Mediterranean Europe. Thus, each fire was assigned to one of four size classes: Medium (30–100 ha), Large (100–1000 ha), Very Large (1000–10,000 ha), and Megafire (≥10,000 ha). These categories enabled a formal investigation of how environmental conditions evolve as fires transition from ordinary events to rare, landscape-scale megafires.

Weather and environmental data

To characterize the meteorological and environmental conditions associated with each fire, we used the MESOGEOS environmental datacube[28], covering the Mediterranean basin from 2006 to 2022. From this datacube, we extracted a subset of variables representing fast-reacting fire-weather conditions: daily maximum 2-m air temperature, daily minimum relative humidity, daily rainfall, max wind speed, and daytime and nighttime land-surface temperature. We also extracted slow-reacting fuel and vegetation variables: soil moisture index, Normalized Difference Vegetation Index (NDVI), and Leaf Area Index (LAI). MESOGEOS datacube integrates reanalysis-based meteorological variables from ERA5-Land, satellite-derived land-surface temperature and vegetation indices (NDVI and LAI) from MODIS, and soil moisture indices from the European Drought Observatory, harmonized 1 km × 1 km × daily grid. To facilitate comparison across variables and regions, all these were transformed into standardized values (z-scores). Specifically, for each variable, we: (i) computed the mean and standard deviation over all JJAS days in 2008–2022 within the Euro-Mediterranean domain, and (ii) subtracted this JJAS mean from the daily value at the fire location and divided by the JJAS standard deviation. Thus, each standardized variable is a dimensionless value (mean 0, unit variance over JJAS 2008–2022), allowing effect sizes to be interpreted on a common scale and reducing the influence of differing climatic and vegetation regimes across the basin.

Drought indices

We characterized drought conditions using the standardized precipitation–evapotranspiration index (SPEI) at 1-, 3-, and 6-month accumulation periods, derived from the global high-resolution (≈5 km) SPEI dataset[29], which spans 1981–2022 and provides multi-scale indices from 1 to 48 months. We focused on 1-, 3-, and 6-month accumulation periods (SPEI-1, SPEI-3, SPEI-6) to test whether short-lived meteorological dryness, seasonal-scale fuel desiccation, or longer-term eco-hydrological stress are more strongly associated with fire-size escalation. Because SPEI is provided at monthly resolution, we assigned each fire a daily value by linearly interpolating between the index values of the previous and current month, so that early-month fires are weighted more towards the previous month and late-month fires towards the current one.

Extraction of predictor variables at fire locations

Pre-processing steps including temporal alignment, spatial intersection, aggregation across intersecting pixels, and treatment of missing coastal values were implemented to align the fire data (target variable) with the weather and drought-related predictors introduced above. Our objective was to produce a harmonized fire-level dataset in which each event is associated with consistent, temporally matched, and spatially explicit environmental conditions around the ignition date. To achieve this, we extracted and aggregated gridded predictor fields at each fire perimeter using a standardized spatial–temporal procedure: all environmental variables were spatially intersected with each fire perimeter to extract gridded values at the fire location. For each fire and each predictor, we proceeded in two steps. First, daily extraction around the reported start date: for each grid cell intersecting a given perimeter, we extracted predictor values on one day before the reported start date (d–1), the reported start date (d), and one day after (d + 1). This ±1-day window accounts for uncertainty in EFFIS start dates, which may not exactly match ignition; the EFFIS burnt area product explicitly notes that reported start dates may not correspond to actual ignition times (EFFIS, 2018). Similar timing uncertainties are documented in other global fire datasets[40]. Secondly, for each fire, variable and day, we averaged the values across all grid cells intersecting the fire perimeter and we computed a 3-day mean over d–1, d, and d + 1 for each predictor, yielding a single value per fire and variable. Mostly for coastal and island fires, some grid cells were missing due to land–sea discontinuities. To mitigate this, we adopted a stepwise buffering strategy around the fires perimeters[16]. we first attempted to extract values using the original perimeter, and, only if no valid pixel was found, we progressively expanded the perimeter to 5 km, 10 km and 20 km buffers, stopping as soon as at least one full pixel was captured; if no pixel was available even within the 20 km buffer, the corresponding fire–variable pair was assigned a missing value (NA) and excluded from further analysis. This procedure yielded near-complete coverage for most variables: out of 11,403 fires, the proportion of missing values was 0.48% for LAI, 0.03% for daytime LST, 0.14% for nighttime LST, 0% for NDVI, 1.19% for relative humidity, 1.19% for 2 m temperature, 1.19% for wind speed and 1.19% for rainfall. For the drought-related variables, the fraction of missing values was 3.08% for SPEI-1 and SPEI-3, 2.76% for SPEI-6, and 10.03% for the soil moisture index. This procedure ensures that most coastal wildfires, quite common and often large in the Mediterranean landscapes, are represented with a complete set of environmental predictors.

