



Quantifying the heterogeneous impacts of drought across the distribution of wildfire scale

Kyunghun Kim^{1,2}, Nivedita Sairam¹, Bruno Merz^{1,3}

¹Section Hydrology, GFZ Helmholtz Centre for Geosciences, Potsdam, 14473, Germany

5 ²Institute of Water Resources System, INHA University, Incheon, 22212, Republic of Korea

³Institute for Environmental Sciences and Geography, University of Potsdam, Potsdam, 14476, Germany

Correspondence to: Bruno Merz (bruno.merz@gfz.de)

Abstract. Wildfire research has traditionally viewed drought as a meteorological factor, but multi-hazard frameworks highlight it as a critical driver of fire characteristics. Despite this conceptual shift, existing studies have largely focused on association between drought and wildfire, leaving a critical gap in quantifying drought's impact on wildfire scale. Addressing this limitation, we analyzed observational records of nearly 12,000 wildfires in South Korea from 2000 to 2024 using the Quantile Treatment Effect (QTE) approach to quantify drought impacts on burned area and wildfire duration across the distribution of wildfire scales (0.05 to 0.95 quantile range). Our analysis showed that the influence of drought increased markedly toward the upper quantiles of the distribution of wildfire scale, leading to a maximum increase in burned area of 15 510 ha and wildfire duration of 1.2 days. At the upper tail, the drought-induced relative increase in burned area was up to 13.7 times higher and strongly exceeded the increase in wildfire duration. To our knowledge, this is the first study to quantify the impacts of drought on wildfire characteristics using observed wildfire data. These findings advance our understanding of drought-wildfire interactions and provide an empirical foundation for multi-hazard risk assessments.

1 Introduction

20 Wildfires burn approximately 400 million hectares of land annually worldwide, threatening communities, ecosystems and infrastructure (UNEP, 2022). Comparing the average wildfire impacts between 2000-2012 and 2013-2025 in the Emergency Events Database (EM-DAT) reveals 5-fold and 3-fold increases in affected population and economic losses from wildfire, respectively. An important driver of this increase is accelerating climate change, which fosters prolonged droughts and extreme weather that amplify wildfire activity. Consequently, wildfire-prone regions are expanding globally, and compound 25 drought-wildfire risks are increasing (Richardson et al., 2022). The relationship between droughts and wildfires has long been used in wildfire research. Early wildfire research treated drought as one of several meteorological factors influencing fire occurrence and behavior. Accordingly, drought indices were incorporated in fire danger rating systems (Griffiths, 1999), statistical models to estimate wildfire probability (Preisler and Westerling, 2007), and meteorological classifications characterizing fire-conducive atmospheric conditions (Littell et al., 2009). However, the emergence of the multi-hazard



30 framework has redefined this perspective. Drought is now understood as a key driver influencing multiple dimensions of wildfire activity, such as fire size, duration, and spread rate (Batllori et al., 2019; Richardson et al., 2022).

Unlike traditional approaches that treat individual hazards as independent events, the multi-hazard framework considers the interactions when hazards overlap in time and space or are causally linked (White et al., 2025). Within this framework, hazard interactions are not merely additive. Instead, one hazard can amplify the intensity and consequences of another in a

35 non-linear way, producing combined effects that exceed the sum of their parts. This amplifying dynamic is also evident in the drought-wildfire relationship. Wildfire occurrence and spread are fundamentally governed by fuel availability, weather, terrain features, and socioeconomic conditions (Flannigan et al., 2009). Drought directly affects two of these components: fuel and weather conditions. Specifically, drought reduces fuel moisture, drying out vegetation and turning it into highly flammable material, thus increasing the fuel load. At the same time, the lack of precipitation reduces atmospheric moisture,

40 creating dry air and favorable weather conditions for rapid fire start and spread. These mechanisms are illustrated by the 2019–2020 Black Summer wildfires in Australia. A multi-year drought created critically dry fuel and weather conditions conducive to catastrophic fire behavior. As a result, the wildfires that followed burned about 17 million hectares of land and destroyed over 3,100 homes, causing severe damage (Royal Commission into National Natural Disaster Arrangements, 2020).

45 Despite this conceptual shift from single-hazard to multi-hazard perspectives, research on the drought-wildfire relationship remains methodologically limited. Prior studies have established positive correlations between drought indices and wildfire characteristics, showing that drought conditions increase wildfire frequency and burned area (Russo et al., 2017; Chen et al., 2022; Ma et al., 2026). Others have demonstrated that drought periods yield higher wildfire frequency and larger burned areas compared to non-drought conditions (Littell et al., 2009; Brando et al., 2014; Richardson et al., 2022). While these

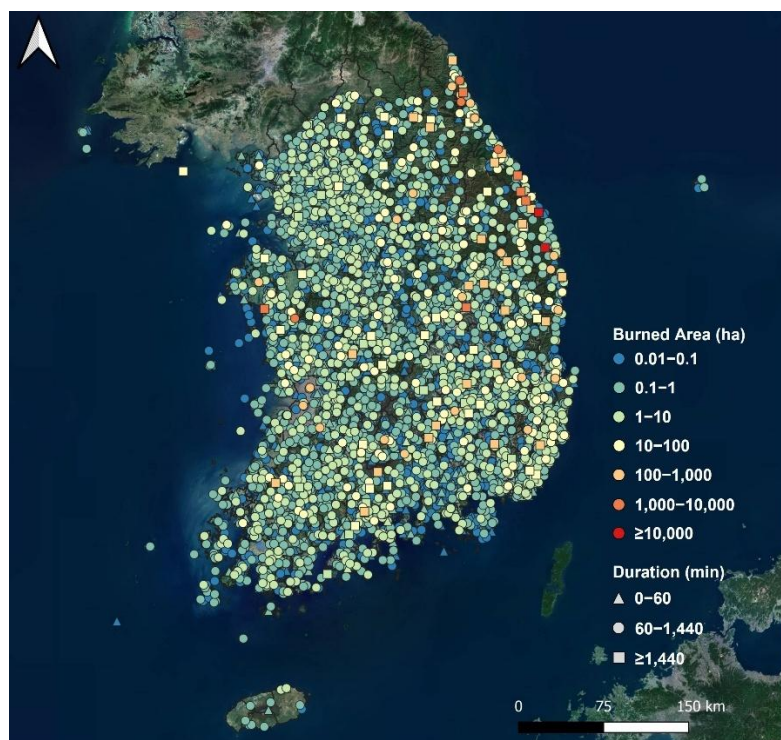
50 approaches have established the existence and direction of drought effects, they focus on average relationships. However, such average-based estimates fail to capture the behavior of skewed distributions; because wildfire scale distributions are highly right-skewed, relying on average impacts risks underestimating the disproportionate damage caused by extreme events, thereby misleading wildfire mitigation strategies and resource allocation (Malamud et al., 2005; Tedim et al., 2018). Consequently, there remains a lack of evidence about the extent to which droughts alter wildfires across the distribution of

55 wildfire scales. Here, we address this gap by employing the Quantile Treatment Effects (QTE) approach to estimate the drought impact on the distribution of wildfire scales, specifically total burned area and wildfire duration. Unlike the traditional Average Treatment Effect (ATE), which captures only mean effects, QTE examines how a specific treatment (i.e., presence of drought conditions) exerts differential impacts across the entire distribution of an outcome variable (i.e., wildfire duration and burnt area). This approach thus provides a more detailed understanding of drought effects across small,

60 moderate, and large wildfire events. Thereby, our approach moves beyond measuring average effects and explicitly captures the heterogeneous influence of drought across the wildfire scale distribution.

