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A review of quantification methodologies for multi-hazard interrelationships

Aloïs Tilloy[a,*], Bruce D. Malamud[a], Hugo Winter[b], Amélie Joly-Laugel[b]

[a] Department of Geography, King's College London, Bush House (North East Wing), 30 Aldwych, London WC2B 4BG, United Kingdom
[b] EDF Energy R&D UK Centre, Interchange, 81- 85 Station Rd, Croydon CR0 2AJ, United Kingdom

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ABSTRACT

Globally and yearly, individual hazards and hazard interrelations have the potential to result in socio-economic losses. Here, in this critical review, we use grey- and peer-review literature to identify and compare current research available for the quantification of hazard interrelations, focussing on 14 different natural hazards. We first provide a historical context for quantitative single hazard and multi-hazard assessment. We then construct a literature database with 146 references related to multi-hazard interrelations. We use our literature database to identify trends for hazard interrelation and multi-hazard and from these group hazard interrelations into five types: triggering, change condition, compound, independence and mutually exclusive. Our critical review identifies 19 different modelling methods to quantify natural hazard interrelationships which we cluster into three broad modelling approaches: stochastic, empirical, and mechanistic. We then synthesize results of our classification of quantification methods for hazard interrelationships and using two matrices illustrate this in practice for 24 different interrelations between 14 natural hazards, one for cascading hazards (temporal order in the multi-hazard event) and one for compound hazards (two or more hazards acting together). Finally, we provide examples of applications for each the three quantitative modelling approaches defined. We believe that this review will lead to a better understanding of quantification methodologies for hazard interrelations between different sub-disciplines that focus on natural hazards, thus aiding cross-disciplinary approaches for better understanding potential risk related to multi-hazard events.

1. Introduction

In this paper we review quantification methodologies for the interrelations between different natural hazards. Here, the term hazard will follow the definition by UNISDR (2009), which refers to a natural hazard (hereafter referred to as a 'hazard') as a natural process or phenomenon that may have negative impacts on society. The magnitude of the hazard is one component of risk (hazard, exposure and vulnerability) (UNISDR, 2017). When a high intensity of a natural hazard is encountered, the word extreme is often used to describe these events. The limitations of single hazard studies have been highlighted in the past decade (e.g., Kappes et al., 2012a; Gill and Malamud, 2014; Terzi et al., 2019). Indeed, the interaction of different hazards can lead to an impact that is greater than the sum of the single hazard effects (Terzi et al., 2019). When dealing with more than one hazard at a time the terms multi-hazard and compound hazard (or compound event), the focus of this review, are often used (Kappes et al., 2012b; Seneviratne et al., 2012; Leonard et al., 2014). The term compound hazard is sometimes encompassed within multi-hazard (e.g., UNISDR, 2017); moreover, the term compound hazard is also frequently used for weather and climate related hazards (Seneviratne et al., 2012; Zscheischler and Seneviratne, 2017).

When considering natural hazards (e.g., landslides, earthquakes, tsunami), each hazard can be linked to other hazards or processes, resulting in the phrase 'multi-hazard', which has a strong link with the term multi-risk in numerous studies (e.g., Greiving et al., 2006; Kappes et al., 2012a, 2012b; Marzocchi et al., 2012; Xu et al., 2014b; Gallina et al., 2016; Terzi et al., 2019). Gill and Malamud (2014) considered four steps of a multi-hazard framework, in which the first step is a multi-layer hazards approach (Gill and Malamud, 2014), where interrelations are not really considered, and hazards are superposed in a region. Other examples of a multi-layer hazards approach in a region include Grünthal et al. (2006), Tarvainen et al. (2006) and Orencio and Fujii (2014). The other three steps of the multi-hazard framework of Gill and Malamud (2014) go further to include hazard interactions (interrelationships), coincident hazards and hazard vulnerabilities, with their work focussing on hazard interactions in a multi-hazard framework context. In this review we will focus specifically on hazard interrelations within the broader context of multi-hazard frameworks.

As shown later in this review, the interest around events that

* Corresponding author.
E-mail address: alois.tilloy@kcl.ac.uk (A. Tilloy).

