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Statistical dependence models for multi-hazard events: an application to the Danube Region

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Abstract
Research about natural hazards has expanded from single-hazard to multi-hazard ones. While single hazards have been extensively studied in the past and many quantitative statements about intensities and severities are available, empirical studies about multi-hazard events and corresponding dependencies are still rare. This paper introduces statistical models for estimating the dependencies between different hazard types based on Poisson-type event processes. Moreover, the models are applied to data for several natural hazard events from the Danube Region within Europe. We found several multi-hazard interactions between extreme temperature, wildfire, drought, and flood hazards. The analysis should help to bridge the gap between the more conceptual contributions to this discussion by providing empirical evidence on interactions on a large-scale region as well as providing statistical models how to estimate them.

Keywords Danube Region · Dependent point-processes · Multi-hazard models · Triggering of events

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1 Introduction

Despite global efforts to lessen the number of natural hazard induced disasters, such events are still on the rise, causing large direct as well as indirect losses across the globe (UNDRR 2025). Especially climate- and weather-related disasters show a continuous increase. Reason for this increase in losses can be partly attributed to increases in exposure within hazard prone areas as well as to climate change effects (IPCC 2022). While such single events caused huge impacts, multi-hazard events as well as corresponding multi-risks are gaining increasing attention due to their combined and often profound effects across various stakeholders and scales (Ward et al. 2022). Indeed, the number of countries which are experiencing overlapping disasters (i.e., instances when two disasters happening in the same country and the second one started before or shortly after the first one ended) has increased over time (IFRC 2023). Worryingly, there are indications that such multi-hazard events have more severe impacts than single events as such situations also drain significant resources at the same time and influence risk-bearers in their ability to respond (Zhang et al. 2022; Jäger et al. 2025; Zscheischler et al. 2025).

As a consequence, there is an increasing interest in multi-hazard and multi-risk assessment and management approaches within the science (Zscheischler and Seneviratne 2017; Grandjean 2025), policy (UNISDR 2015; Tiggeloven et al. 2025) and practice domain (Trogrlić et al. 2024) today. One of the fundamental tasks in all of them is to identify qualitative and quantitative wise relationships between different types of hazards and risks (Hochrainer-Stigler et al. 2023). This can be based on quantitative probabilistic methods that focus on dependency measures, e.g., using correlation or so-called copula approaches (Joe 2014; Claassen et al. 2024), or through specific analysis of past or possible future events, e.g., using storylines (Shepherd et al. 2018; Hurk et al. 2023). We refer for a detailed review of quantitative assessment methodologies to Tilloy et al. (2019). In case of limited empirical data availability (which is often the case in regards to multi-hazard events as well as multi-risk situations) semi-quantitative approaches such as heatmaps that present a discrete visualization of the likelihood of multi-hazard events can be used, or purely qualitative ones that include expert opinions or anecdotal evidence. We refer for a review of qualitative approaches to Tsiplakidis and Photis (2019). From a more conceptual point of view Gill and Malamud (2014) presented a matrix of causalities between different types of hazards. They considered 21 different types of hazards and filled a corresponding 21 by 21 table with indications of possible dependencies or independencies. Note, this matrix is not symmetric. For our discussion we focus on a sub-matrix of their matrix as shown in Table 1.

Within the table the rows symbolize the triggering hazard and the columns symbolize the triggered hazard. The entry 0 means no causality, 1 to 3 means increasing evidence for possible causality. In order to get to such a table, Gill and Malamud (2014) introduced the notions of *spatial overlap* and *temporal likelihood*. For determining the spatial overlap, they found (by visual inspection of disaster maps) the answer to the question “In all the locations where the primary hazard is present, what proportion of these could occurrences of the secondary hazard also occur?”.

Table 1 Dependencies between different hazards. Source: based on Gill and Malamud (2014)

	EQ	LS	FL	DR	WF
EQ	3	3	2	0	0
LS	0	2	2	0	0
FL	0	2	2	0	0
DR	0	0	0	0	1
WF	0	1	1	0	2

The temporal likelihood is found by a “qualitative analysis of reviewed literature, which enabled an understanding of the relative occurrence of secondary hazards after primary cases of a primary hazard.” A point score for spatial overlap (1=limited, 2=medium, 3=large) as well as for the temporal likelihood (1=low, 2=medium, 3=high) was defined. The product of the two values gives the overlap-likelihood factor, which can be defined for each triggering ⇒ triggered event relationship. In addition, “a more mechanistic approach, using a form of engineering judgment” complemented this review of case studies. According to the two judgments, a score for the degree of dependency (in our above example 0,1,2,3) was assessed. They call the highest degree of dependency as "triggering" and a lower degree as "increasing probability".