2 Study area and data

Wildfire is a major hazard in South Korea. Over the past 25 years, Korea Forest Service (KFS) has documented 11,800 wildfires, burning a total area of 79,139 ha (Fig. 1, KFS, 2025). While most wildfires are small in extent and duration, a small fraction of large-scale wildfires, defined by KFS as those affecting at least 100 ha, contribute disproportionately to overall impact. The 2022 Uljin-Samcheok wildfire and the 2025 Gyeongsangbuk-do wildfire are the most prominent examples (Fig. S1 in the Supplement). The Uljin-Samcheok wildfire burned for 222 hours, destroyed 16,302 ha, and caused \$605 million in economic losses, a national record at that time. The fire that ignited on March 4, 2025 rapidly spread from Uiseong to neighboring regions (Andong, Yeongyang, Cheongsong, and Yeongdeok). While its duration was similar to the 2022 fire, it devastated an unprecedented 99,417 ha and incurred \$4,225 million in economic losses, making it the most catastrophic wildfire in South Korean history. Such large-scale wildfires have occurred almost annually over the last decade, suggesting an intensification of this threat. Academia and authorities identify drought as a primary driver of this trend (Sung et al., 2022; Kim et al., 2024; Kim et al., 2026). Indeed, South Korea has faced an unprecedented rise of severe drought conditions in recent years. Between 2022 and 2023, the southern region suffered the longest consecutive meteorological drought since 1974. This was followed by another severe drought in early 2025, which caused reservoir water levels in some areas to drop to a critical low of 11.5%. These worsening drought patterns create conditions highly vulnerable to large-scale wildfires. The resulting increase of drought-compounded wildfire risk makes South Korea a critical region for quantifying these impacts.





80 **Figure 1.** Spatial distribution of wildfire cases in South Korea during 2000 to 2024. Each point indicates the ignition of a wildfire event, where shapes represent wildfire duration (min) and colors denote the total burned area (ha). Map data: © Kakao Corp.

We extracted wildfire records for the period 2000-2024 from the Annual Statistical Yearbook of Wildfire (KFS, 2025), an officially certified national dataset. For each fire event, it provides start and end time, location, ignition cause, and total burned area. Meteorological and hydrological variables were obtained from the Korea Meteorological Administration Open
 85 MET Data Portal and the Water Management Information System (WAMIS), respectively. Because droughts are a key component of the hydrological cycle, we adopted watersheds rather than administrative units as our spatial unit of analysis. The daily meteorological datasets include relative humidity, temperature, wind speed, and precipitation. Point weather observations were converted to areal values using Thiessen weights obtained from WAMIS. Watershed topography was characterized by mean elevation, slope, and aspect. We obtained land cover and forest type maps from the Environmental
 90 Geographic Information Service and the Forest Geospatial Information Service, respectively.

3 Methodology

3.1 Classification of wildfire events: multi-hazard vs single-hazard

We classified wildfire events as multi-hazard or single-hazard based on the spatiotemporal overlap between wildfires and drought events. Each wildfire was assigned to a specific watershed based on its ignition coordinates. For drought event
 95 identification, we calculated the 6-month Standardized Precipitation Index (SPI-6), a standard metric for drought risk assessment in South Korea (Kim et al., 2026). Following McKee et al. (1993), we defined a drought event as a period of at least three consecutive months with $\text{SPI-6} \leq -1.0$. This three-month minimum distinguishes droughts from temporary dry spells (Konapala et al., 2022). To ensure alignment between daily wildfire data and monthly drought events, we converted the monthly drought indicators to a daily scale. Specifically, if a drought occurred from March to April, the drought period
 100 was defined as spanning from March 1st to April 30th. Wildfire events occurring within the same watershed during a drought period were classified as multi-hazard event. Wildfires with no such overlap are classified as single-hazard events.

3.2 Quantile Treatment Effect (QTE) approach

3.2.1 Correcting selection bias in Average Treatment Effect (ATE) estimation

To estimate the effect of drought on wildfire scale, we considered the presence of drought as a binary treatment indicator.
 105 Based on this indicator, the treatment group comprises multi-hazards (drought + wildfire events), whereas the control group represents single-hazards (only wildfire events). The difference in wildfire scale between multi- and single-hazards was captured by evaluating the influence of drought on two outcomes: total burned area and wildfire duration. Based on the counterfactual framework of the Roy–Rubin causal model (Roy, 1951; Rubin, 1974), the ATE for each outcome is defined in Eq. (1).



110 $ATE(T) = E[Y(T = 1) - Y(T = 0)],$ (1)

where T denotes the binary treatment indicator ($T = 1$ for multi-hazard, $T = 0$ for single hazard), E is the expectation operator, and $Y(T = 1)$ & $Y(T = 0)$ are the potential outcomes under the treatment and control conditions, respectively. Y is sequentially substituted by total burned area (ha) and wildfire duration (minutes).

Due to inherent heterogeneity across watersheds and wildfire events, differences in wildfire characteristics between the multi- and single-hazards cannot be solely attributed to drought. Rather, the likelihood of a watershed experiencing drought is systematically confounded by local baseline conditions. Attributes that simultaneously influence drought occurrence and wildfire dynamics are the confounding variables (Table S1 in the Supplement). If left uncontrolled, these confounders introduce selection bias, as watersheds with distinct environmental conditions possess unequal probabilities of experiencing drought, confounding the impact of drought with pre-existing localized weather, watershed condition, landcover and forest characteristics. Failing to account for this distortion leads to either an overestimation or underestimation of drought's role in amplifying wildfires. To isolate the true causal influence of drought on wildfire severity, the counterfactual framework must be conditioned on the full set of confounding variables. Consequently, the ATE formulation in Eq. (1) was adjusted to a conditional framework represented by Eq. (2).

120 $ATE(T) = E[Y(T = 1, X) - Y(T = 0, X)],$ (2)

125 where X denotes the multi-dimensional vector of pre-treatment confounders

3.2.2 Propensity score estimation

To isolate the causal effect of drought on wildfire scale, treatment and control groups must be compared under equivalent pre-treatment conditions, i.e., balanced for confounding variables. However, finding exact matching pairs given multiple confounders is practically impossible in observational data. To overcome this limitation and align the baseline conditions between groups, we used propensity scores, a scalar summary of the multidimensional confounders, defined as the conditional probability of an event receiving the treatment (i.e., being multi-hazard) given its baseline attributes (Heinze and Jüni, 2011). Propensity scores were estimated using a logistic regression model as shown in Eq. (3):

130 $p_i = P(T_i = 1|X_i) = \frac{1}{(1+e^{-X_i\beta})},$ (3)

where p_i is the propensity score of i th wildfire event, T_i is the drought indicator (Treatment), X_i is the set of confounding variables, β is the set of regression coefficients, and e represents the exponential function

The overall fit and statistical significance of the logistic regression model were evaluated using the likelihood ratio test. Following the estimation of propensity scores, we restricted the analysis to events in the common support area (Eq. (4)), where the propensity score distributions of the treatment and control groups overlapped. Wildfire events falling outside this



region were excluded from the matching process to ensure that the compared units share a similar environmental baseline,
 140 thereby eliminating biased extrapolation (Williamson and Forbes, 2014).

$$\text{Common support area} = [\max(\min(P_m, P_s)), \min(\max(P_m, P_s))], \quad (4)$$

where p_m and p_s are propensity scores of wildfire events in the multi-hazard and single-hazard groups, respectively.
 Based on the estimated propensity scores, we applied Inverse Probability of Treatment Weighting (IPTW) as matching
 method to obtain a balanced dataset. This weighting-based approach homogenizes confounding variables across treatment
 145 and control groups (Austin, 2012). To verify that the pretreatment confounding variables were successfully controlled
 through the weighting procedure, the Standardized Mean Difference (SMD) was evaluated for each variable (Eq. (5)). An
 SMD threshold below 0.1 indicates effective elimination of the systematic differences between the two groups (Zhang et al.,
 2019).

$$SMD = \frac{\bar{X}_T - \bar{X}_C}{\sqrt{(S_T^2 + S_C^2)/2}}, \quad (5)$$

150 where $\bar{X}$ is the covariate mean, S is the covariate standard deviation of treatment (T) and control (C) groups.