Fire-size transitions

Here, the term *fire-size transition* is used in an event-based sense and refers to transitions between successive fire-size classes (e.g., from medium to large fires, and from large fires to megafires) defined by final burned area across different fire events, rather than to the temporal growth of individual fires. For each transition type, we constructed a binary dataset by pooling fires in the lower and upper classes and assigning 0 to events in the lower size class and 1 to events in the upper size class. As an initial, non-parametric assessment, we compared the distributions of each standardized predictor between the lower and upper classes using pairwise two-sided Wilcoxon rank–sum tests. This provides a first indication of whether, for example, anomalously high temperature, low humidity, strong winds, or severe drought disproportionately occur in larger fires.

Random Forest modelling

To identify which predictor variables are most strongly associated with transitions between two fire-size classes, we implemented a Random Forest classification framework[41]. The candidate predictors comprised all standardized variables from MESOGEOS, including fast-reacting fire-weather variables (temperature, humidity, wind, rainfall, daytime and nighttime land surface temperature) and slow-reacting indicators of fuel and vegetation status (soil moisture, NDVI, LAI) together with the interpolated multiscale SPEI.

For each transition, we carried out 250 repeated stratified random train–test splits, using an 80%/20% split, combined with down-sampling of the majority class experiments. By "down-sampling experiments" we refer to a set of repeated Random Forest training experiments designed to address class imbalance in the binary classification. Specifically, the majority class was randomly reduced to match (or closely approach) the sample size of the minority class, and the model was repeatedly trained and evaluated on these balanced subsets. In each experiment, we drew a random split of the data, using 80% of the fires for training and 20% for testing while preserving the proportion of lower- and upper-class events (i.e., 0/1). Within each split we removed non-finite or zero-variance predictors, assigned class weights inversely proportional to the class frequencies in the training set to alleviate imbalance (particularly for rare megafires). We then fitted a probabilistic Random Forest classifier using the ranger package by Wright and Ziegler[42], implemented in R free software[43]. Random Forests are ensembles of decision trees fitted on bootstrap resamples and random subsets of predictors. We used 500 trees in each forest (ntree = 500) and set the number of predictors considered at each split to one (mtry = 3). This configuration provides stable predictions at modest computational cost while limiting higher-order interactions and emphasising the marginal effects of individual variables on fire-size transitions, in line with recent applications to weather/climate and fire activity[21,44]. Results obtained using an alternative Random Forest configuration are reported in Fig. S1. The model outputs the predicted probability that a given fire belongs to the upper size class, from which we computed the Area Under the ROC curve (AUC) on the test set as a measure of predictive skill. To quantify variable importance, we adopted a permutation-based approach. For each fitted RF and its corresponding test set, we first computed a baseline AUC; we then permuted each predictor in turn, recomputed the AUC, and recorded the drop relative to the baseline. This permutation-based importance directly measures the contribution of each variable to correctly predict the observed output (i.e., the upper-class "1") by assessing the loss in out-of-sample performance when its information is disrupted, and differs from impurity-based measures (i.e. GINI importance). The GINI index quantifies variable importance based on reductions in node impurity during tree construction; it is known to be biased in the presence of correlated predictors or class imbalance (Strobl et al., 2008). Correlations among all candidate predictors were examined and are reported in Fig. S3: as expected, variables describing similar processes (e.g. different SPEI accumulation periods and temperature metrics) are correlated. While Random Forests are robust to multicollinearity in terms of predictive performance, both Gini-based and permutation-based importance metrics can be affected by correlated predictors: in this case Gini-based variable importance should not be interpreted as a strict ranking of individual drivers, but rather as an indication of the relative contribution of groups of variables representing shared underlying processes.

The AUC value, averaged over all repeated random train–test splits, provides a robust, model-agnostic measure of how much each variable contributes to correctly distinguishing larger from smaller fires. For every fire-size transition and each predictor, the distribution of AUC drops is characterized by its mean and the 95% empirical interval. Model performance and variable importance were evaluated on independent test data to avoid optimistic bias associated with class imbalance. We further grouped variables into "fast" (fire-weather) and "slow" (fuel and drought) processes to assess whether rapid atmospheric anomalies or slower fuel-related conditions dominate in explaining escalation towards larger fires and megafires following Luo et al.[21].