Contrary to this approach we do not distinguish here between "triggering a secondary event " and "increasing the probability of a secondary event" but rather argue that it is necessary to distinguish whether the primary event influences the timing of the secondary event or the severity (the magnitude) of the secondary event or both. Under the assumption that the primary event influences timing of the secondary event, by changing its timing, say from λ_0 to λ_1, one may set λ_1 to infinity to model immediate triggering. Values of λ_1 larger than λ_0, but less than the infinity, model the "increasing probability" of the secondary event. Based on these observations our contribution to the literature is an empirical multi-hazard analysis of the Danube Region using pairs of discrete event processes to estimate and test the dependency by statistical methods. According to statistical convention, related parameters are usually called intensity parameters which in our case are related to the timing of the event and should not be confused to the use of intensity in regards to severity and magnitude of hazard events (IPCC 2022).

Without doubt, the expert opinion of a relationship matrix of the above type is an important guideline to select the relationships one wants to test in a second step with empirical data. Hence, we argue that qualitative statements about multi-hazard relationships need an additional quantitative argument based on data observation to become a statistically significant relationship. In our discussion of multi-hazard events we will introduce some statistical models to investigate such relationships, quantify the strength of the relationships and give concrete examples using real data. Our starting point is Table 1 above and we first introduce the Poisson-type event process to discuss possible interdependence as well as triggering models in regards to the timing of multi-hazard events. Afterward, we shortly discuss amplifying as well as location related interdependencies of such events as well (see also Pflug

2026). The statistical models presented will be then applied to the suggested case study area, namely the Danube Region, and we investigate several multi-hazard events, their possible relationships as well as statistical significance. The results found will be then put into a broader context of multi-hazard and multi-risk analysis, including a discussion of measurement, modeling and managing aspects. Our paper is organized accordingly: the next section introduces two models for estimating and testing the triggering effect (i.e., the occurrence of event type Y triggers the occurrence of event Z, in symbol: $Y \Rightarrow Z$) and afterward introduces the case study and data used and the results found. Finally, we conclude with a discussion and outlook to the future.

2 Methodology

Before introducing the suggested models, some overview over the well known existing models of Poisson-type event processes is given. Since the event times are ordered $T_1 < T_2 < T_3 < \ldots$, the inter-event times $V_1 = T_2 - T_1, V_2 = T_3 - T_2, \ldots$ are non-negative random variables. If they are mutually independent, we speak of a *renewal process*. Let $N(t_1, t_2)$ be the (random) number of events in the interval $[t_1, t_2]$. For any discrete event process, we may formulate the *intensity* λ_t as the instantaneous event rate:

$$\lambda_t = \lim_{h \to 0} \frac{1}{h} \mathbb{P}\{N(t, t+h) > 0 \mid \text{there is an event at time t}\}.$$

Then the expected number of events in $[t_1, t_2]$ is

$$\mathbb{E}[N(t_1, t_2)] = \int_{t_1}^{t_2} \lambda_t \, dt.$$

The most important special case is the *homogeneous Poisson process* which has constant intensity λ, implying that the V_t's are i.i.d. Exponential variables with expectation $1/\lambda$. For a homogeneous Poisson process with constant intensity λ we have that $N(t_1, t_2)$ follows a Poisson distribution with expectation

$$\mathbb{E}[N(t_1, t_2)] = (t_2 - t_1)\lambda.$$

If the intensity is time-dependent, the process is an *inhomogeneous Poisson process*. For an inhomogeneous Poisson process with intensity function λ_t, the next event time T_{i+1} after an event at time $T_i = t$ follows the conditional distribution function

$$\mathbb{P}(T_{i+1} \leq t + u \mid T_i = t) = 1 - \exp\left(\int_t^{t+u} \lambda_s \, ds\right).$$

If the severities X_t are included in the model, we speak of a marked Poisson process. Here, one assumes that the severities X_t are i.i.d. and independent of the inter-event times V_t. However, for some types of events, there may be a dependency between V_t and X_t expressed by some copula. A copula is a function that splits multivariate distribution functions into two parts. The name derives from the verb 'to couple'. The univariate marginal distributions are separated from the copula function, which describes the dependency structure of the random variables (Nelsen 2006). For instance, a model with damage sizes X_t depending on the inter-arrival times D_t in insurance mathematics was developed in Pflug and Mueller (2001). Due to data limitations such advanced modeling approaches cannot be considered here.