3.2.3 Postmatching regression and sensitivity analysis

To address any residual confounding biases that might persist even after the weighting procedure, we implemented
 postmatching regression. Incorporating the covariates back into the regression model provides a doubly robust estimation
 (Sairam et al., 2019), ensuring that the causal effect of drought on wildfire severity is consistently and accurately estimated.
 155 Specifically, a quantile regression model was employed rather than a standard Ordinary Least Squares (OLS) regression.
 While OLS only estimates the ATE, drought impacts on wildfire characteristics may vary substantially between small and
 large wildfire events. Analyzing different conditional quantiles of the outcome distribution allows us to capture the
 heterogeneous and non-linear causal effects of drought across the entire spectrum of wildfire events. Accordingly, rather than
 estimating the conventional ATE, we rewrote the causal framework to define the QTE at a specific quantile τ as shown in Eq.
 160 (6).

$$QTE(\tau) = Y_\tau(T = 1, X) - Y_\tau(T = 0, X) = \gamma(\tau), \quad (6)$$

where $Y_\tau(T = 1, X)$ and $Y_\tau(T = 0, X)$ are the τ th conditional quantiles of the outcome under the treatment and control groups,
 respectively, and γ is the corresponding quantile regression coefficient

Assuming the postmatching regression effectively controls for all relevant covariates, the presence or absence of the
 165 treatment condition remains the sole systematic difference between the two groups (Sairam et al., 2025). Consequently, the
 conditional quantile difference between the two distributions directly equals the model parameter $\gamma(\tau)$. To evaluate
 statistical significance (95% confidence intervals), we employed a bootstrapping approach with 1,000 replications.



While the propensity score weighting and postmatching regression control for observed covariates, observational studies remain susceptible to bias from unobserved or omitted confounders (Caliendo and Kopeining, 2008). To evaluate the robustness of our findings against such hidden biases, we conducted a simulation-based sensitivity analysis following Rosenbaum (1995). A virtual binary unobserved confounder (U) was added into the matched dataset. The distribution of U was simulated to generate an artificial disparity in the treatment assignment probability between the two groups. This disparity was controlled by a sensitivity parameter Γ ($\Gamma \in \{1.2, 1.5, 2.0\}$), where higher Γ indicates the factor by which U increases the odds of receiving the treatment. We then re-estimated the weighted post-matching quantile regression by explicitly conditioning on U across major conditional quantiles ($\tau \in \{0.1, 0.2, \dots, 0.9\}$). By tracking the variations in the updated parameter $\gamma(\tau)$ and its statistical significance under varying levels of Γ , we evaluated the threshold at which the causal conclusion would be overturned, thereby assessing the sensitivity of our results to unobserved confounders.

4 Results

4.1 Empirical distributions of total burned area and wildfire duration: multi-hazard vs single-hazard

Between 2000 and 2024, South Korea recorded 11,800 wildfires, resulting in a total burned area of 79,139 ha and a cumulative duration of approximately 3.6 years. Despite accounting for only 0.5% (63 cases) of total occurrences, large-scale wildfires were responsible for 86% of the total burned area. Wildfire frequency, burned area and duration showed consistent temporal behavior. While annual values show no clear trends, there was a strong seasonality with highest values in March and April (Fig. 2). This seasonal concentration reflects the combination of three factors. First, cumulative winter precipitation deficits reduce fuel moisture content in forest material (such as leaf litter and dead vegetation) to its annual minimum, creating conditions where even minor sparks can ignite easily. Second, the high-north, low-south atmospheric pressure gradient typical for this period generates the year's strongest winds, which act as a primary catalyst for rapid fire expansion. Third, the onset of spring increases outdoor activities, such as hiking and agricultural land clearing. Burning of agricultural waste and accidental ignition sources like discarded cigarettes can then escalate into uncontrollable fires under these dry and windy conditions.

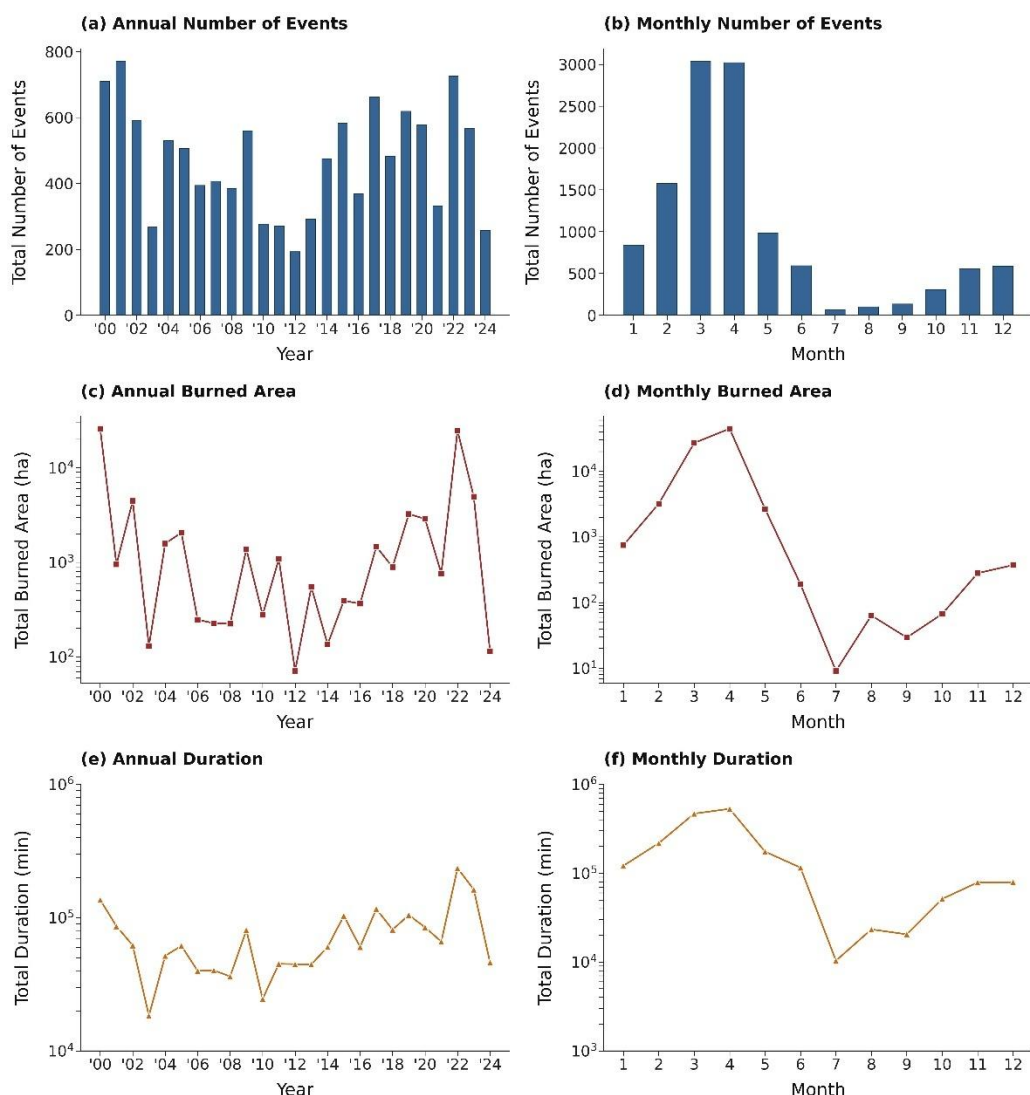


Figure 2. Annual trends for 2000 to 2024 (left) and seasonal variability over the same period (right) of wildfire characteristics in South Korea. (a & b) total number of wildfire events, (c & d) total burned area (ha), and (e & f) total duration of wildfire events (min).

