Energy Economics 148 (2025) 108549

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Weather-induced power plant outages: Empirical evidence from hydro and thermal generators in Europe

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ARTICLE INFO

Keywords:
Electricity
Power generation
Outages
Climate change

ABSTRACT

This paper investigates how extreme weather conditions affect power generators across Europe, with a focus on the differing vulnerabilities and adaptive responses of hydropower and thermal plants. Using a granular panel dataset of daily power plant outages and local weather conditions (2017–2023), we assess the influence of extreme temperatures, floods, and droughts on outage risks. We distinguish between forced and planned outages to identify how operators anticipate or react to weather-related stress. Our findings show that extreme weather events raise outage risks across multiple technologies, though their responses vary. Sudden shocks, such as unexpected temperature extremes, are more likely to trigger unplanned operational failures, while planned outages tend to align with longer-term maintenance cycles rather than immediate environmental pressures. These results highlight the need for climate-resilient strategies to protect energy systems from growing weather variability.

1. Introduction

The Intergovernmental Panel on Climate Change (IPCC) highlights that urban infrastructure – including transportation, water, sanitation, and energy systems – is being compromised by climate change-related extreme and slow-onset events, causing economic losses, service disruptions, and negative impacts on well-being (IPCC, 2023). Developed under historical climate conditions, energy system infrastructures – including generation units, transmission and distribution networks – now face more frequent and intense extreme weather events (Yalew et al., 2020; Jufri et al., 2019). For example, between 2010 and 2019, around 4000 weather-related disturbances impacted nuclear power plants worldwide, mainly due to elevated cooling water temperatures, marking a threefold increase compared to 1990–2009 and resulting in nearly 50 TWh of lost electricity generation (Kromp-Kolb et al., 2021). As climate change intensifies heatwaves and droughts, thermoelectric plants struggle to maintain effective cooling and turbine efficiency, limiting their generating capacity (Bartos et al., 2016; Coffel and Mankin, 2021; Portugal-Pereira et al., 2024). Under such conditions, these facilities may curtail output or shut down if they cannot dissipate heat effectively. Moreover, water stress can add operational constraints to meet environmental and water use regulations, as evidenced in France and Switzerland, where recent heatwaves forced operators to reduce reactor output to prevent river overheating (Stewart et al., 2013; Mideksa and Kallbekken, 2010; Portugal-Pereira et al., 2024).

Generation outages can carry substantial economic and social costs. At the power plant level, they lead to forgone profits from unsold electricity, refurbishment and safety upgrades (International Atomic Energy Agency, 2021). At the power system level, outages increase grid management costs by requiring additional services to maintain stability (Eicke et al., 2021). Although transmission system operators typically correct single-unit interruptions with remedial actions, large shifts in load or generation can propagate failures. For instance, an unexpected lack of generation can cause a line to trip due to overload (ENTSO-e, 2024). If these disruptions spread to end-users, additional economic and welfare losses arise (Chen et al., 2023; Gorman, 2022). In Europe, a one-hour outage costs about €17.10 per kilowatt hour (Reichl et al., 2013), while indirect expenses – such as those from disrupted infrastructure – can amplify direct costs by about 50% (Vennemo et al., 2022). Meanwhile, households' willingness to pay to avoid outages has more than doubled between 2004 and 2017 (Carlsson et al., 2021).

Although technical studies have thoroughly examined how weather affects generation capacity, the extent to which these vulnerabilities translate into actual outages remains unclear. Previous research has focused on how extreme weather affects power generation efficiency and

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https://doi.org/10.1016/j.eneco.2025.108549
Received 23 December 2024; Received in revised form 7 April 2025; Accepted 23 April 2025
Available online 16 May 2025

on model-based assessment of power plant vulnerabilities, while little empirical work has examined generation unit-level power interruptions caused by extreme weather events. To address this gap, we investigate weather-induced outages at the power plant level and explore how these outages differ across various generation technologies and types of outages. We exploit high-frequency power outage data from 2017 to 2023, matched with detailed weather exposure at the power plant level across 20 European countries. We use publicly available data from the European Network of Transmission System Operators for Electricity (ENTSO-E), categorizing interruptions into planned outages (scheduled maintenance) and forced outages (unforeseen unavailability of units). In the empirical analysis, we employ a fixed-effects logistic regression model with temperature bins to assess how extreme temperatures and water runoff influence the likelihood of outages across different technologies. This methodology follows similar studies analyzing the impact of weather fluctuations on economic outcomes (e.g. Deschênes and Greenstone, 2011), allowing us to control for both unobserved heterogeneity among power plants and the nonlinear effects of extreme temperatures.

We contribute to the literature in several ways. First, we focus explicitly on power plant outages rather than efficiency losses, addressing a critical gap in existing research. While most previous studies examine how extreme weather affects the efficiency of electricity production (e.g., Behrens et al., 2017), our study empirically analyzes the occurrence of actual outages, the worst-case scenario where power plants are forced to shut down. Building on these insights, we develop technology-specific hypotheses and assessments that reveal differential vulnerabilities among various types of power plants, an approach that expands the aggregated estimates presented in Coffel and Mankin (2021) and is unprecedented in scope. These results add an empirical dimension to predominantly model-based assessments, such as Behrens et al. (2017) and Bartos et al. (2016), thus providing a greater understanding of the impacts of climate on Europe's energy resilience. Second, by studying both forced and planned outages we offer a more complete understanding of how climate variables impact the resilience of power plants. Planned outages, although scheduled, may still be influenced by broader climate patterns, which require adjustments to ensure operational stability. Third, we examine heterogeneity in the response to extreme weather events between plants reliant on inland water bodies and those on coasts, adding a spatial dimension to our understanding of power plant resilience. Finally, using high-frequency data, we capture the short-term impacts of extreme weather, offering insights into power system resilience beyond studies that rely on annual aggregated data (e.g. Van Vliet et al., 2016).

Our findings reveal that extreme weather conditions increase the risk of outages across several power generation technologies. Importantly, we observe significant differences between forced and planned outages. Consistent with our expectations, extreme hot temperatures significantly increase the probability of forced outages in thermal power plants. However, we also find that planned outages are substantially affected by extreme weather events. In particular, nuclear power plants proactively schedule maintenance during drought conditions. This suggests that operators adapt to gradual and predictable extreme weather events to mitigate the risk of more costly unplanned outages, highlighting a form of operational adaptation in the energy sector.

The remainder of the paper is structured as follows. The next section presents our hypotheses based on the identified research gaps and theoretical considerations. Section 3 details the data sources and empirical methodology used in our analysis. Section 4 presents the results of our empirical investigation, focusing on the effects of extreme weather on outages in thermal and hydropower technologies. It also includes robustness checks to validate our findings, a heterogeneity analysis examining how the source of water availability influences plant vulnerability, and an analysis of how weather conditions affect outage duration across different thermal technologies. Finally, Section 5 discusses the implications of our results for energy system resilience and operational adaptation strategies, and concludes the paper by summarizing the main findings.

2. Conceptual framework

Power plants face different challenges from extreme weather depending on their technology. While existing research highlights how temperature and water availability affect the efficiency of electricity production, less attention has been given to the occurrence of outages. In this section, we build on the understanding of the weather impacts on power plants' efficiency to explore how extreme weather contributes to planned and forced outages, providing a perspective on each technology's role and vulnerabilities and the foundation for our hypotheses.

In 2023, nuclear power produced a significant portion of Europe's electricity supply, contributing 23% of total generation, which amounts to 619 TWh (Brown et al., 2024). France, in particular, relies heavily on nuclear energy, with 65% of its electricity mix derived from this source. Other countries such as Germany, Belgium, and Sweden also maintain substantial nuclear capacities. The reliance of these plants on efficient cooling systems makes them especially vulnerable to extreme weather events. Their thermal efficiency depends on the temperature difference between the heat source and the cooling environment. When ambient temperatures rise, this differential decreases, leading to reduced electricity production from the same amount of fuel. For instance, Linnerud et al. (2011) reported that a 1 °C increase in ambient temperature can lower nuclear power output by approximately 0.4%, with reductions reaching up to 2.3% as condenser pressure approaches its operational limits. The output can be further reduced by regulations, which often cap the maximum allowable temperature of discharged cooling water to protect aquatic ecosystems (Stewart et al., 2013). Droughts and severe flooding can also affect nuclear power generation by reducing the availability of cooling water or damaging infrastructure (Kim et al., 2024). For example, the 1999 flood of the Le Blayais nuclear plant in France led to the shutdown of multiple reactors due to the inundation of critical equipment and loss of off-site power, highlighting the vulnerability of nuclear facilities to extreme hydrological events (Kopytko and Perkins, 2011).