2.1 Inter-dependencies of event processes of different types

Consider now two types of hazards Y and Z and the pertaining event time processes $T_1^Y, T_2^Y, \dots$, respectively $T_1^Z, T_2^Z, \dots$, each following a homogeneous Poisson process with intensities λ_t^Y and λ_t^Z. We call Y the primary (triggering) hazard and Z the secondary (triggered) hazard. One of the first models is the self-exciting Poisson model by Hawkes (1971a, 1971b). It assumes that past events of type Y influence events of type Z and vice-versa. It reads

$$\lambda_t^Y = \nu^Y + \sum_{T_i^Y \le t} \gamma^Y(t - T_i^Y) + \sum_{T_j^Z \le t} \gamma^{YZ}(t - T_j^Z)$$
$$\lambda_t^Z = \nu^Z + \sum_{T_j^Z \le t} \gamma^Z(t - T_j^Z) + \sum_{T_i^Y \le t} \gamma^{ZY}(t - T_i^Y)$$

where $\gamma^Y, \gamma^Z, \gamma^{YZ}, \gamma^{ZY}$ are *forgetting functions*, which determine the influence of past events onto the future intensity of events of the same type or of the other type. Hawkes indicates a method to calculate the covariance of the intensities based on the forgetting functions. A special case is the univariate model

$$\lambda_t^Y = \nu^Y + \sum_{T_i^Y \le t} \gamma^Y(t - T_i^Y)$$

which is known as *self-exciting point process*, since the occurrence of type Y triggers a change of intensity of the same process. Such a model can be used for contagious processes, like infections, but not used here, since the focus in this study is about the relation of different natural hazards.

Another model of this type is due to Doss (1989), going back to an idea of Ripley (1977). Let as before $N^Y(t_1, t_2)$ be the number of events of type Y with expectation $\lambda^Y(t_2 - t_1)$. In case of independence, the expression

$$K(t_1, t_2) = \frac{1}{\lambda^Y} \mathbb{E}[N^Y(t_1, t_2) \,|\text{an event of type } Z \text{ occurred at time } 0]$$

equals $t_2 - t_1$. To test this for data in the interval [0, T] with n^Y Y-observations and n^Z Z-observations one may use the test statistic

$$\hat{K}(t_1, t_2) = \frac{T}{n^Y n^Z} \sum_{i=1}^{n^Y} \sum_{j=1}^{n^Z} 1_{T_i^Y - T_j^Z \in (t_1, t_2)}$$

where 1 is the indicator function. Doss shows some properties of this test. Note, both models, Hawkes and Doss, are symmetric, that is the roles of Y and Z are exchangeable. This is however not always justified, since there is often a clear causality between different types of hazards: An earthquake may cause a landslide, but a landslide will not cause an earthquake. For this reason, asymmetric models seem to be more appropriate. In the next section we therefore introduce new basic triggering models (we also refer to the discussion in Pflug 2026).

2.2 Triggering models

Assume now that we observe two processes Y and Z and ask whether we may prove or disprove the triggering effect $Y \Rightarrow Z$. We will discuss two related models next, the switching intensity model as well as the first follower times model.

2.2.1 The switching intensity model

If process Y has an event at time t, it may increase or decrease the intensity of process Z for some time. Suppose that the basic intensity of process Z is λ_0^Z. Then one may consider the following model

$$\lambda_t^Z = \begin{cases} \lambda_0^Z & \text{if no event of process } Y \text{ happened in period } [t-\delta, t] \\ \lambda_0^Z + a & \text{if at least one event of process } Y \text{ happened in period } [t-\delta, t] \end{cases}.$$

Here a denotes the shift in intensity caused by process Y and δ denotes the duration of the effect of Y on Z. These parameters can be estimated from data.