Analyzing SPI-6 for the period 2000–2024 resulted in 610 drought events across all watersheds, with an average cumulative severity of -9.0 and an average duration of 5.6 months. While annual drought frequency had no clear trend, several years showed a high number of droughts (> 50), including 2000 and 2022 that coincided with large-scale wildfire damage (Fig. S2(a) in the Supplement). Drought frequency peaks in May, while March and April, the months with the highest wildfire activity, also exhibit drought frequencies well above the monthly average (Fig. S2(b) in the Supplement). This temporal alignment suggests a potential link between drought conditions and peak wildfire season.

Analysis of spatiotemporal overlap between drought and wildfire events resulted in 1,479 multi-hazard events. Although representing only 13% of all wildfires, this group accounts for 51% (40,668 ha) of the total burned area. The average



duration of multi-hazard events was 226 min, 1.5 times longer than that of single-hazards (151 min). Among large scale wildfires, 23 cases (37%) were classified as multi-hazard events, yet they accounted for 58% (39,038 ha) of the total burned area. Similarly, the average duration of multi-hazards was 3,555 min (59.3 hr), representing a 53% increase over the 2,326 min (38.6 hr) recorded for single-hazards. These findings demonstrate that multi-hazard events exert substantially greater impacts than single-hazards across both wildfire scale characteristics.

We compared the Empirical Cumulative Distribution Functions (ECDFs) of single- and multi-hazard events to capture their distributional differences. For total burned area, both groups show similar distributions for small fires up to 1.0 ha, but multi-hazards caused more extensive damage beyond this threshold (Fig. 3(a)). For wildfire duration, multi-hazard events exhibit a consistent rightward shift across the entire distribution (Fig. 3(b)). For large scale wildfires (≥ 100 ha), the rightward shift for multi-hazard events is much more pronounced in burned area than in duration (Fig. 3(c) & (d)), suggesting that drought amplifies extreme burned areas more severely than wildfire duration. Overall, multi-hazard ECDFs shift rightward with varying degree across the distribution, motivating the QTE approach.

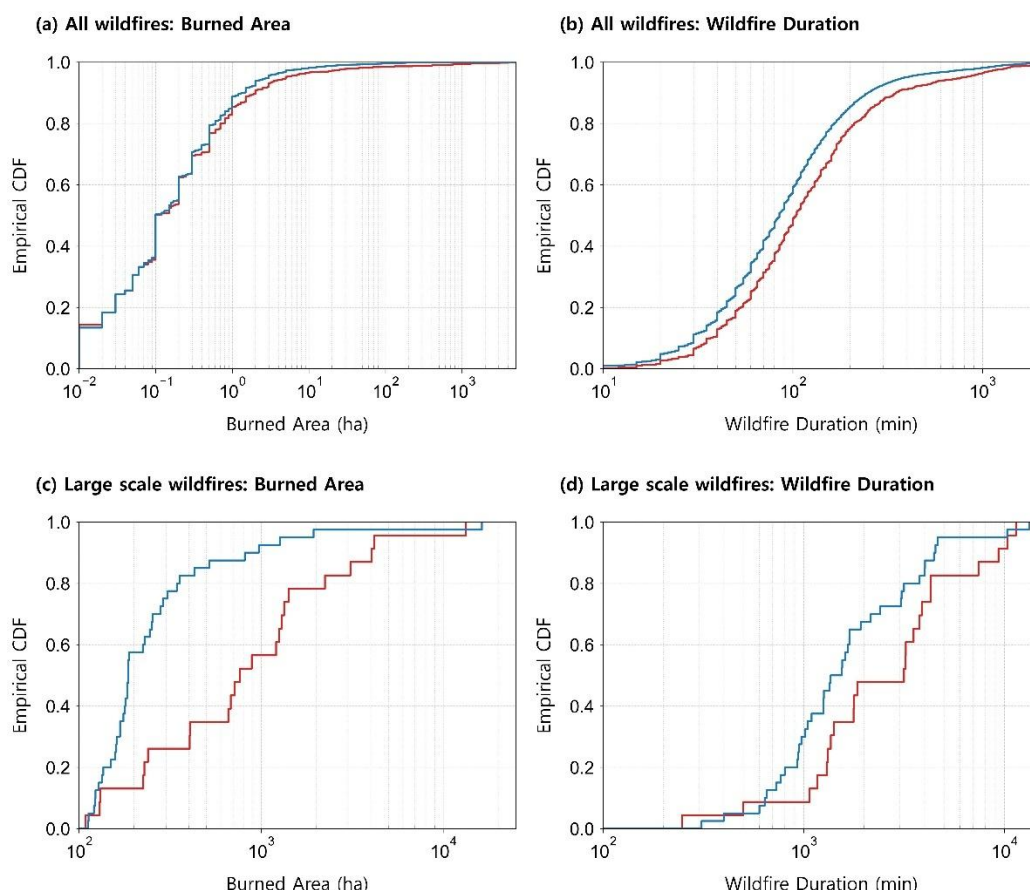


Figure 3. Empirical cumulative distribution functions (ECDFs) of total burned area and wildfire duration for multi-hazard (red) and single-hazard (blue) events for all wildfires (a & b) and large scale wildfires (c & d).



4.2 Role of drought across the distribution of wildfire scale using QTE approach

To apply IPTW, we first developed a logistic regression model estimating the propensity score (see Section 3.2.2). The likelihood ratio test for the model yielded a p-value of less than 0.001, confirming that the model exhibits statistically significant predictive performance for drought occurrence (for details, see Table S2 in the Supplement). Based on estimated propensity scores, events outside the common support area (0.02–0.39) were removed to ensure comparability. Subsequently, we calculated IPTW for each remaining event and estimated SMD considering the weights (Eq. (5)). The SMD results confirmed that all confounding variables achieved a satisfactory balance between the single- and multi-hazard groups (Table S3 in the Supplement).

Postmatching regression was applied to control residual confounding effects, and QTE was estimated across quantiles from 0.05 to 0.95. Following the QTE calculation, we conducted sensitivity analysis to evaluate the robustness of the QTE against potential bias from unobserved confounders. For total burned area, QTE and sensitivity analysis results are as follows (Fig. 4(a) & Fig. S3(a) in the Supplement):

- The average QTE remains within 2.2 ha across all quantiles. The QTEs stayed near zero up to the 0.7 quantile and then increased gradually. However, the lower boundary of the 95% confidence interval includes zero up to the 0.85 quantile, i.e., the QTEs in this range are not statistically significant.
- The sensitivity analysis corroborates the findings from the 95% confidence intervals, confirming the lack of statistical significance. Specifically, similar to the confidence interval results, high p-values ($p > 0.95$) are maintained up to the 0.7 quantile.