Fossil fuel power plants are a significant component of the European energy landscape. In 2023, thermal power from coal, gas, and oil accounted for 33% of the electricity generation in the European Union (Brown et al., 2024). Countries like Germany have historically relied heavily on coal and gas, though they are now transitioning towards renewable energy sources. Poland, on the other hand, generates nearly three-quarters of its electricity from fossil fuels. While fossil-based technologies differ in fuel source from nuclear power, they share a reliance on effective cooling systems, making them vulnerable to climate-induced challenges. Ambient air and water temperatures affect their operational efficiency. Heatwaves can impair cooling efficiency, leading to reduced power output or increased operational costs. Droughts and floods disrupt water supplies necessary for cooling processes, potentially forcing plants to reduce output or shut down. Additionally, extreme temperatures can directly impact plant infrastructure; high temperatures cause mechanical stress and expansion in pipelines, whereas cold weather increases corrosion and causes contraction, affecting pressure systems (Sieber, 2013). As climate change intensifies, the frequency and severity of these extreme events are expected to increase, making it increasingly important to understand and mitigate the vulnerabilities of thermal power plants.

Hydroelectric power contributed 12% of Europe's electricity generation in 2023, producing 317 TWh (Brown et al., 2024). Countries such as Norway, Sweden, and Austria rely heavily on hydropower, with Norway generating almost all its electricity from this source. There are three main types of hydropower systems: reservoir, pumped storage, and run-of-river. Each type shows varying vulnerabilities. Reservoir and pumped storage systems depend on consistent long-term water availability, which can be disrupted by alterations in precipitation patterns and increased evaporation rates due to higher temperatures.

Run-of-river, on the other hand, are impacted by immediate fluctuations in river flow, making them sensitive to short-term variations in water runoff (Wasti et al., 2022). Climate change affects hydropower generation through several mechanisms. The depletion of glaciers and ice reduces long-term water storage, initially increasing streamflow but ultimately decreasing it as glaciers recede. Reduced seasonal snow storage leads to earlier snowmelt, altering the timing and availability of water for power generation. Increased precipitation variability results in more frequent and severe floods and droughts, which can disrupt operations and damage infrastructure. Higher temperatures also elevate evaporation rates, lowering reservoir levels and intensifying competition for water resources with other sectors, such as agriculture (Wasti et al., 2022). Regional studies highlight significant variability in climate impacts across Europe. In the Alps, glacier melt has temporarily boosted hydropower generation but is projected to decrease by about 3% as glaciers continue to shrink. Conversely, in the Nordic and Baltic regions, increased streamflow and earlier snowmelt may enhance hydropower production; for example, Chernet et al. (2013) found that hydroelectric energy generation in Norway could increase by 9%–20% under current reservoir operation strategies.

The European Network of Transmission System Operators for Electricity (ENTSO-E) classifies these interruptions into two main categories: planned outages, which are scheduled maintenance activities, and forced outages, which are an unforeseen unavailability of generation units. Both events are recorded when they involve changes of 100 MW or more in a unit's availability and are referred to as plant-level planned and forced outages. Building on the mechanisms discussed for thermal and hydropower technologies, we investigate the conditions under which extreme weather events contribute to both planned and forced outages. By focusing on these events, our study provides insights into extreme weather's most severe operational consequences, complementing existing research on weather effects on generation efficiency.

We develop specific hypotheses to guide our empirical investigation. We hypothesize that planned and unplanned outages respond differently to extreme weather events due to their inherent operational characteristics. By definition, generators typically schedule planned outages for maintenance and refueling purposes, often timed to coincide with periods of lower demand or favorable conditions. Therefore, we expect these events to be unaffected by extreme weather conditions after controlling for seasonal patterns. This expectation aligns with the notion that operators have the flexibility to plan around predictable climate variations. In contrast, forced outages result from unplanned conditions, such as equipment failures or external disruptions. These outages are presumed to be influenced by sudden and severe weather shocks.

Furthermore, we hypothesize that thermal power technologies exhibit a U-shaped response to temperature extremes. While moderate deviations from optimal conditions may primarily reduce efficiency, reaching more severe temperature or precipitation extremes can push plants beyond mere performance losses into forced outages. High temperatures can diminish the efficiency of steam and gas cycles and increase the likelihood of equipment overheating, while low temperatures may exacerbate issues such as fuel viscosity problems, corrosion, and mechanical stress (Coffel and Mankin, 2021; Sieber, 2013; Bartos and Chester, 2015). Excessive precipitation or severe drought can similarly undermine cooling systems and water availability, driving operations towards abrupt failures under the most extreme circumstances. Rather than a simple continuum of diminishing returns, we anticipate that thermal plants become vulnerable to sudden operational breakdowns as environmental conditions approach these critical extremes. Additionally, we propose that hydroelectric plants are particularly susceptible to both droughts and floods due to their reliance on water availability. Drought conditions can lead to insufficient water flow for electricity generation, while floods can damage infrastructure and necessitate operational shutdowns. While previous studies like van Vliet et al. (2016) focus on aggregate capacity reductions over longer periods, we aim to identify overlooked short-term impacts manifested as generation outages triggered by extreme water levels.

3. Methods

3.1. Data

We use panel data from the ENTSO-E Transparency Platform at the power plant level, detailing both forced and planned outages from 2017 to 2023 across 20 European countries. The dataset includes 929 power plants, encompassing different technologies: nuclear, coal, gas, and three hydro types (reservoir, run-of-river, pumped storage), along with their geographical coordinates (latitude and longitude) and nominal power capacity (see Fig. 1, panel a). The dataset includes 44,637 recorded forced outages and 62,672 planned outages. Planned outages stem from maintenance schedules and operational strategies, while unplanned outages occur due to technical failures. From this data, we construct a panel dataset at the power plant and daily level, where a binary variable indicates the occurrence of an outage (1 for an outage, 0 for no outage), resulting in over 1.4 million observations. The original hourly outage data has been aggregated to a daily level to simplify analysis by matching it with daily-level weather data. At the European level, the total number of daily outages shows both an upward trend and significant seasonal variation, particularly for planned outages (see Fig. 1, panel b). The average frequency of these events varies by technology and outage type (forced vs. planned). Planned outages are slightly more common than forced ones, with hydro-power pumped generators experiencing the highest likelihood of outages, while nuclear power has the lowest (see Fig. 1, panel c).

We compile a dataset of weather variables, including temperature, precipitation, and water runoff, sourced from the Copernicus ERA5 reanalysis data (Hersbach et al., 2020). Hourly data is used to calculate daily maximum and minimum temperatures, while water runoff is used to compute the Standardized Runoff Index (SRI), a common indicator for floods and droughts.

To assess the impact of extreme temperatures on energy systems, we apply a binning strategy based on percentiles at the power plant level. Upper percentiles (above 98th, 95th–97th, 90th–94th) represent heatwave exposure, while lower percentiles (10th–6th, 5th–3rd, below 2nd) indicate cold spells. Due to the geographical diversity of our dataset, spanning 20 European countries, temperature bins are based on local percentiles rather than fixed temperature ranges. This ensures relevance to each plant's climate.[1] This approach allows us to analyze how temperature extremes affect power supply across different regions.