An alternative model would assume a decreasing effect of Y on the intensity of Z:

$$\lambda_t^Z = \lambda_0^Z + a(t - T^Y) \quad \text{where } T^Y \text{ is the last event of type } Y \text{ before } t.$$

Here $a(t)$ is a *forgetting function* like

$a(t) = a1_{t\in[0,\delta]}$ (the previous example), or
$a(t) = a\exp(-\alpha(t))$ (the exponential forgetting).

Examples for the statistical estimation of such models, e.g., for the relation DR $\Rightarrow$ FL, answering the question how much does the occurrence of drought event trigger floods and other such relations is contained in the next section.

In order to account for time, one can consider a model which explicitly contains it as a driver for intensity. For testing the model $Y => Z$, we assume that the process Z is an inhomogeneous Poisson process with intensity function

$$\lambda_Z(t) = \exp(\beta_0 + \beta_1 \cdot t + \beta_2 \cdot I^Y(t))$$

where

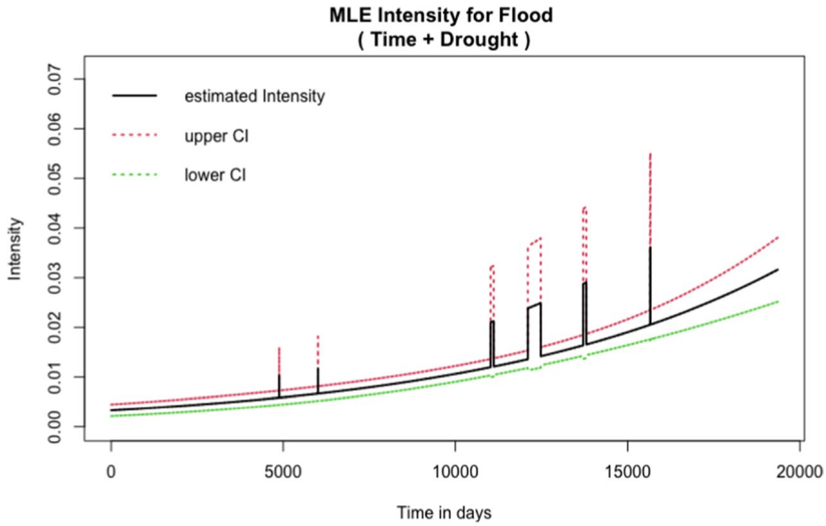

Fig. 1 The dependency of flood intensity as a function of time and the trigger DR

$$I_t^Y = \begin{cases} 1 & \text{there was an event } Y \text{ in the interval } [t-\delta, t] \\ 0 & \text{otherwise} \end{cases}.$$

Here β_2 denotes the shift in intensity of process Z caused events of process Y and δ denotes the duration of the effect of Y on Z. These parameters can be estimated from data. We introduce the Models 0 ($\beta_1 = \beta_2 = 0$), Model D (only dummy variable, i.e. $\beta_2 = 0$), Model T (only time variable, i.e. $\beta_1 = 0$) and Model DT (full model).

For example, the estimated intensity function for FL as dependent on time and the trigger DR for the Danube Region is shown in Fig. 1. The x-axis represents the observation period, starting from 1.1.1970 (day 1) till 31.12.2022 (day 19358), the y-axis shows the corresponding maximum-likelihood based intensity estimate (see for more information the case study section).

There are two ways to estimate the *'Intensity function'* $\lambda(t)$.

- **Fixed intervals:** the standard way to estimate the intensity of an event process is to choose $\lambda(t) = \frac{\text{number of events in the interval}}{\text{time interval}}$. For instance, taking the time interval as one year, a stepfunction is assigned to each year of observation.
- **Variable intervals:** another way of estimating the intensity can be done by looking at the intervals between each pair of events occurring. Then the intensity will be calculated as follows:

$$\lambda_t = \frac{1}{T_{i+1} - T_i} \qquad \text{for } T_i \leq t < T_{i+1}.$$

2.2.2 The first follower times model

If an event of type Y happens at time t, then denote by $\tau^Z(t)$ the (random) time of the next event of process Z. The difference

$$W_t^Z = \tau^Z(t) - t$$

is called the *first follower time*. Under the Poisson model and the independence hypothesis of the two processes, the distribution of the first follower time W_t^Z equals the distribution of the inter-event times V_t^Z of process Z. Any deviation from this equality can be interpreted as dependency of process Z on process Y. We may test the dependency by performing a nonparametric test such as Kolmogorov-Smirnov test or Wilcoxon test for the equality of the distributions W_t^Z and V_t^Z. Examples of this test methodology are also contained in the next section.