For wildfire duration, we obtained (Fig. 4(c) & Fig. S3(b) in the Supplement):

- The average QTE remained below 400 min and exhibited a continuous upward trend across all quantiles. Unlike burned area, the lower boundary of the 95% confidence intervals remained greater than zero, demonstrating that all QTEs are statistically significant.
- The sensitivity analysis confirms the robustness of this relationship, as p-values remain consistently below 0.05 across all quantiles even under a high degree of unobserved confounding ($\Gamma = 2.0$)

However, the QTE findings appear to diverge from the distributional differences observed in Fig. 3. While the ECDF comparison shows a substantial difference in burned area between the two groups, the QTE results reveal a smaller discrepancy. For instance, at the 95th percentile, the ECDFs exhibited a difference of 659 ha in burned area and 1,790 min in duration, whereas the QTE results show a gap of only 2.2 ha and 394 min. We attribute this divergence primarily to the highly skewed distribution of the wildfire dataset, where 85% of the recorded burned areas were under 1 ha, and 82% of the recorded wildfire durations lasted less than 180 min. Indeed, across the entire dataset, the 95th percentile values were only 3 ha for burned area and 426 min for duration. This demonstrates that the regression model was predominantly trained on lower-magnitude values, thereby restricting its capacity to represent catastrophic, large-scale wildfire events.



To address this imbalance, we removed wildfires with a burned area less than 1 ha. This threshold was selected based on our full-data analysis. The QTEs for burned area failed to achieve statistical significance up to the 0.85 quantile, which corresponds to a value of 1 ha. After removing these small events, we implemented the methodology again. The updated logistic model and subsequent homogeneity tests yielded statistically significant results, while the SMD analysis confirmed adequate covariate balance (Table S4 & S5 in the Supplement).

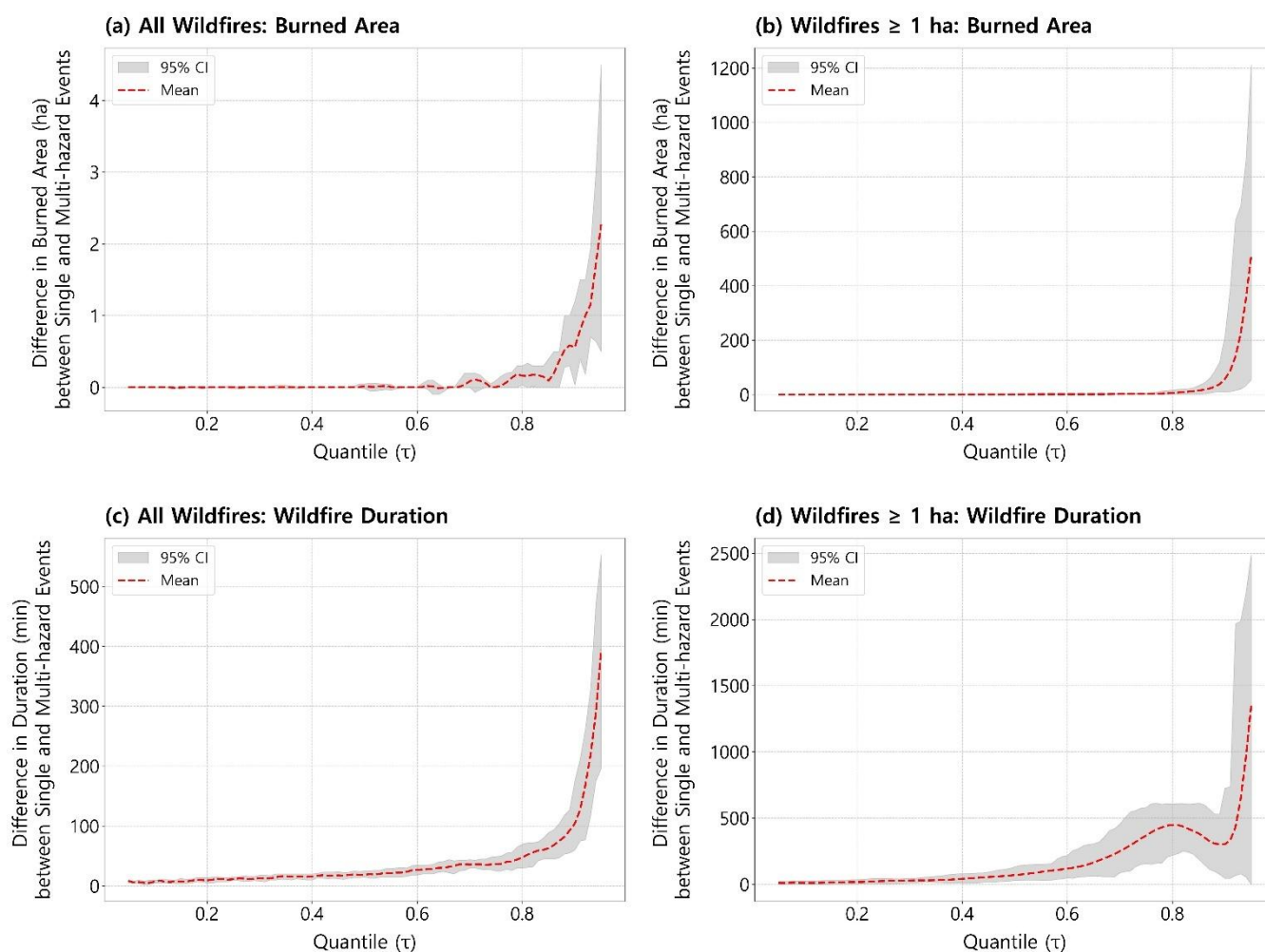


Figure 4. Drought impact on wildfire burned area (top) and duration (bottom). Red dotted line is the average QTE for each quantile, and gray shaded area is 95% confidence interval for all wildfires (a & c), and for wildfires ≥ 1 (b & d).

The QTE results for total burned area (Fig. 4(b)) showed modest impacts, ranging between 0.1 and 13 ha up to the 0.85 quantile. However, beyond this point, they grew exponentially, peaking at nearly 510 ha. This rise represents a remarkable 232-fold increase compared to the maximum value observed in the full-dataset analysis. A similar upward shift was observed for wildfire duration, with QTE values increasing 3.4-fold (Fig. 4(d)). These increases illustrate the strong influence of drought on wildfire characteristics once the statistical noise and skewness caused by small-scale events are removed.



Furthermore, for events ≥ 1 ha burnt area, the lower bounds of the 95% confidence interval remained above zero across all quantiles (Fig. S4 in the Supplement), though confidence intervals are wider at higher quantiles compared to the full dataset. The higher uncertainty is attributable to the low density of extreme events.

265 The differences in ECDFs for multi- and single-hazard events reflect the combined influence of drought alongside other exogenous variables, such as topographical characteristics and meteorological conditions. In contrast, QTE represents the pure drought impact. Dividing QTE by the ECDF difference thus quantifies the relative contribution of the drought to the overall disparity between the two groups (Fig. S5 in the Supplement). Drought's contribution exceeded 50% for all quantiles for both wildfire characteristics. For total burned area, its share increased sharply beyond the 0.15 quantile, consistently
 270 exceeding 70% and reaching a maximum of 98% at the 0.90 quantile. For wildfire duration, the contribution was even more pronounced, remaining above 80% across almost the entire quantile range with a peak of 99.7%. This indicates that for most wildfires, drought-induced changes act as the primary driver amplifying fire spread and persistence. However, at the extreme upper tail (0.95 quantile), drought's relative contribution dropped sharply for both characteristics. This drop suggests that at the most extreme wildfire events, non-drought factors may play a proportionally larger role. Alternatively, it may reflect the
 275 sparse sample size at the upper tail, where a small number of extreme events makes the attribution less stable.