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include multiple natural hazards (or multi-hazard events) has been growing since the beginning of the 21st century. The methods and approaches to tackle multi-hazard vary between different natural hazard communities (e.g., geophysical vs. hydrological vs. atmospheric hazard communities). A comprehensive multi-hazard approach could also enhance other disciplines such as forecasting and early warning or climate change studies. There are several challenges associated with quantifying multi-hazard interrelationships which this work aims to tackle, including the following:

(i) *Fragmentation of literature in the field*, with a challenge that a wide variety of terms are used to define hazard interrelationships (e.g., cascade, interaction, compound) (Pescaroli and Alexander, 2018).
(ii) *Gaps in the multi-hazard approaches taken by different institutions* (e.g., single hazards layered without considering interrelationships vs. holistic multi-hazard approaches which include interrelationships and dynamic vulnerability) (Gill and Malamud, 2014, 2016).
(iii) *The complexity of multi-hazard events* and how to address a deterministic equation based (theoretical) understanding which might apply to 'all' events that are similar vs. a case study based empirical understanding which might be applicable just to a given scenario of a specific event (Geist et al., 2009; Catane et al., 2012; Bout et al., 2018; Kumbier et al., 2018).

We believe there is a need to not only study case studies inclusive of multi-hazard interrelationships but to generalize to more inclusive frameworks that are applicable to a broad range of hazards and locations. In this paper we propose what we consider is a more general and inclusive framework based on a systematic review of quantitative methods and terminology in the broader multi-hazard literature. We believe this will be useful for those responsible for hazards in given regions to put into context methods being used more generally globally. This can be done by applying methods that are not yet applied to certain hazard interrelations or by studying interrelations that have not yet been quantified. This review is focused on reviewing modelling methods for quantifying hazard interrelations; whereas, previous studies have focussed on either documenting qualitative interrelationship between natural hazards or the modelling methods alone (Kappes et al., 2012a, 2012b; Gill and Malamud, 2014; Hao and Singh, 2016; Hao et al., 2018; Terzi et al., 2019). The different classifications and hazard interrelations matrices developed in this review, combined with an extensive literature database (see Supplementary Material) offer tools and keys to understand the main challenges of quantifying natural hazards interrelations.

Many regions in the world are prone to events that include more than one natural hazard, with interrelationships between the hazards that impact the same location during the same time period (Gill and Malamud, 2014; Leonard et al., 2014). We call these events multi-hazard events. These are usually based on physical phenomena (e.g., thunderstorm, mid-latitude cyclone). Examples of these include the following:

(i) In 2010, storm Xynthia hit the west coast of France. The storm itself was not particularly extreme for the season but the coincidence of extreme wind, high tides, storm surge and the fact that the soils were already saturated led to huge damage (CCR, 2018).
(ii) In winter 2014, the UK experienced a succession of major storms that led to severe damage due to wind, flooding and avalanches in Scotland (Met Office, 2015).
(iii) In 2011, the Great North East Japan earthquake and resultant tsunami had devastating consequences (Davis, 2015; Kumasaki et al., 2016).
(iv) In 2018, Wildfires in California increased the severity of flash floods (AghaKouchak et al., 2018).

These four multi-hazard events all include multiple natural hazards that are interrelated (in different ways), with the events impacting on a given region within a time period.

In this critical review we used as evidence a hazard interrelationship literature database consisting of 146 references from the peer- and grey-literature. This review aims to be representative of the current state of modelling interrelationships between natural hazards. In addition to discussing strengths, weaknesses, and commonalities of multi-hazard quantification approaches, we include a background on selected diverse modelling methods that are used for multi-hazard modelling. Although we believe our review is representative of the broader literature on multi-hazard, it is not intended to be inclusive of every work or every quantitative approach relating to multi-hazard from the 1980s to when this paper is published.

This critical review article is organized as follows. We first (Section 2) present a literature database built in the context of this review and three subgroups of this database: (i) terminology around multi-hazard and compound events, (ii) interrelationship types for natural hazards, (iii) natural hazards interrelationships. We then present (Section 3) different models used in the scientific community to quantify relationships between two and three natural hazards, including some practical examples. We finish (Section 4) with a discussion and conclusions.

2. Construction of a hazard interrelationship literature database

We first created a multi-hazard interrelationship literature database with three main objectives:

(i) To encompass the broadest possible number of terms and approaches for multi-hazard assessments.
(ii) To understand different possible interrelations between natural hazards
(iii) To focus on quantitative methods for hazard interrelations.

To construct this database, we searched for relevant peer-reviewed references in the Web of Science™ online platform and Google Scholar™ using key words and Boolean search criteria. We also considered in Google Scholar™ conference proceedings, grey literature (e.g., government, technical, and project reports), and PhD dissertations. After a preliminary iterative approach of a couple dozen references to decide on key-words, we used the following key-words (with appropriate inclusion of plural and other derivatives where appropriate): "multi-hazard", "compound", "hazard", "dependence", "cascade", "multi-risk", "model", "probability". The key word searches we did were not systematic but rather used combinations of these key words, combined with some searches that added specific terms for natural hazards (see Section 2.3), to gain a representative sample of papers in the literature that addressed the three objectives given above.