Logistic regression modelling

To complement the Random Forest analysis, which provides a robust ranking of predictors but not their direction of effect, we constructed out-of-sample logistic regression models to quantify how fast- and slow-reacting variables control transitions between fire-size classes (Fig. 4). Guided by the Random Forest permutation-importance results, which consistently highlighted nighttime land-surface temperature (LSTn), wind speed, SPEI-3, and NDVI as key predictors across most of the transitions, we restricted attention to standardized anomalies of these four variables as candidate best predictors in the logistic models.

All predictors enter the models as standardized values (z-scores), and the response variable is again binary, with 0 for fires in the lower size class and 1 for fires in the upper class, so that positive coefficients indicate conditions that increase the probability of a fire reaching the larger class.

For each transition, we fitted all 15 non-empty combinations of the four predictors (from single-variable models to the full four-predictor model) and evaluated them with a repeated cross-validation scheme. We generated 5-fold stratified partitions of the data, repeated 50 times, resulting in 250 resamples per model and transition. In each resample, four folds were used for training and one-fold for testing. Within the training folds, we balanced the classes by down-sampling the majority class, fitted a logistic regression model with the chosen predictor set, and then predicted the probability of belonging to the upper size class for the held-out fold. Down-sampling was implemented by randomly reducing the majority class within each training fold to match the number of observations in the minority class, while leaving the test fold unchanged. This approach was adopted to stabilise coefficient estimation and uncertainty quantification under strong class imbalance. From these predictions, we computed the AUC, the recall (true positive rate for the upper size class at a threshold of 0.5), and the corresponding false positive rate. We then summarized, for each transition and model, the distribution of these metrics across the 250 resamples using the median and 95% empirical intervals.

For every resample, we stored the estimated regression coefficients (excluding the intercept), and for each transition–model–predictor combination, we derived the median coefficient and a 95% empirical interval from the 2.5th and 97.5th percentiles of this resampled distribution. To guard against multicollinearity, we also performed a pre-screening based on the full (non-downsampled) dataset: for each candidate model with more than one predictor, we fitted a logistic regression once, computed the variance inflation factor (VIF) for each term, and discarded models with a maximum VIF exceeding 2.

Model selection proceeded in two steps. First, we restricted attention to models in which all predictors had 95% coefficient intervals that did not cross zero, ensuring a stable sign of association across resamples while satisfying the VIF criterion. Among these, we then selected, for each transition, the model with the highest median AUC; in the case of identical median AUC values, we favoured higher median recall and, if necessary, the more parsimonious model with fewer predictors. This logistic regression framework therefore provides interpretable effect estimates and uncertainty ranges that complement the Random Forest variable ranking, clarifying whether fast fire-weather anomalies or slower drought and vegetation conditions exert stronger control on the probability of fires transitioning into larger size classes, particularly megafires following Luo et al.[21]. As a robustness check, we implemented a leave-one-megafire-out jackknife by iteratively excluding each megafire event and refitting the logistic regression models, in order to assess the sensitivity of model performance and coefficient estimates.

Data availability

All predictors used in this study are publicly available from the MESOGEOS environmental fire datacube (https://orionlab.space.noa.gr/mesogeos/) and from the global standardized precipitation–evapotranspiration index dataset described in Gebrechorkos et al.[29]. Fire perimeter data were obtained from the European Forest Fire Information System (EFFIS) under its data-sharing agreement. Derived fire–environment datasets generated in this work is publicly available at https://zenodo.org/records/18934902.

Code availability

Reproducible code is available publicly at https://zenodo.org/records/18934902. .

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Author contributions

Conceptualization: F.G., M.To., P.F. and M.Tu. Methodology: F.G., M.To., P.F. and M.Tu. Investigation: F.G., M.To. and M.Tu. Visualization: F.G., M.To. and M.Tu. Funding acquisition: P.F. Project administration: P.F. Supervision: M.To., P.F. and M.Tu. Writing—original draft: F.G. and M.Tu. Writing—review and editing: F.G., M.To., P.F. and M.Tu.

Competing interests

The authors declare no competing interests. Author M.Tu. is an editor of this journal but was not involved in the review or decision process for this manuscript.

Additional information

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