4.3 Comparative analysis of drought impacts on total burned area and wildfire duration

Total burned area and duration show a Pearson correlation coefficient of 0.50 and do not always increase proportionally (Fig. S6 in the Supplement). Some fires cover vast areas despite a short duration, while others persist for a long time yet affect only a small area. This indicates that while spatial and temporal extension are related, they are affected differently by
 280 environmental and anthropogenic factors. Here, we compared the influence of drought on burned area and duration to identify which wildfire characteristic is more strongly affected by drought. Since total burned area and duration have different physical units, a direct comparison of QTE was inappropriate. Instead, we compared the percentage change of multi-hazard events relative to single-hazard events for each quantile, based on the reduced dataset (wildfires > 1 ha). Up to the 0.80 quantile, the stronger impact fluctuated between the two characteristics (Fig. 5). Beyond this point, drought's impact
 285 is stronger for total burned area, with a widening gap. This divergence suggests that for large fires, drought acts primarily as a spread accelerator, rather than a duration extender. In other words, drought amplifies burned area more than it prolongs fire duration, implying that its dominant effect is to increase the rate of fire spread – likely through reduced fuel moisture and drier atmospheric conditions rather than merely sustaining combustion over a longer period.

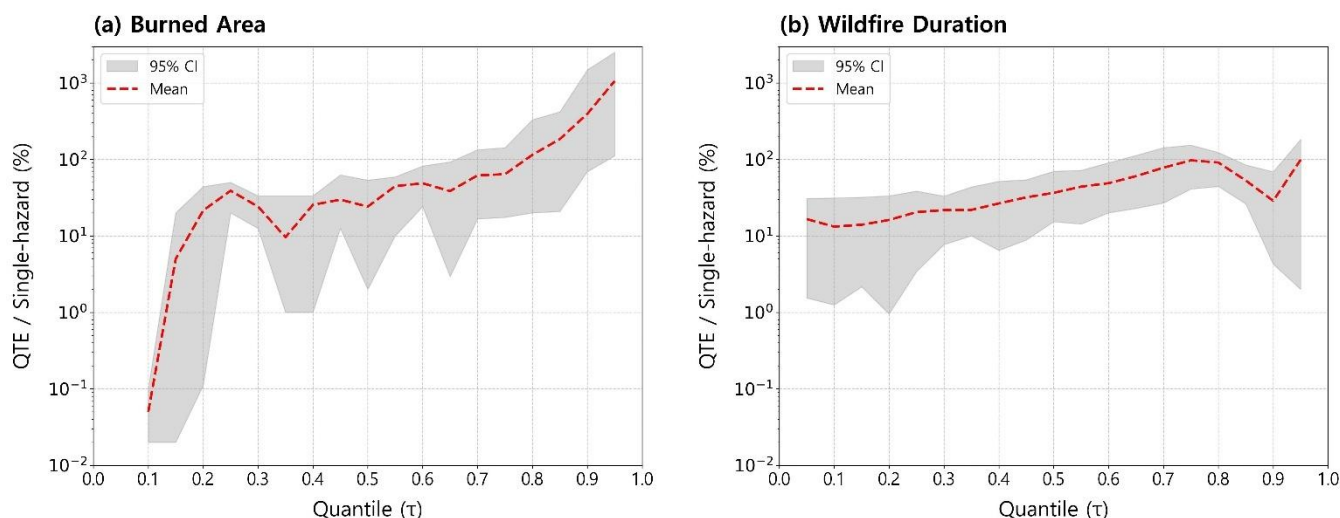


Figure 5. Relative impact of drought on wildfire characteristics across quantile. Relative impacts are calculated as the percentage change in QTE of multi-hazard relative to single-hazard baselines. Red dotted line is the average for each quantile, and gray shaded area is 95% confidence interval.

5 Discussion

Although previous research has confirmed that droughts influence wildfire characteristics, it has remained unclear whether this impact is uniform for small and large wildfires. Using ECDF comparisons and QTE estimation, we found that the influence of drought on wildfires amplifies strongly with wildfire scale. This differential response likely reflects how drought interacts with fire suppression capacity. Small scale wildfires share a common trait: early detection followed by rapid initial attack that quickly terminates the fire. The short duration limits the temporal window required for drought-impacted meteorological factors to escalate fire behavior. Even when drought creates environmental conditions favorable to wildfire growth, firefighting intervention effectively interrupts the manifestation of these meteorological drivers before their potential is fully realized (Ruffault, and Mouillot, 2015; Littell et al., 2016). Consequently, the drought contribution in small scale wildfires does not indicate an absence of drought influence, rather it indicates that the initial attack mitigates the impact of drought.

In contrast, large scale wildfires represent cases where initial attack systems reach their limits, allowing the fire to escape human control and become prolonged. Once a wildfire exceeds the threshold scale manageable by firefighting capacity, a wider window of opportunity opens for potential drivers including drought to compound fire spread and persistence. Here, drought plays a foundational role, as evidenced by its substantial contribution to the observed differences in both burned area and duration. However, we caution that this mechanism is not directly testable with our data. Large wildfires are rare events in which multiple risk factors such as drought, high wind, low humidity, and high fuel loads may coincide. The amplified drought effect we observed at large quantiles may therefore reflect the convergence of multiple extreme conditions rather than a suppression threshold alone. Disentangling these effects remains an important direction for future research.



While this study successfully quantified the impact of drought across the distribution of wildfire characteristics, several methodological limitations warrant consideration. First, categorizing wildfires into multi- and single-hazard events relies on spatiotemporal overlap criteria. This method struggles in cases where the impact persists even after the hazard has ended (De Angeli et al., 2022). While incorporating temporal lags could address this, their estimation remains an open challenge (Zscheischler et al., 2020; Yousefi et al., 2020; Kim et al., 2024). Alternatively, one could trace individual event processes to verify interactions. However, such process-based approaches are constrained by subjectivity and limited generalizability (Tilloy et al., 2019). As the multi-hazard perspective advances, integrating lag effects will enable more robust classification. Another methodological constraint is that the analysis only reflects the occurrence of drought, neglecting other characteristics such as drought intensity or duration. The QTE approach requires a binary treatment variable, forcing us to categorize drought as present or absent. This homogenizes all drought events, thereby excluding key attributes known to influence fuel dryness and fire behavior differently. Alternative approaches can avoid this limitation. Generalized propensity score methods (Hirano and Imbens, 2004) extend matching and weighting to continuous treatments, allowing drought severity or duration to remain continuous. Similarly, quantile regression with a continuous treatment variable (Koenker, 2005) could directly estimate how increasing drought intensity shifts different parts of the wildfire outcome distribution, without requiring binarization. Future research employing these approaches could capture more nuanced relationships between drought and wildfire characteristics.

6 Conclusions

This study moved beyond simple correlations to quantify the causal impact of drought on wildfire characteristics. We classified almost 12,000 wildfires that occurred in South Korea between 2000 and 2024 into multi- and single-hazard events and applied the QTE approach to estimate drought impacts across the distribution of wildfire scale (0.05–0.95 quantiles). Our analysis reveals that the impacts of drought on both total burned area and wildfire duration become progressively stronger as the wildfire scale reaches higher quantiles, exhibiting a distinct non-linear relationship. Specifically, at the upper quantiles, the drought-induced relative increase in burned area significantly outpaces that of wildfire duration. These results suggest that drought is more than a precursor that increases fire frequency; instead, it prolongs fire duration and expands wildfire extent during its development phase, ultimately leading to disproportionately larger burned areas during extreme events. To our knowledge, this is the first study to quantify the quantile-specific causal effects of drought on wildfire characteristics using observational wildfire records. By demonstrating that drought exerts increasingly severe impacts on large wildfires, our findings provide new insights useful for wildfire risk assessment under a changing climate.