2.3 Amplifying

The two models (switching intensity and first follower) deal only with the timing of the events, not with their size. It might happen that an event of type Y does not influence the timing of an subsequent event Z, but its severity. A simple model would distinguish between severities with and without preceding other events:

$$\begin{aligned} X_t^Z &\sim F_1 \qquad \text{if no event of type } Y \text{ occurred in the interval } [t-\delta, t] \\ X_t^Z &\sim F_2 \qquad \text{if at least one event of type } Y \text{ occurred in the interval } [t-\delta, t] \end{aligned}$$

Any nonparametric test for the hypothesis $F_1 = F_2$ can be used for verifying of discarding the amplifying effect. An example is shown in the discussion section.

2.4 Dependent locations

If $X_t^{Y,1}$ and $X_t^{Y,2}$ are processes of the same type, but at different locations, occurring at the same or nearly same event times, then these severity variables may be dependent (and their degree of dependency may depend on the distance of the two locations). We may estimate the degree of dependency by a copula between them as was done, for example, for flood risk on the Pan-European level (Jongman et al. 2014).

The location model can be incorporated into the timing model: Suppose that the Y-process has an event at time t_0 and location L_t^Y. Then one may consider a model where the intensity function for Z depends on time t_0 since the last event of Y and on the distance

$$\lambda_t^Z = \lambda_t^Z(t - t_0, dist(L_t^Z, L_{t_0}^Y)),$$

where *dist* is the distance between the locations, modeling the effect that the intensity jump becomes smaller for more distant locations. Due to the lack of data, this model could not be implemented for the Danube Region.

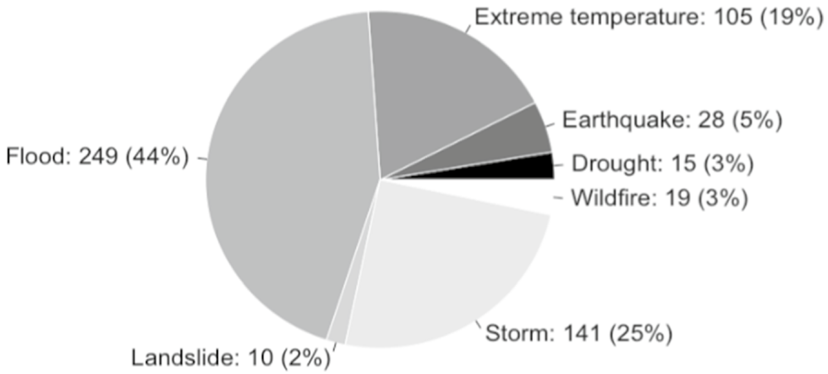

Fig. 2 Different disaster types observed within the Danube Region (total = 567). Source: based on EM-DAT 2024

3 Case Study

The statistical models explained above were tested in the Danube Region which consists of several countries including Austria, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Germany, Hungary, Moldova, Montenegro, Romania, Serbia, Slovakia, Slovenia and Ukraine. While detailed hazard assessments for some of these countries exist, an empirical multi-hazard risk assessment for the whole region has not been done yet (Hochrainer-Stigler et al. 2024). The Danube Region is actually exposed to various disaster types that also caused huge losses in the past. In addition, it is also very heterogeneous in economic terms and it therefore can be expected that single- and multi-hazard events will have quite some significant impact across countries as well as within countries. Hence, it provides an excellent case study for analyzing possible multi-hazard interactions based on past empirical observations.

Past observations of natural hazard events were taken from the International Disaster Database EM-DAT (EM-DAT 2024) for the time period between the beginning of 1970 to the end of 2022. This entire data set consisted of 2918 observations and 50 variables. In a first step some selections have been made, like the restriction on the Danube Region and excluding irrelevant data (e.g., data about chemical accidents). The final resulting data set consisted of 567 observations. The pie chart in Fig. 2 represents the absolute and relative frequencies in percent for each disaster type within this dataset. As one can see, the majority of events are weather and climate related, with 44 percent being floods and 25 percent being storms as well as 19 percent extreme temperature. Since the duration of the respective events will play a major role for further analysis, in a next step a date variable (specifically Start Month, Start Day and End Month, End Day) was calculated. This was done by a 'k-nearest-neighbor imputation' (for other approaches see the discussion section). After this, the duration was determined as the difference between the end and start dates. Hence, one can analyze the occurrence and duration of each disaster type for a certain country as well as the whole Danube Region. In what follows we focus on some selected interactions (based on data availability) and corresponding statistical models between different hazards for the whole Danube Region.