The Standardized Runoff Index (SRI) represents the unit standard normal deviate for precipitation or hydrologic runoff accumulated over a specific period. Unlike the Standardized Precipitation Index (SPI), the SRI incorporates seasonal hydrologic processes, accounting for factors like snow and soil moisture storage, making it a more stable measure than SPI (Shukla and Wood, 2008). For this reason, we prioritize the SRI over SPI to evaluate droughts and floods impacting power plants. To assess the impact of extreme hydrological conditions, we apply a binning strategy based on percentiles at the power plant level, consistent with our approach to extreme temperatures. We classify the 3-month SRI into bins corresponding to different degrees of hydrological stress: above the 98th percentile (extreme wet conditions), 95th–98th percentile (severe wet), 90th–95th percentile (moderate wet), 5th–10th percentile (moderate drought), 2nd–5th percentile (severe drought), and below the 2nd percentile (extreme drought). To

[1] For example, a plant in northern Scandinavia rarely experiences 30–35 °C temperatures, so applying uniform bins across regions would be inappropriate. Using local bins maintains accuracy in capturing temperature extremes at each location.

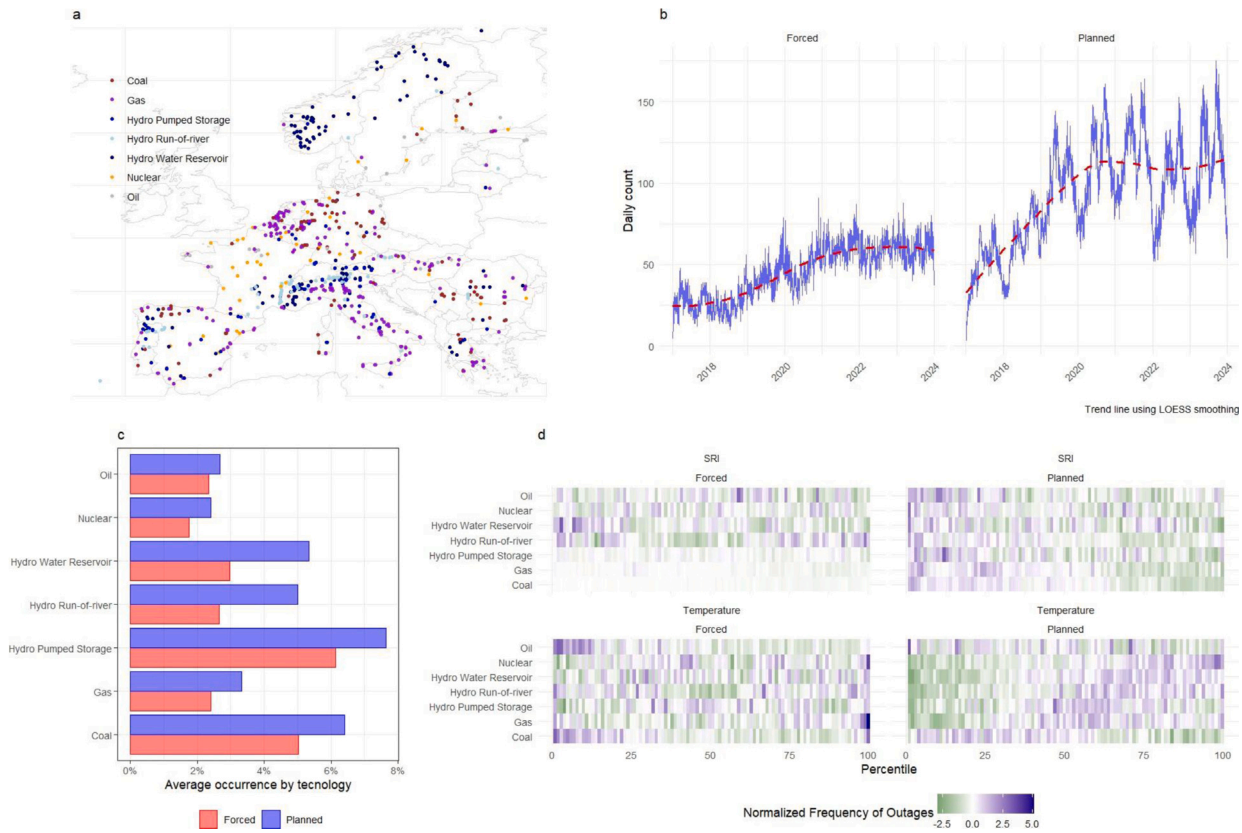

Fig. 1. Panel a: Map showing the geographical distribution of the power plants considered in the study, colored by technology type. Panel b: EU-level daily sum of outages (blue line) and its smoothed trend (red line). Panel c: Observed average outage probability by technology and outage type. Panel d: heatmap of the normalized EU-level frequency of outages ordered by the percentiles of temperatures and SRI computed at the power-plant level. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

ensure robustness, we also test 1-month period to capture different time horizons of hydrological anomalies.[2]

All ERA5 data is provided at a spatial resolution of 0.25° by 0.25° grid (approximately 27.5 km by 27.5 km at the equator), representing a uniform grid system over Europe. For each power plant in our study, we use the geographical coordinates (latitude and longitude) to match its location to the corresponding grid point in the ERA5 dataset. This ensures that the local weather conditions (e.g., temperature, precipitation, and water runoff) are accurately associated with the precise geographical location of each power plant. In this way, we maintain a high level of spatial accuracy for weather variables that directly impact the operational performance of the power plants.

Inspecting the frequency of occurrence of outages by the power-plant specific percentiles of daily maximum temperatures and daily SRI, we can identify interesting patterns (see Fig. 1, panel d): both forced and planned outages tend to be concentrated in days where the power plant experiences uncommon exposure to weather, although the type of outage affects this correlations: planned outages tend to be more concentrated in days with extreme temperatures, while planned outages in days with either extreme temperatures or extreme SRI values, with effects being more uniform across technologies in the latter case.

[2] We use the R package "SCI" to compute the SRI for the 3-month accumulation period. The SRI is calculated by fitting runoff data to a probability distribution, which is then normalized. For details on the algorithm, see Stagge et al. (2015).

3.2. Empirical framework

To test our hypotheses regarding the differential impacts of extreme weather on planned and forced outages, we use a fixed-effects logistic regression model. This model has the advantage of not requiring restrictive assumptions about the relationship between unobserved heterogeneity and observed covariates (Wooldridge, 2010). This is particularly important in our case, where characteristics such as plant location, maintenance routines, capacity, and operational history influence outage risks but cannot be directly observed. To address this issue, we follow approaches from similar studies, such as Deschênes and Greenstone (2011), which examine the impact of temperature fluctuations on health outcomes. Therefore, we use plant-by-month and country-year fixed effects to control for both spatial and temporal heterogeneity.

Given that planned and forced outages are driven by different mechanisms, we estimate two separate models to capture their distinct determinants. The probability of an outage occurring at power plant i on day t is modeled using a fixed-effects logistic regression:

$$\Pr(planned_outage_{it} = 1)$$
$$= \Phi\left(\alpha^p + \sum_k \beta_k^p T_{i,t}^{(k)} + \sum_m \gamma_m^p SRI_{i,t}^{(m)} + \delta_{i,m}^p + \theta_{c,y}^p\right) + \varepsilon_{i,t}^p$$

$$\Pr(forced_outage_{it} = 1)$$
$$= \Phi\left(\alpha^f + \sum_k \beta_k^f T_{i,t}^{(k)} + \sum_m \gamma_m^f SRI_{i,t}^{(m)} + \delta_{i,m}^f + \theta_{c,y}^f\right) + \varepsilon_{i,t}^f$$

In these models, the dependent variable, outage_{it}, represents a binary indicator for the occurrence of an outage at power plant i on day

t. The superscripts p and f indicate that the parameters are estimated separately for planned and forced outages, respectively. Specifically, coefficients with superscript p correspond to the model for planned outages, while coefficients with superscript f correspond to the model for forced outages.

The terms $T_{i,t}^{(k)}$ and $SRI_{i,t}^{(m)}$ capture the effects of extreme temperature and water stress-related factors. The kth included temperature bins $T_{i,t}^{(k)}$ are: $\mathrm{T}_{i,t}^{98\mathrm{th}}$, $\mathrm{T}_{i,t}^{95\mathrm{th}}$, $\mathrm{T}_{i,t}^{90\mathrm{th}}$, $\mathrm{T}_{i,t}^{10\mathrm{th}}$, $\mathrm{T}_{i,t}^{5\mathrm{th}}$, and $\mathrm{T}_{i,t}^{2^{\mathrm{nd}}}$, capturing temperature extremes at different percentiles. These are constructed as binary indicators for whether daily temperature falls into extreme high or low bins, as proposed in studies like Dell et al. (2014a) and Auffhammer (2022). Maximum and minimum temperatures are used for hot (>90th) and cold (<10th) exposures, respectively.