340 **Code and data availability**

The research data used in this study are publicly accessible through several data portals in South Korea. Historical wildfire statistics are available in the Statistical Yearbook of Forestry published by the Korea Forest Service (KFS; <https://www.forest.go.kr>). Meteorological observation data is accessible from the Open Met Data Portal (Korea Meteorological Administration Weather Data Service) (<https://data.kma.go.kr/resources/html/en/aowdp.html>). Watershed related data and Thiessen polygon-based precipitation weights are available through Water Management Information System (WAMIS; <http://www.wamis.go.kr>). Land cover datasets and forest maps can be obtained from the Environmental Geographic Information Service (EGIS; <https://aid.mcee.go.kr>), and the Forest Geospatial Information Service (FGIS; <https://map.forest.go.kr/forest>), respectively. The processed datasets and Python code used for the ECDF and QTE analyses are available from the corresponding author upon reasonable request.

350 **Author contributions**

K.K. and B.M. conceptualized the study. N.S. developed the methodology. N.S. and K.K. developed the software and validated the analysis. K.K. performed the formal analysis, curated the datasets, created the visualizations, and wrote the original draft. K.K., N.S., and B.M. reviewed and edited the manuscript. B.M. supervised the research project. All authors have read and agreed to the published version of the manuscript. Competing interests

355 **Acknowledgements**

Kyunghun Kim was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (RS-2025-02317771). Nivedita Sairam is funded by BMFTR Grant FKZ 01LN2209A.

Competing interests

360 The authors declare that they have no conflict of interest.

References

Addington, R. N., Hudson, S. J., Hiers, J. K., Hurteau, M. D., Hutcherson, T. F., Matusick, G., and Parker, J. M.: Relationships among wildfire, prescribed fire, and drought in a fire-prone landscape in the south-eastern United States, *Int. J. Wildland Fire*, 24, 778–783, <https://doi.org/10.1071/WF14187>, 2015.



- 365 Austin, P. C.: The performance of different propensity score methods for estimating marginal hazard ratios, *Stat. Med.*, 32, 2837–2849, <https://doi.org/10.1002/sim.5705>, 2013.
 Batllori, E., De Cáceres, M., Brotons, L., Ackerly, D. D., Moritz, M. A., and Lloret, F.: Compound fire–drought regimes promote ecosystem transitions in Mediterranean ecosystems, *J. Ecol.*, 107(3), 1187–1198, <https://doi.org/10.1111/1365-2745.13115>, 2019.
- 370 Brando, P. M., Balch, J. K., Nepstad, D. C., Morton, D. C., Putz, F. E., Coe, M. T., Silvério, D., Macedo, M. N., Davidson, E. A., Nóbrega, C. C., Alencar, A., and Soares-Filho, B. S.: Abrupt increases in Amazonian tree mortality due to drought–fire interactions, *Proc. Natl. Acad. Sci. U.S.A.*, 111, 6347–6352, <https://doi.org/10.1073/pnas.1305499111>, 2014.
 Caliendo, M. and Kopeinig, S.: Some practical guidance for the implementation of propensity score matching, *J. Econ. Surv.*, 22, 31–72, <https://doi.org/10.1111/j.1467-6419.2007.00527.x>, 2008.
- 375 Chen, A.: Evaluating the relationships between wildfires and drought using machine learning, *Int. J. Wildland Fire*, 31(3), 230–239, <https://doi.org/10.1071/WF21145>, 2022.
 De Angeli, S., Malamud, B. D., Rossi, L., Taylor, F. E., Trasforini, E., and Rudari, R.: A multi-hazard framework for spatial-temporal impact analysis, *Int. J. Disaster Risk Reduct.*, 73, 102829, <https://doi.org/10.1016/j.ijdrr.2022.102829>, 2022.
 Firpo, S.: Efficient semiparametric estimation of quantile treatment effects, *Econometrica*, 75, 259–276, <https://doi.org/10.1111/j.1468-0262.2007.00738.x>, 2007.
- 380 Flannigan, M. D., Krawchuk, M. A., de Groot, W. J., Wotton, B. M., and Gowman, L. M.: Implications of changing climate for global wildland fire, *Int. J. Wildland Fire*, 18, 483–507, <https://doi.org/10.1071/WF08187>, 2009.
 Griffiths, D.: Improved formula for the drought factor in McArthur's forest fire danger meter, *Aust. For.*, 62, 202–206, <https://doi.org/10.1080/00049158.1999.10674783>, 1999.
- 385 Heinze, G. and Jüni, P.: An overview of the objectives of and the approaches to propensity score analysis, *Eur. Heart J.*, 32(14), 1704–1708, <https://doi.org/10.1093/eurheartj/ehr031>, 2011.
 Hirano, K. and Imbens, G. W.: The propensity score with continuous treatments, in: *Applied Bayesian Modeling and Causal Inference from Incomplete-Data Perspectives*, edited by: Gelman, A. and Meng, X.-L., John Wiley & Sons, Ltd, Chichester, UK, 73–84, <https://doi.org/10.1002/0470090456.ch7>, 2004.
- 390 Ichino, A., Mealli, F., and Nannicini, T.: From temporary help jobs to permanent employment: What can we learn from matching estimators and their sensitivity?, *J. Appl. Econometrics*, 23, 305–327, <https://doi.org/10.1002/jae.998>, 2008.
 Kim, K. and Kim, H. S.: Quantitative risk assessment for the compound drought-wildfire disaster, *Sci. Rep.*, 16, 7034, <https://doi.org/10.1038/s41598-026-36589-w>, 2026.
 Kim, K., Ahn, H., Kim, J. H., Lee, T., and Kim, H. S.: Study on forest fire risk analysis based on drought scenarios, *J. Korean Soc. Hazard Mitig.*, 24, 7–18, <https://doi.org/10.9798/KOSHAM.2024.24.1.7>, 2024.
- 395 Kim, K., Bae, Y. H., and Kim, H. S.: Estimating the natural disaster inter-event time definition (NIETD) to define compound natural disasters in South Korea, *Nat. Hazards*, 120, 8761–8778, <https://doi.org/10.1007/s11069-024-06549-6>, 2024.