4 Results

The focus will be on the switching intensity and first follower models for selected specific hazard interactions. For the switching intensity model the results can be found in Table 2 showing the estimated parameters, standard errors as well as the Akaike information criterion (AIC) for the different model specifications as discussed within the Methodology section.

We first take a look at how flood hazards could be affected by other hazard types starting with droughts. It seems first to be counterintuitive that the trigger relation $DR \Rightarrow FL$ can be significant. However, since hot air can contain more humidity than dry air, the potential for heavy rain is much higher after drought periods. Moreover, in dry periods, the soil gets typically so much compacted, that water cannot penetrate and is flowing on the surface. This gives one argument that possibly the triggering relation can be found in the data. As indicated, we begin with considering the switching intensity model for FL for a time lag of 30 days. The smallest AIC is for the full Model DT, i.e., including time and triggering events, and can therefore be considered as the best among the candidate models. Regarding the significance of the more complex model compared to the others, the log-likelihood ratio test in Table 3 shows that the full model gives a non-significant improvement in the model fit compared to the others on the 0.05 significance level (however, very close to significance), especially in regards to the triggering event. A non-significant relationship between DR and FL is further indicated by the first follower model shown in Table 4 which does not show any significant differences in the two distributions. Hence, for a selected time lag of 30 days a non-significant (or very weak) interrelationship was found. Moving on, another possible reason for the occurrence of floods can be previous storms. Storms (ST) are often accompanied by heavy rain, which of course leads to large amounts of water. The time lag δ for this relation was chosen as 10 days. The parameter estimations of the different models are shown in Table 2. In addition, the log-likelihood ratio test is significant, indicating that the more complex model leads to a statistically significant improvement to the model fit. Also the first follower model shows clear significant differences of the distributions. Hence, there are strong indications that storm and flood hazards are interrelated. Moving forward, the most common cause of flooding is water due to rain and/or snowmelt that accumulates faster than soils can absorb it, or rivers can carry it away. A possible reason for the occurrence of floods may be preceding extreme temperatures. These temperatures could be the reason for snowmelt, which in turn leads to large amounts of water.The estimates for this model can be found in Table 2. In this case, the time only model shows the lowest AIC and is also indicated through the log-likelihood ratio test. Nevertheless, the first follower model showed significant differences in the distribution indicating some dependencies between those hazards.

As indicated above, extreme temperature can indeed influence many other possible hazards, and we specifically look at relationships now to storms, droughts and

Table 2 Switching intensity models, estimated parameters and corresponding AIC

Estimate (std. error)	Model 0 constant intensity	Model D dummy trigger	Model T time	Model DT time and trigger
DR→FL				
β_0	−4.3534	−4.385	−5.6769	−5.7089
	(0.0634)	(0.0652)	(0.1778)	(0.1809)
β_1			0.000116	0.00012
			(0.000013)	(0.00013)
β_2		0.6802		0.5627
		(0.2751)		(0.2752)
AIC	2667	2664	2577	2575
ST→ FL				
β_0	−4.3534	−4.3969	−5.6769	−5.6998
	(0.0634)	(0.0648)	(0.1778)	(0.1793)
β_1			0.000116	0.00011
			(0.000013)	(0.000013)
β_2		3.3609		3.1437
		(0.3084)		(0.3086)
AIC	2667	2617	2577	2531
ET→ FL				
β_0	−4.3534	−4.3727	−5.6769	−5.6795
	(0.0634)	(0.0651)	(0.1778)	(0.1779)
β_1			0.000116	0.00012
			(0.000013)	(0.000013)
β_2		0.4561		−0.0827
		(0.2849)		(0.2877)
AIC	2667	2667	2577	2579
ET→ ST				
β_0	−4.9221	−4.9734	−5.7473	−5.7241
	(0.0842)	(0.0867)	(0.20799)	(0.2078)
β_1			0.000076	0.00007
			(0.000016)	(0.000016)
β_2		2.1329		1.8304
		(0.3640)		(0.3687)
AIC	1672	1654	1649	1636
ET→DR				
β_0	−7.1628	−7.4682	−7.4227	−7.4914
	(0.2582)	(0.3015)	(0.5515)	(0.5996)
β_1			0.0000258	0.00000239
			(0.0000465)	(0.0000532)
β_2		4.3327		4.326
		(0.5839)		(0.6023)
AIC	246	223	243	225
ET→WF				