Similarly, the mth bins represented by the term $SRI_{i,t}^{(m)}$ capture the non-linear effect of hydrological extremes as measured by the Standardized Runoff Index ($\mathrm{SRI}_{i,t}$). The SRI percentiles used in the model include $\mathrm{SRI}_{i,t}^{>98\mathrm{th}}$, $\mathrm{SRI}_{i,t}^{95\mathrm{th}-98\mathrm{th}}$, $\mathrm{SRI}_{i,t}^{90\mathrm{th}-95\mathrm{th}}$, $\mathrm{SRI}_{i,t}^{5\mathrm{th}-10\mathrm{th}}$, $\mathrm{SRI}_{i,t}^{2\mathrm{nd}-5\mathrm{th}}$, and $\mathrm{SRI}_{i,t}^{<2\mathrm{nd}}$. This approach ensures that the classification of extreme wet and dry conditions is relative to the plant's local hydrological variability rather than fixed thresholds, making the results comparable across different geographic regions.

Plant-by-month fixed effects account for unobserved time-invariant characteristics specific to each plant, such as location, capacity and age, while also capturing monthly variations in plant operations, such as fluctuations in electricity generation or seasonal refueling and maintenance strategies affecting planned outages (Bell et al., 2020). The country-year fixed effects control for time-varying macroeconomic factors and policy changes that differ between countries and years. For example, they capture the influence of national economic trends, energy policies, regulatory shifts, and significant shocks. By incorporating these country-year fixed effects, we also account for broader global trends, such as fluctuations in the international energy market, cross-border energy agreements, or EU-wide regulatory frameworks that may have different impacts between countries.

We use Conley standard errors (Conley, 1999) to account for spatial and temporal correlations in our error terms, as power plants nearby or experiencing similar weather conditions may have correlated errors. This correction improves the accuracy of our standard errors by accounting for potential spillover effects of extreme weather across plants within a certain distance or time window, as discussed by Dell et al. (2014b).

Finally, we differentiate between forced and planned outages to identify how extreme weather impacts power plant operations. Forced outages are typically unplanned, arising from sudden operational failures or external factors and can disrupt power supply immediately. In contrast, planned outages are scheduled in advance for maintenance or other operational reasons and are usually timed to minimize their impact, often coinciding with periods of reduced demand.

To complement our analysis on outage occurrence using the fixed-effects logistic regression, we extend our empirical framework by employing a negative binomial regression model to examine the duration of outages. This approach accounts for the overdispersion observed in the count data of outage hours, offering a more flexible alternative to Poisson regression. The model specification is as follows:

$$\mathbb{E}(planned\_outage\_hours_{it}|X) = \exp\left(\sigma^p + \sum_k \mu_k^p T_{i,t}^{(k)} + \sum_m \nu_m^p SRI_{i,t}^{(m)} + \delta_{i,m}^p + \theta_{c,y}^p\right)$$

$$\mathbb{E}(forced\_outage\_hours_{it}|X) = \exp\left(\sigma^f + \sum_k \mu_k^f T_{i,t}^{(k)} + \sum_m \nu_m^f SRI_{i,t}^{(m)} + \delta_{i,m}^f + \theta_{c,y}^f\right)$$

where $\mathrm{planned\_outage\_hours}_{it}$ and $\mathrm{forced\_outage\_hours}_{it}$ represent the number of hours a power plant i is under outage on day t, alternatively for planned p and forced f outages. The terms $T_{i,t}^{(k)}$ and $SRI_{i,t}^{(m)}$ and fixed effects $\delta_{i,m}$ and $\theta_{c,y}$ are modeled as in Equation 1 and Equation 2 . By modeling outage duration on top of outage occurrence, we provide additional insights into how prolonged outages correlate with extreme weather conditions.

4. Results

4.1. Thermal power technologies

Overall, we find that in several cases, both forced and planned outages of thermal power technologies are affected by extreme weather events, with notable differences across technologies and outage categories. All fossil-based technologies exhibit a U-shaped response to extreme temperatures, with high daily maximum temperatures increasing the likelihood of an outage more than extreme cold temperatures. Coal is the most vulnerable fossil technology to extreme heat, as the probability of a forced outage increases by approximately 3.2 percentage points [2.4%–4.0% 95th confidence interval][3] under extreme heat. Gas-fired plants also show a significant increase in forced outages under extreme heat, though the magnitude is smaller (1.3 percentage points). The effect of cold spells on forced outages is moderate for gas-fired power plants, which experience a 0.8 percentage point increase [0.5%–1.1%] under extreme cold (below the 2$^{\mathrm{nd}}$ percentile). The impact is more pronounced for coal and oil-fired power plants, with forced outages increasing by 1.4 percentage points [0.8%–2.0%] for coal and 1.2 percentage points [0.3%–2.1%] for oil. The effects of hydrological anomalies on forced outages are generally small. For gas-fired plants, moderate flood conditions (SRI 90th–95th percentile) are associated with a slight decrease of 0.3 percentage points [0.1%–0.5%] in forced outage probability. In contrast, moderate droughts (SRI 5th–10th percentile) correspond to a small increase of 1.0 percentage point [0.4%–1.6%] for coal-fired plants, while oil-fired plants show a slight decrease of 0.9 percentage points [0.3%–1.5%] under the same conditions.

When focusing on planned outages of fossil-based technologies, the U-shaped temperature response is less evident for gas and coal. We find a statistically significant increase in planned outages for oil-based power plants under extreme cold, with a rise of approximately 1.7 percentage points [1.2%–2.2%]. For gas-fired power plants, planned outages do not exhibit a clear response to temperature extremes, while for coal, we observe a minor but significant effect under high temperatures, with planned outages increasing by 0.8 percentage points [0.3%–1.3%] under extreme heat (above the 98th percentile). Planned outages of fossil-based technologies show varied responses to extreme drought conditions. Gas-fired plants exhibit a small increase of 1.0 percentage point [0.4%–1.6%] in planned outages under severe drought (SRI 2nd–5th percentile). A similar effect is observed for oil-fired plants, where planned outages increase by 0.6 percentage points [0.2%–1.0%]. The most pronounced response is found for coal plants, with extreme drought conditions (SRI below the 2nd percentile) leading to a 3.0 percentage point increase [0.9%–5.1%] in planned outages.

Nuclear power presents a unique response pattern to temperatures. Unlike fossil-based technologies, the effect of temperature on nuclear outages increases monotonically, ranging from negative effects at cold temperatures to positive effects at hot temperatures. Forced outages rise significantly under extreme heat, with the probability increasing by 1.0 percentage point [0.4%–1.6%] at the highest temperature percentiles. Planned outages also show a mild positive response to moderately high temperatures, with an estimated increase of 0.2 percentage points [0.0%–0.4%]. In contrast, cold spells reduce the likelihood of both forced and planned outages, with the probability of a forced outage

[3] Henceforth, numbers presented in square brackets represent the 95th confidence interval.

Table 1
Overview of climate impacts on different power generation technologies.

Extreme event	Thermal fossil (Coal, Gas, Oil)	Hydropower	Nuclear
Extreme Temperatures	Reduced cooling efficiency; increased stress on pipelines and mechanical components	Long-term changes in evaporation rates and earlier snowmelt	Reduced thermal efficiency; regulations might limit water discharge temperatures
Cold Spells	Increased fuel viscosity, corrosion, and mechanical stress; possible frozen coal stockpiles	Limited research available	Potential efficiency gains due to increased thermal gradient, but risk of freezing water intakes
Floods	Limited research available	Risk of dam overflow or damage; sudden fluctuations in river flows might negatively impact run-of-river plants	Risk of reactor shutdown due to flooding of critical infrastructure, loss of off-site power, or cooling system failure
Droughts	Limited cooling water availability may force output reductions or shutdowns	Reduced river flow and reservoir levels decrease generation capacity; competition with other water users	Reduced cooling water availability affects reactor operations; potential regulatory constraints on water use

decreasing by 0.5 percentage points [0.1%–0.9%] under extreme cold. These findings align with the thermodynamic properties of nuclear plants, where higher ambient temperatures reduce cooling efficiency, while colder conditions may enhance the thermal gradient, improving overall efficiency. The effects of drought conditions, as measured by the Standardized Runoff Index, are small and mostly insignificant. We observe a weak negative association between moderate drought conditions and forced outages, while planned outages show a slight increase of 0.4 percentage points [0.0%–0.8%] under severe droughts. This suggests that nuclear maintenance schedules remain largely unaffected by short-term hydrological variations, reinforcing the idea that planned outages follow long-term operational planning rather than immediate environmental constraints.