- Koenker, R.: Quantile Regression, Econometric Society Monographs, Cambridge University Press, Cambridge, UK, 349 pp., <https://doi.org/10.1017/CBO9780511754098>, 2005.
- 400 Konapala, G., Mondal, S., and Mishra, A.: Quantifying spatial drought propagation potential in North America using complex network theory, *Water Resour. Res.*, 58, e2021WR030914, <https://doi.org/10.1029/2021WR030914>, 2022.
- Korea Forest Service: 2024 Wildfire Statistic Yearbook (in Korean), available at: https://eng-nifos.forest.go.kr/kfswweb/cop/bbs/selectBoardArticle.do;jsessionid=UW1qecX11avigtK1IUt9lIWvo7HRMsKq51J3PuuPNHJITfevJWKWNGG1eWQ8nR4.frsas01_servlet_engine5?ntId=3205390&bbsId=BBSMSTR_1008&pageUnit=10&pageIndex=1&searchtitle=title&searchcont=&searchkey=&searchwriter=&searchWrd=&ctgryLrcls=&ctgryMdcls=&ctgrySmcls=&ntcStartDt=&ntcEndDt=&mn=NKFS_02_15_01 (last access: 16 September 2026), 2025.
- 405 Littell, J. S., McKenzie, D., Peterson, D. L., and Westerling, A. L.: Climate and wildfire area burned in western US ecoprovinces, 1916–2003, *Ecol. Appl.*, 19, 1003–1021, <https://doi.org/10.1890/07-1183.1>, 2009.
- Ma, F., Yuan, X., and Otkin, J. A.: Hot drought increased the occurrence probability of the 2025 Los Angeles destructive wildfires, *Adv. Atmos. Sci.*, 43, 723–735, <https://doi.org/10.1007/s00376-025-5109-y>, 2026.
- 410 Malamud, B. D., Millington, J. D. A., and Perry, G. L. W.: Characterizing wildfire regimes in the United States, *Proc. Natl. Acad. Sci. U.S.A.*, 102(13), 4694–4699, <https://doi.org/10.1073/pnas.0500880102>, 2005.
- McKee, T. B., Doesken, N. J., and Kleist, J.: The relationship of drought frequency and duration to time scales, *Proceedings of the 8th Conference on Applied Climatology*, Anaheim, CA, USA, 17–22 January 1993, 179–183, available at: https://www.droughtmanagement.info/literature/AMS_Relationship_Drought_Frequency_Duration_Time_Scales_1993.pdf
- 415 (last access: 16 September 2016), 1993.
- Preisler, H. K. and Westerling, A. L.: Statistical model for forecasting monthly large wildfire events in western United States, *J. Appl. Meteorol. Climatol.*, 46, 1020–1030, <https://doi.org/10.1175/JAM2513.1>, 2007.
- Richardson, D., Black, A. S., Irving, D., Matear, R. J., Monselesan, D. P., Risbey, J. S., Squire, D. T., and Tozer, C. R.: Global increase in wildfire potential from compound fire weather and drought, *npj Clim. Atmos. Sci.*, 5, 23, <https://doi.org/10.1038/s41612-022-00248-4>, 2022.
- 420 Rosenbaum, P. R.: *Observational Studies*, Springer Series in Statistics, Springer, New York, NY, USA, pp. 1–12, https://doi.org/10.1007/978-1-4757-2443-1_1, 1995.
- Roy, A. D.: Some thoughts on the distribution of earnings, *Oxf. Econ. Pap.*, 3, 135–146, <https://doi.org/10.1093/oxfordjournals.oep.a041827>, 1951.
- 425 Royal Commission into National Natural Disaster Arrangements: *Royal Commission into National Natural Disaster Arrangements Report*, Commonwealth of Australia, Canberra, Australia, 594 pp., ISBN 9781921091469, available at: <https://www.nema.gov.au/about-us/governance/reviews/royal-commission-into-natural-disaster#TheReport> (last access 16 September 2026), 2020.
- 430 Rubin, D. B.: Estimating causal effects of treatments in randomized and nonrandomized studies, *J. Educ. Psychol.*, 66, 688–701, <https://doi.org/10.1037/h0037350>, 1974.



- Ruffault, J. and Mouillot, F.: How a new fire-suppression policy can abruptly reshape the fire-weather relationship, *Ecosphere*, 6(10), 1-19, <https://doi.org/10.1890/ES15-00182.1>, 2015.
- Russo, A., Gouveia, C. M., Páscoa, P., DaCamara, C. C., Sousa, P. M., and Trigo, R. M.: Assessing the role of drought
 435 events on wildfires in the Iberian Peninsula, *Agricultural and Forest Meteorology*, 237-238, 50–59, <https://doi.org/10.1016/j.agrformet.2017.01.021>, 2017.
- Sairam, N., Sánchez, D. M. J., Dillenardt, L., and Thieken, A. H.: Evacuating flash flood victims: Key drivers and psychological burden, *J. Flood Risk Manag.*, 18, e70065, <https://doi.org/10.1111/jfr3.70065>, 2025.
- Sairam, N., Schröter, K., Lüdtke, S., Merz, B., and Kreibich, H.: Quantifying flood vulnerability reduction via private
 440 precaution, *Earth's Future*, 7, 235–249, <https://doi.org/10.1029/2018EF000994>, 2019.
- Sung, J. H., Ryu, Y., and Seong, K. W.: Deep learning-based prediction of fire occurrence with hydroclimatic condition and drought phase over South Korea, *KSCE J. Civ. Eng.*, 26, 2002–2012, <https://doi.org/10.1007/s12205-022-1270-3>, 2022.
- Tedim, F., Leone, V., Amraoui, M., Bouillon, C., Coughlan, M. R., Delogu, G. M., Fernandes, P. M., Ferreira, C., McCaffrey, S., McGee, T. K., Parente, J., Paton, D., Pereira, M. G., Ribeiro, L. M., Viegas, D. X., and Xanthopoulos, G.:
 445 Defining extreme wildfire events: difficulties, challenges, and impacts, *Fire*, 1, 9, <https://doi.org/10.3390/fire1010009>, 2018.
- Tilloy, A., Malamud, B. D., Winter, H., and Joly-Laugel, A.: A review of quantification methodologies for multi-hazard interrelationships, *Earth-Sci. Rev.*, 196, 102881, <https://doi.org/10.1016/j.earscirev.2019.102881>, 2019.
- United Nations Environment Programme: Spreading like wildfire: The rising threat of extraordinary landscape fires – A rapid response assessment, UNEP, Nairobi, Kenya, 122 pp., ISBN 9789280739268, available at:
 450 <https://wedocs.unep.org/items/5d3e5267-17bd-4b06-9964-494dd01f7791> (last access: 16 September 2026), 2022.
- United Nations International Strategy for Disaster Reduction (UNISDR): UNISDR Terminology on Disaster Risk Reduction, Geneva, Switzerland, 30 pp., available at: <https://www.undrr.org/publication/2009-unisdr-terminology-disaster-risk-reduction> (last access: 16 September 2026), 2009.
- White, C. J., Adnan, M. S. G., Arosio, M., Buller, S., Cha, Y., Ciurean, R., Crummy, J. M., Duncan, M., Gill, J., Kennedy,
 455 C., Nobile, E., Smale, L., and Ward, P. J.: Review article: Towards multi-hazard and multi-risk indicator – a review and recommendations for development and implementation, *Nat. Hazards Earth Syst. Sci.*, 25, 4263–4281, <https://doi.org/10.5194/nhess-25-4263-2025>, 2025.
- Williamson, E. J. and Forbes, A.: Introduction to propensity scores, *Respirology*, 19, 625–635, <https://doi.org/10.1111/resp.12312>, 2014.
- Yousefi, S., Pourghasemi, H. R., Emami, S. N., Pouyan, S., Eskandari, S., and Tiefenbacher, J. P.: A machine learning
 460 framework for multi-hazards modeling and mapping in a mountainous area, *Sci. Rep.*, 10, 12144, <https://doi.org/10.1038/s41598-020-69233-2>, 2020.
- Zhang, Z., Kim, H. J., Lonjon, G., and Zhu, Y.: Balance diagnostics after propensity score matching, *Ann. Transl. Med.*, 7, 16, <https://doi.org/10.21037/atm.2018.12.10>, 2019.



- 465 Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B., AghaKouchak, A., Jézéquel, A., Mahecha, M. D., Maraun, D., Ramos, A. M., Ridder, N. N., Thiery, W., and Vignotto, E.: A topology of compound weather and climate events, *Nat. Rev. Earth Environ.*, 1, 333–347, <https://doi.org/10.1038/s43017-020-0060-z>, 2020.