Table 2 (continued)

Estimate (std. error)	Model 0 constant intensity	Model D dummy trigger	Model T time	Model DT time and trigger
β_0	−6.9264 (0.22943)	−7.0944 (0.25)	−8.0427 (0.6106)	−8.2096 (0.6609)
β_1			0.0000997 (0.0000448)	0.0000997 (0.0000485)
β_2		3.8755 (0.6292)		3.7398 (0.6292)
AIC	303	288	299	285

Table 3 Log likelihood-ratio tests for different switching intensity models

Explaining	DR⇒ FL	ST⇒ FL	ET⇒ FL	ET⇒ ST	ET⇒ DR	ET⇒ WF
T more than 0	< 2.2e-16	< 2.2e-16	< 2.2e-16	8.7e-07	0.5781	0.02011
DT more than D	< 2.2e-6	< 2.2e-16	< 2.2e-16	8.1e-06	0.9642	0.03179
DT more than T	0.059	5.1e-12	0.7712	8.8e-05	5.18e-07	6.08e-05

wildfires. Regarding storms it was found that for the switching intensity model the full model provides the lowest AIC with a significant improvement of the model if time and trigger event are included, indicating some dependency between those hazards. However, these results have to be treated with caution as the Wilcoxon Rank sum test as well as the Kolmogorov-Smirnov test for the first follower model showed non-significant differences in the two distributions. Moving on, the process of droughts is driven by the heat of the sun. The hotter it is, the greater the rate of evaporation. Thus, if the temperature of the ocean or the surface of the land is relatively cool in a certain area, drought may occur in regions that rely on those sources of moisture. The results of the estimation are shown in Table 2. The results indicate that the dummy variable for the ET-influence is significant, while the time does not contribute to a better fit of the model, see Table 3. Hence, no dependencies between extreme temperature and droughts for a time-lag of 30 days were found. Proceeding, in general it can be said that wildfires are caused by a mixture of factors such as high temperatures, drought conditions following a period of vegetation growth and a trigger which can be natural such as lightning. Lightning is a potential cause of a wildfire, however the analysis could not determine a connection because no observations with a suitable time period were recorded in the data. In the following the dependence of wildfires and extreme temperatures will be studied instead. The result of the estimation is shown in Table 2. According to the likelihood ratio test in Table 3, model DT that is, including both covariates into the model improves the fit significantly. Since the third model is statistically significant, it follows that a relationship between wildfires and previously extreme temperatures could be assumed in the switching intensity model. Note, however, that for the first follower model only the Kolmogorov-Smirnov test showed significance in the differences between the two distributions. In summary, it can be said that a dependency of wildfire and previously extreme temperatures

Table 4 Testing the first follower models

Interaction	Wilcoxon Rank sum test		Kolmogorov-Smirnov test	
DR⇒ FL	W = 1466	p-value = 0.4766	D = 0.24164	p-value = 0.3506
ST⇒ FL	W = 12624	p-value = 0.000857	D = 0.21877	p-value = 0.001926
ET⇒ FL	W = 7687	p-value = 0.003863	D = 0.23195	p-value = 0.007472
ET⇒ ST	W = 3770	p-value = 0.7466	D = 0.10033	p-value = 0.7333
ET⇒ WF	W = 630	p-value = 0.102	D = 0.35152	p-value = 0.00797

could be determined using the switching intensity model. In case of the first follower model, the Kolmogorov-Smirnov test showed a significant result.