These findings highlight the complex interactions between extreme weather events and thermal power generation. The U-shaped response of fossil-based technologies to extreme temperatures confirms that both high and low temperatures can disrupt operations. High temperatures reduce the efficiency of steam and gas cycles, increasing the risk of equipment stress and outages. Conversely, cold weather can lead to pipeline contraction, corrosion, and mechanical failures. Cooling water availability is a crucial factor for thermal power plants. Drought conditions can lower water levels and raise water temperatures, reducing cooling efficiency and forcing operational adjustments. While previous studies (Sieber, 2013) suggest that floods can inundate sites and impact cooling water withdrawal, our analysis does not find strong evidence linking flood events to power outages. For nuclear power, our results align with established mechanisms in the literature. Temperature variations affect nuclear plants through two primary channels: (i) reduced thermal efficiency, as the efficiency of the steam cycle depends on the temperature differential between the heat source and the cooling environment, and (ii) regulatory constraints on maximum discharge temperatures to protect aquatic ecosystems (Linnerud et al., 2011; Stewart et al., 2013) (see Fig. 2).

4.2. Hydro-power technologies

We find that hydropower generation plants are primarily affected by variations in water runoff rather than extreme temperatures, though some temperature effects emerge for specific plant types. For storage plants, extreme cold appears to reduce the likelihood of forced outages, with a 1.0 percentage point decrease [−2.0% to 0.0%] under moderately low temperatures (T_{min} 2nd–5th percentile). Planned outages in storage plants, however, decline by 1.4 percentage points [−2.8% to 0.0%] under extreme high runoff conditions (SRI > 98th percentile), suggesting that increased water availability reduces the need for scheduled maintenance.

Run-of-river plants exhibit a stronger response to hydrological extremes. Both forced and planned outages increase under high runoff conditions, with severe floods (SRI 95th–98th percentile) raising outage probabilities by 1.8 percentage points [0.3%–3.3%] for forced outages and 2.3 percentage points [0.7%–3.9%] for planned outages. Additionally, moderate flood conditions (SRI 90th–95th percentile) increase forced outages by 1.4 percentage points [0.4%–2.4%]. Planned outages also rise under low runoff conditions, with a 1.5 percentage point increase [0.5%–2.5%] when SRI falls between the 2nd and 5th percentiles.

Reservoir plants, in contrast, exhibit limited sensitivity to extreme weather. Planned outages increase slightly under moderate cold conditions (T_{min} 2nd–5th percentile) by 1.0 percentage points [0.0%–2.0%] but decrease under extreme cold (T_{min} < 2nd percentile) by 1.2 percentage points [−1.8% to −0.6%], possibly reflecting improved thermal efficiency at lower temperatures. Additionally, high runoff conditions (SRI > 98th percentile) reduce planned outages by 1.5 percentage points [−2.5% to −0.5%], suggesting that greater water availability allows plants to delay maintenance and maximize production.

Overall, these findings highlight the distinct sensitivities of hydropower technologies to environmental variability. While storage and reservoir plants exhibit minor responses, run-of-river plants are particularly affected by both floods and droughts, reinforcing their reliance on stable hydrological conditions (see Fig. 3 and Table 3) .

4.3. Robustness checks

We performed several robustness checks, detailed in the Supplementary Materials. First, we re-estimated our models clustering standard errors at the power plant level and using a non-parametric bootstrap procedure with 300 seeds. Both approaches produced results nearly identical to those of our main model, supporting the robustness of our standard error estimates. In addition, we explored various alternative model specifications. These included testing different temperature quantiles, employing alternate binning strategies based on both relative distributions (e.g., T> 90th percentile) and absolute temperature cutoffs (e.g., T> 33 °C). We also relaxed the fixed effects structure and incrementally introduced additional control variables. Across all these variations, the magnitude and statistical significance of our key coefficients remained consistent. Finally, we estimated a Linear Probability Model (LPM) as an alternative to our nonlinear specification, and again, the core findings did not change.

4.4. Heterogeneity

We explore whether the source of cooling water influences thermal plants' vulnerability to extreme weather events, differentiating between those relying on inland freshwater (rivers or lakes) and those drawing seawater along the coast. We find statistically significant increases in the probability of forced outage occurrence during drought conditions (< 2nd percentile of SRI) only as for inland gas, coal and oil generation, while coastal power plants exhibit effects close to zero. Furthermore, we find negative but non statistically significant effects for coal and oil generation forced outages. Our findings suggest that inland-based

Table 2
Marginal effect of temperatures and SRI on forced and planned outages of European thermal power plants.

Variable	Nuclear		Gas		Coal		Oil	
	Forced	Planned	Forced	Planned	Forced	Planned	Forced	Planned
T_{max} > 98th	0.010***	0.006	0.013***	0.006	0.032***	0.008*	0.018*	0.007*
	(0.003)	(0.005)	(0.004)	(0.005)	(0.008)	(0.005)	(0.015)	(0.005)
T_{max} 95th–98th	0.004***	0.005***	0.003	0.001	0.008*	0.002	−0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)	(0.006)	(0.003)
T_{max} 95th–90th	−0.001	0.002***	0.001	0.000	0.001	0.004**	−0.005	−0.002
	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.002)	(0.007)	(0.002)
T_{min} 5th–10th	−0.002*	−0.004***	0.003**	−0.003	0.007***	0.005	0.011***	0.004
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)
T_{min} 2nd–5th	−0.004*	−0.003	0.004*	−0.003	0.005	0.001	0.013***	0.008**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.006)	(0.003)	(0.004)
T_{min} < 2nd	−0.005***	−0.010***	0.008***	−0.002	0.014***	−0.006	0.012*	0.017***
	(0.002)	(0.003)	(0.003)	(0.005)	(0.006)	(0.005)	(0.009)	(0.005)
sri_{3m} > 98th	−0.001	0.007	−0.001	−0.004	0.006	−0.015	−0.009**	−0.004
	(0.003)	(0.008)	(0.004)	(0.004)	(0.005)	(0.010)	(0.004)	(0.007)
sri_{3m} 95th–98th	−0.003	0.002	0.002	−0.003	0.000	−0.011	−0.011***	−0.003
	(0.003)	(0.005)	(0.002)	(0.004)	(0.005)	(0.015)	(0.003)	(0.005)
sri_{3m} 90th–95th	0.001	0.001	−0.003**	−0.001	0.006	−0.007	−0.002	0.003
	(0.001)	(0.002)	(0.001)	(0.004)	(0.006)	(0.009)	(0.003)	(0.003)
sri_{3m} 5th–10th	−0.002*	−0.002	−0.002	0.001	0.010*	0.006	−0.009***	0.003
	(0.001)	(0.003)	(0.002)	(0.005)	(0.006)	(0.007)	(0.002)	(0.007)
sri_{3m} 2nd–5th	0.002	0.004*	−0.002	0.010*	−0.001	0.019	−0.003	0.006**
	(0.003)	(0.002)	(0.002)	(0.006)	(0.006)	(0.015)	(0.006)	(0.003)
sri_{3m} < 2nd	−0.002	0.008	0.000	0.006	0.007	0.030*	−0.001	0.007
	(0.003)	(0.006)	(0.003)	(0.006)	(0.008)	(0.021)	(0.006)	(0.005)
Power Plant	✓	✓	✓	✓	✓	✓	✓	✓
Power Plant-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	167,735	171,055	345,097	306,948	168,050	129,061	43,939	46,667
Dependent variable mean	0.024	0.027	0.023	0.026	0.023	0.027	0.030	0.033
BIC	45,148.9	54,144.7	118,181.3	129,021.0	77,439.8	75,885.4	14,327.3	16,434.7
Pseudo R^2	0.050	0.077	0.133	0.225	0.155	0.249	0.110	0.069

Notes: The dependent variable is the occurrence of forced or planned outages in a power plant. Standard errors are clustered based on Conley. Significance levels: *p<0.10, **p<0.05, ***p<0.01.