5 Discussion and conclusion

Multi-hazard events can be devastating and there are indications that in such situations the exposed risk-bearers are affected more severely compared to single-hazard events as resources are drained at the same time, i.e., effecting their ability to respond (Reichstein et al. 2021; Zscheischler et al. 2020). We presented some statistical modeling approaches to determine possible interrelationships of hazards (Gallina et al. 2016, Pflug 2026) and tested them for the specific case of the Danube Region (for a global analysis we refer to Lee et al. (2024). We especially focused on the question whether certain hazards are more likely to occur due to preceding hazards. The analysis presented here focused primarily on floods, droughts, storms and wildfire hazards and possible relationships. However, the statistical models presented can be extended to other hazards and on different spatial scales as well. Especially if more data becomes available also the statistical models can be extended. For example, non-linear dependencies of multi-hazard as well as multi-risk events (e.g., triggering, amplifying, location wise) could be incorporated, e.g., through copula approaches. This also enables the analysis of possible risk management options, including insurance applications, which rely on risk pooling of independent risks. In addition, Bayesian approaches are nowadays very often applied as well, also in cases were small sample sizes have to be considered and updating of data and results is considered as important (for a review we refer to Wang et al. 2025; Graf et al. 2009; Zheng et al. 2021). In this context, data augmentation techniques are also gaining importance (Wang et al. 2025).

The presented methodology aimed at revealing the relationship between the timing of hazard events of different types. Equally important is the question how the severity of a preceding event affects the severity of the triggered event. Recall that the damage curve models the relationship between severity of an event, exposure and vulnerability on one side and amount of damage on the other side. In some cases, the preceding event does not change severity of the triggered event, but increases the vulnerability of the system (Jäger et al. 2024). For example, in regards to the amplifying model, for the case of Romania (the only country where the model could be applied on the country level due to lack of data) it can be shown that drought (DR) triggers flood (FL) in terms of intensity. However, there might also be an effect on

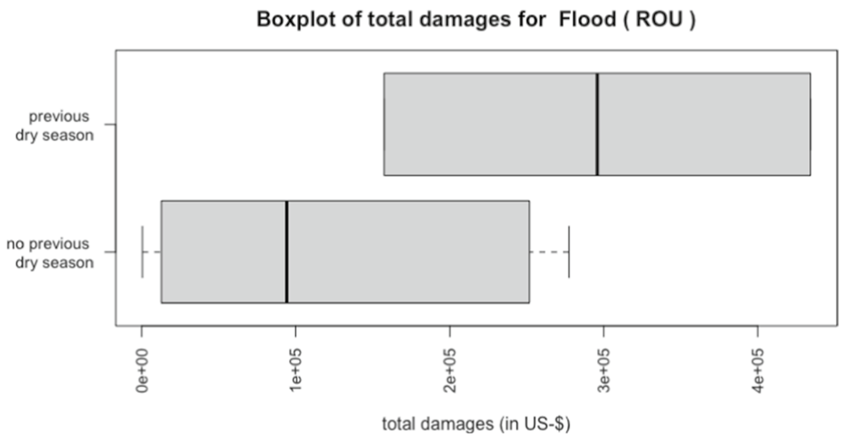

Fig. 3 Boxplot of total damages compared to past drought events for Romania. Source: based on EM-DAT (2024)

severity and one can test the amplifying relation between *DR* and *FL* using the data from Romania which confirms this hypothesis (see Fig. 3 and the methodology section). We also not included (again due to lack of data) an analysis of dependent locations which for the Danube Region may have a huge influence in regards to multi-risks impacts and the efficiency of corresponding disaster risk financing instruments (Hochrainer-Stigler et al. 2024). All this needs detailed investigation and has to be embedded within multi-hazard as well as multi-risk frameworks (Hochrainer-Stigler et al. 2023). We argued here that while such considerations need to be explicitly incorporated conceptually as well as from a causality related point of view, it is equally important to investigate these relationships also empirically to assess the case specific magnitude as well as significance of dependencies on different scales.

Regarding our analysis it must be acknowledged that the small sample size of hazard observations can affect the reliability of this analysis. Especially in case of datasets such as EM-DAT, the significance of the time component may be also due to the increase in observational data due to higher global attention to this issue (Panwar and Sen 2020). In addition, it is also clear that our analysis is restricted to the selected case study area, namely the "Danube Region", and may not be valid for other geographical/geological/meteorological regions. Nevertheless, the presented models and related tests in this paper, can be readily applied for other regions as well.

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Author contributions S.H.S. conceived and designed the research question, analyzed the results, and contributed material. G.P. and V.K. developed the mathematical and statistical models. V.K. did the data handling, statistical analysis, interpretation and implementation. All three authors contributed in writing the paper.

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Data availability No datasets were generated or analyzed during the current study.

Declarations

Competing interests The authors declare no competing interests.

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