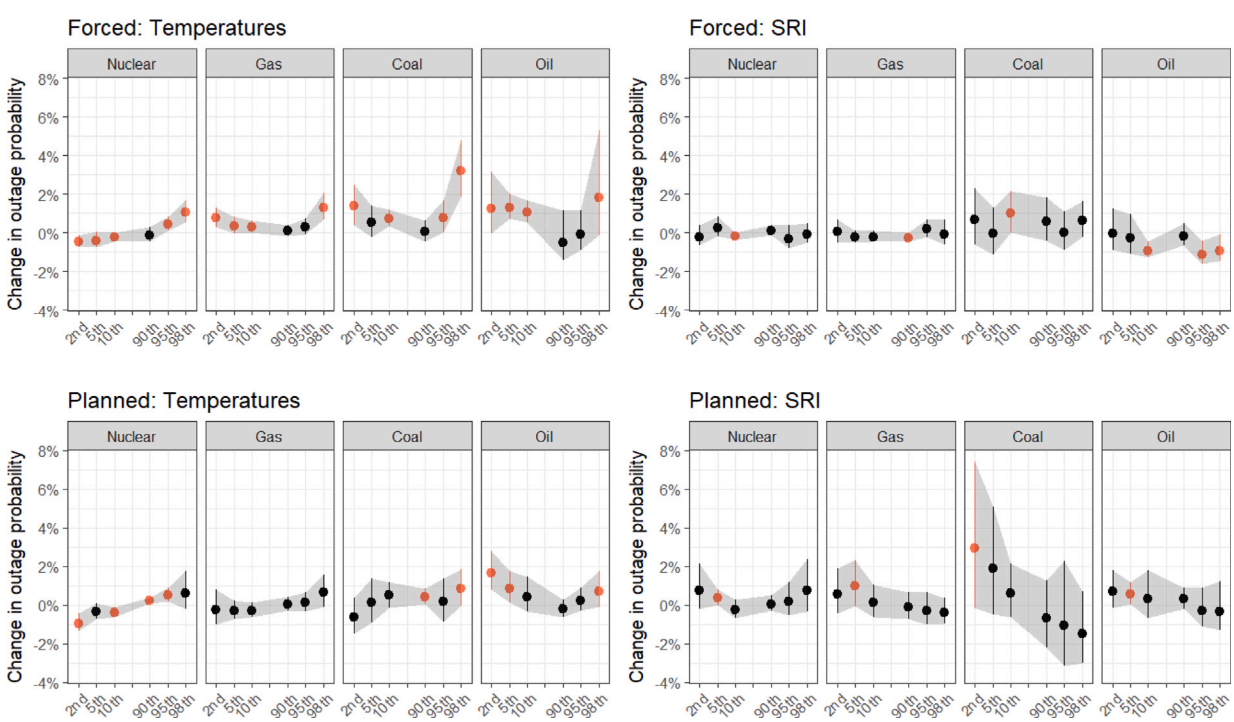

Fig. 2. Estimated probability of occurrence of thermoelectric power plants. Segments represent the 95th confidence interval. Statistically significant estimates are colored in orange, while all other estimates in black. Marginal effects are derived from the coefficients in Table 1.

Table 3
Marginal effect of temperatures and SRI on forced and planned outages of European hydropower plants.

Variable	Storage		Run-of-River		Reservoir	
	Forced	Planned	Forced	Planned	Forced	Planned
T_{max} > 98th	0.008	0.005	−0.009	0.007	0.005	−0.002
	(0.006)	(0.011)	(0.010)	(0.008)	(0.004)	(0.005)
T_{max} 95th–98th	0.003	−0.009*	0.000	0.000	0.000	−0.002
	(0.006)	(0.005)	(0.010)	(0.005)	(0.004)	(0.004)
T_{max} 90th–95th	−0.003	−0.005	−0.001	0.002	0.004	0.000
	(0.004)	(0.005)	(0.007)	(0.003)	(0.004)	(0.004)
T_{min} 5th–10th	−0.001	0.001	0.002	−0.002	0.000	0.000
	(0.004)	(0.004)	(0.004)	(0.006)	(0.002)	(0.003)
T_{min} 2nd–5th	−0.010*	−0.001	0.002	−0.003	0.000	0.010*
	(0.005)	(0.006)	(0.008)	(0.011)	(0.003)	(0.006)
T_{min} < 2nd	−0.012	0.009	0.007	−0.007	−0.003	−0.012***
	(0.007)	(0.013)	(0.006)	(0.012)	(0.004)	(0.004)
sri_{3m} > 98th	−0.009	−0.003	0.012	0.028	−0.004	−0.015***
	(0.009)	(0.011)	(0.012)	(0.038)	(0.003)	(0.005)
sri_{3m} 95th–98th	−0.007	−0.014*	0.018*	0.023*	0.003	−0.004
	(0.005)	(0.007)	(0.015)	(0.016)	(0.005)	(0.005)
sri_{3m} 90th–95th	−0.002	−0.005	0.014**	0.008	−0.001	−0.002
	(0.004)	(0.006)	(0.010)	(0.007)	(0.002)	(0.004)
sri_{3m} 5th–10th	0.006	0.001	0.003	0.005	0.004	0.006
	(0.135)	(0.088)	(0.254)	(0.145)	(0.091)	(0.091)
sri_{3m} 2nd–5th	0.002	0.003	0.002	0.015**	0.006	0.002
	(0.097)	(0.088)	(0.345)	(0.111)	(0.122)	(0.184)
sri_{3m} < 2nd	0.001	−0.004	0.003	0.000	−0.001	0.012
	(0.008)	(0.013)	(0.009)	(0.012)	(0.004)	(0.013)
Power Plant	✓	✓	✓	✓	✓	✓
Power Plant-Month FE	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓
Observations	124,656	119,839	47,465	61,649	153,256	165,831
Dependent variable mean	0.03049	0.05668	0.02624	0.05339	0.03884	0.06477
BIC	62,776.3	69,247.4	17,392.4	32,122.1	54,336.8	84,318.2
Pseudo R^2	0.15663	0.22399	0.38313	0.22470	0.20164	0.13355

Notes: The dependent variable is the occurrence of forced or planned outages in a hydropower plant. Standard errors are clustered based on Conley. Significance levels: *p<0.10, **p<0.05, ***p<0.01.

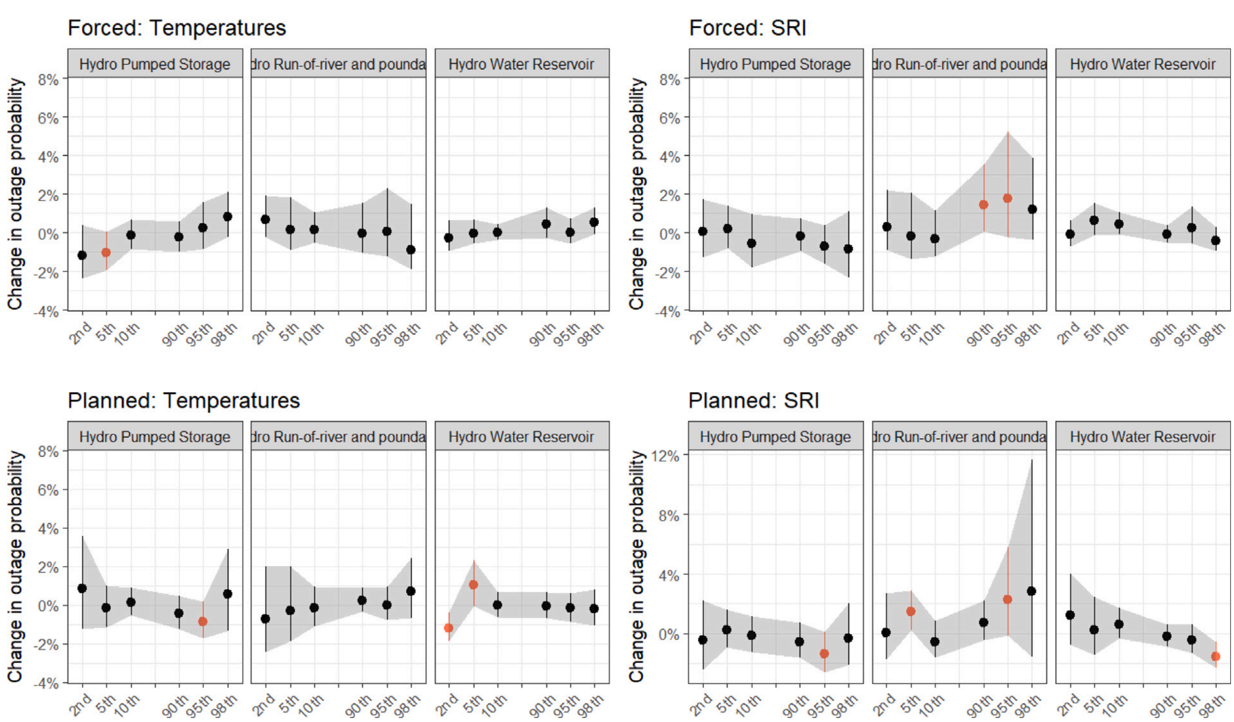

Fig. 3. Estimated probability of occurrence of hydropower plants. Segments represent the 95th confidence interval. Statistically significant estimates are colored in orange, while all other estimates in black. Marginal effects are derived from the coefficients in Table 2. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

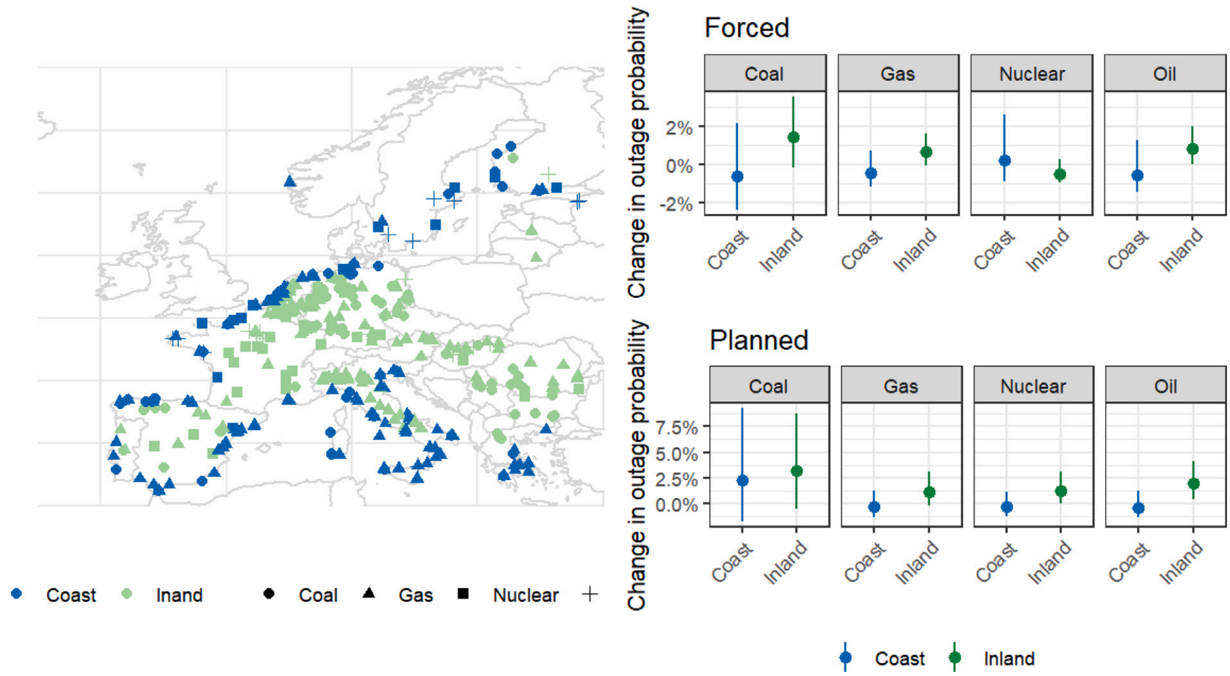

Fig. 4. Map of thermal power plant locations by location group (Coast vs Inland). Estimated probability of outage occurrence by location group under exposure of extreme droughts, by outage type and plants. Segments represent the 95th confidence interval. Marginal effects are derived from the coefficients presented in the Appendix.

facilities are generally more susceptible to drought-induced outages, likely reflecting tighter constraints on freshwater usage and stricter environmental regulations. By contrast, coastal plants appear more resilient under similar conditions, benefiting from the comparatively stable cooling properties of seawater (see Fig. 4). Overall, the findings highlight how spatial factors matter, showing that the location where a plant is located can shape its ability to handle climate-related challenges.

4.5. Outage duration

In this section, we examine how extreme weather conditions influence the duration of outages across different thermal power technologies. Our findings indicate that extreme heat significantly increases the average number of hours a power plant is expected to face a forced outage, across all fossil-based technologies and nuclear plants, reinforcing the result that high temperatures increase stress on power plant components and cooling systems. Under extreme heat (T_{max} > 98th percentile), the average number of hour under a forced outage rises by approximately 2.9 h for oil-fired plants, 1.4 h for nuclear plants, and around 1.0 h for both gas and coal plants. The estimated marginal effects are substantial since the average number of hours under outage in our sample ranges between 0.56 and 0.69 depending on the technology. These results suggest that sustained high temperatures exacerbate mechanical failures, leading to longer downtimes for repairs and system stabilization.

In contrast, cold temperatures have mixed effects. For gas-fired plants, extreme cold (T_{min} < 2nd percentile) increases the average hours under a forced outage by about 0.7 h, likely due to operational challenges such as fuel transport disruptions and increased mechanical stress. Conversely, nuclear plants experience a slight but statistically significant reduction in the average hours under forced outage under extreme cold, possibly reflecting efficiency gains from improved thermal gradients.

Planned outages, that exhibit a longer average duration ranging between 2.7 to 4.9 h depending on the technology, show no strong or consistent response to temperature extremes, suggesting that maintenance schedules remain primarily driven by long-term operational planning rather than short-term weather fluctuations. Similarly, hydrological extremes, as measured by the Standardized Runoff Index (SRI), exhibit limited and inconsistent effects on outage duration. Overall, these results suggest that extreme heat is the primary driver of prolonged forced outages in thermal power plants, while cold temperatures and hydrological anomalies have more limited and technology-specific impacts (see Fig. 5 and Table 4).

5. Discussion and conclusions

This study provides new evidence on the impact of extreme weather events on European power systems, drawing on a rich dataset of daily forced and planned outages across multiple generation technologies. We quantify the vulnerability of each technology and highlight how system operators respond to extreme conditions in temperature and water runoff, finding distinct patterns between forced and planned outages.

Our results indicate that extreme heat is a key driver of *forced* outages across all fossil-based technologies and nuclear power plants, likely due to increased mechanical stress and cooling inefficiencies. In contrast, we find little evidence that extreme weather conditions significantly affect *planned* outages. This suggests that maintenance schedules are largely predetermined and not directly influenced by short-term hydrological fluctuations. The absence of strong effects reinforces the idea that planned outages follow long-term operational cycles rather than immediate environmental constraints. We also find that extreme heat not only increases the probability of forced outages but also significantly prolongs the average expected hours under outages. Under high temperatures, the average hours under outage rise across all thermal technologies, particularly in oil-fired and nuclear plants, suggesting that mechanical failures may be more severe or take longer to resolve. Planned outage durations, again, show no clear response to weather extremes, further underscoring the role of long-term scheduling over short-term climate variability.

Among fossil-based technologies, coal remains the most vulnerable to extreme heat, while oil-fired plants exhibit increased forced outages under both temperature extremes. Run-of-river hydropower plants also show sensitivity to hydrological variability, with both floods and

Table 4
Marginal effect of temperatures and SRI on the number of hours under outage of European thermal power plants.

Variable	Nuclear		Gas		Coal		Oil	
	Forced	Planned	Forced	Planned	Forced	Planned	Forced	Planned
T_{max} > 98th	1.378***	2.271	1.064***	1.636	1.021***	−0.125	2.899***	−0.251
	(1.036)	(3.660)	(0.511)	(1.528)	(0.601)	(2.017)	(3.834)	(1.482)
T_{min} < 2nd	−0.341**	−2.048	0.731**	−0.859	0.063	−2.899*	0.371	5.274
	(0.0993)	(3.712)	(4.246)	(0.451)	(0.215)	(1.234)	(0.488)	(10.328)
sri_{3m} > 98th	−0.083	6.220	−0.140	−0.948	0.026	−2.680	0.007	1.021
	(0.293)	(7.518)	(0.208)	(1.022)	(0.212)	(2.566)	(0.482)	(2.044)
sri_{3m} < 2nd	−0.319	0.475	0.048	3.199	0.727	18.971	0.173	1.857
	(0.183)	(2.103)	(0.264)	(3.788)	(0.721)	(25.537)	(1.024)	(2.388)
Power Plant	✓	✓	✓	✓	✓	✓	✓	✓
Power Plant-Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Country	✓	✓	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	167,086	167,852	342,845	292,778	166,739	122,913	43,839	45,929
Dependent variable mean	0.69	3.90	0.59	4.91	0.57	6.84	0.56	2.70
BIC	71,992	101,957	202,512	318,460	152,692	227,541	25,799	31,039
Pseudo R^2	0.024	0.023	0.039	0.022	0.041	0.026	0.034	0.024

Notes: The dependent variable is the number of hours of forced or planned outages in a power plant. Standard errors are clustered based on Conley. Significance levels: *p<0.10, **p<0.05, ***p<0.01.

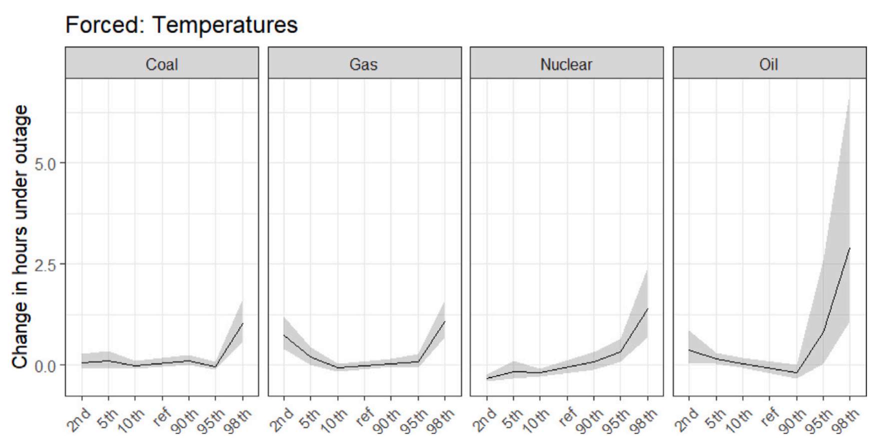

Fig. 5. Marginal effect of temperatures on the number of hours under outage of European thermal power plants.

droughts affecting outage patterns. In contrast, reservoir and storage hydropower plants demonstrate greater resilience, with only minor adjustments observed in response to extreme conditions.

Overall, our findings highlight the technology-specific nature of climate stressors' impact on power plant reliability. While extreme temperatures primarily drive unforeseen forced outages, the effect of hydrological extremes is more nuanced and largely confined to technologies directly reliant on river flow. The contrast between forced and planned outages suggests that adaptive responses depend on the predictability of climatic conditions, with operators reacting to sudden disruptions while maintaining long-term stability in scheduled maintenance.

Our findings have potential applications in climate risk and policy assessments. The average construction year of power plants in our dataset is 1984, meaning that many of these facilities were designed for climatic conditions quite different from today. As climate change intensifies, extreme weather events are becoming more frequent and severe, underscoring the need for resilient infrastructure to ensure a reliable electricity supply. Thermal technologies, especially nuclear plants – currently generating over half of Europe's electricity (Brown et al., 2024) – appear particularly vulnerable. The resilience of thermal and hydropower generation plants to climate change can be improved through technological and organizational adaptations. In terms of thermal generators, particularly nuclear reactors, feasible technological measures include retrofitting existing plants with improved cooling systems, such as reducing water intake, adopting closed-cycle systems, or installing enhanced heat exchangers. Converting once-through cooling into closed-cycle or hybrid systems, for instance, can limit water withdrawal and associated thermal discharges (Kromp-Kolb et al., 2021). Although these solutions help mitigate thermal sensitivity and reduce water usage, they often involve high costs and pose significant design challenges. Estimates for the United States suggest that retrofitting once-through cooling systems to closed-cycle cooling systems would cost approximately 500 million USD per nuclear power plant and 100 million USD per fossil-fueled plant (EPRI, 2011). For new facilities, strategic siting is crucial. Locating plants on the coast rather than near rivers or lakes can significantly reduce vulnerability to drought conditions, especially for nuclear plants. Currently, about 40% of nuclear units under construction worldwide are located inland, near rivers or lakes (Kromp-Kolb et al., 2021). However, coastal siting is not without its own risks, as rising sea levels and more frequent storm surges threaten to increase flood hazards (Portugal-Pereira et al., 2024). Mitigating these flood risks can involve raising dykes, bolstering flood barriers, and installing watertight structures, with costs ranging from several million to several hundred million euros (Kromp-Kolb et al., 2021). Other technical measures that improve adaptability to water stress include employing advanced cooling technologies and drawing on alternative water sources, such as municipal wastewater (Epiney et al., 2018). Organizational strategies like advanced planning, fleet-wide management, and periodic safety reviews can further support resilience. Finally, enhanced weather forecasting capabilities can help utilities optimize maintenance schedules and operational planning, mitigating the impacts of temperature and water availability fluctuations.

From a systems perspective, Europe is progressing with an expansion of renewable energy sources to reduce the energy sector's carbon footprint. However, renewable sources-particularly wind—are also vulnerable to climate risks. Csereklyei et al. (2021) emphasize that wind generation is highly susceptible to stormy weather conditions, with high winds and storms significantly contributing to outages. Additionally, Petersen et al. (2024) find that wind intermittency imposes additional costs on the electricity grid, increasing congestion and reliability expenses. To mitigate these risks and enhance supply security, renewable plants should be strategically located in regions with lower climate risks and supported by an expanded transmission grid. Recognizing the vulnerabilities of power production and diversifying the energy mix is crucial for strengthening Europe's resilience to power disruptions. While large-scale blackouts and widespread load losses due to single power plant outages remain unlikely, even temporary disruptions can have significant consequences. Generation outages can lead to substantial financial losses for producers and drive up electricity prices, negatively impacting household welfare. In fact, recent evidence highlights that nuclear power outages can influence prices across multiple EU countries (Rinne, 2019).

Integrating our findings into power dispatch and capacity expansion models would allow researchers to simulate how power systems may react to generation outages or efficiency losses caused by extreme events. These simulations can reveal changes in plant operations, cross-border electricity flows, and the need for extra capacity to meet demand. Therefore, our results provide a foundation for future research and policy recommendations aimed at mitigating climate risks. This could include assessing the economic losses from outages and understanding the broader impact of these disruptive events on energy prices.

CRediT authorship contribution statement

Alberto Sergio: Writing – review & editing, Writing – original draft, Validation, Software, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Francesco Pietro Colelli:** Writing – original draft, Visualization, Software, Resources, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this manuscript, the authors used OpenAI's ChatGPT to help refine the language and improve clarity in certain sections of the text. After using this tool, the authors carefully reviewed and edited the content to ensure its accuracy and coherence, and they take full responsibility for the final version of the published article.

Acknowledgments

This study was funded by the European Union - NextGenerationEU, Mission 4, Component 2, in the framework of the GRINS - Growing Resilient, Inclusive and Sustainable project (GRINS PE00000018) and from the European Union's Horizon Europe Research and Innovation Program under Grant Agreement number 101081358 (ACCREU). The views and opinions expressed are solely those of the authors and do not necessarily reflect those of the European Union, nor can the European Union be held responsible for them.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2025.108549.

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