Our final literature database consisted of 146 references from 83 sources for a 38-year period (1980–2018). Among the 146 references, 84% are peer-reviewed scientific journal articles, 6% are reports from projects or institutions, 5% are books, 4% are conference proceedings and 1% are PhD theses. This database is the material for our analysis and is available in the Supplementary Material Table A of this review. Fig. 1 uses violin plots to display the distribution of articles over time for those nine journals in the multi-hazard database with ≥ 3 articles.

In our literature review database, those journals the most represented include *Natural Hazards* (n = 13)*, Natural Hazards and Earth System Sciences* (n = 6)*, Coastal Engineering* (n = 5)*, Nature* (n = 4)*, and Geomorphology* (n = 4). One can speculate that the variety of hazards studied in these journals might also require a variety of methods to quantify their interrelations. We can also note the growing interest in fields related to multi-hazard from the late 1990s.

As we are interested in terminology around multi-hazard, hazard interrelations and methodologies for quantifying these interrelations, this database is divided into three interrelated subgroups which we

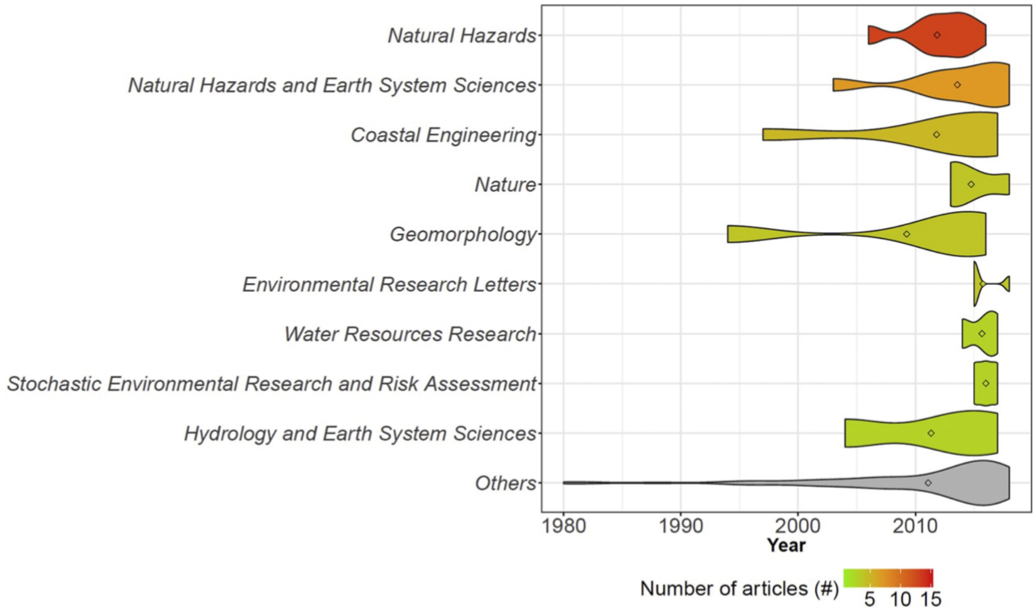

Fig. 1. Journals in terms of number of articles listed in our multi-hazard literature database of 146 references and as a function of year. Shown are the 9 journals (out of 83 total sources in the database) which have 3–13 articles, ranked from most articles (journal *Natural Hazards* with 13 articles) to fewest articles (*Hydrology and Earth System Sciences* with 3 articles). Each journal is represented by a violin plot showing the smoothed density of publication per year, 1980 to 2018. The green to red colour (legend) within bars shows the number of articles for that journal. A category for 'Others' references is displayed as the bottom-most violin plot, in grey, and is comprised of 10 sources with 2 references each and 64 sources with 1 reference each (84 references from 74 sources). Small circles within each violin plot represents the mean year of publication for each source. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

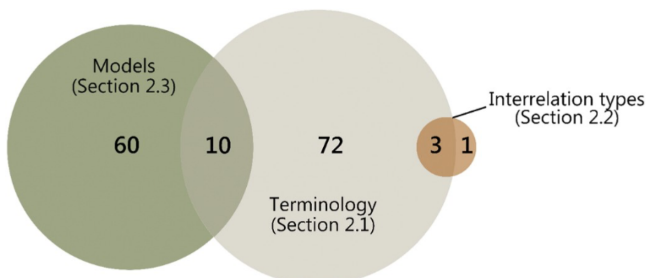

Fig. 2. The 146 references in our multi-hazard literature database divided into three subgroups of literature (and their overlaps) which we will discuss in Section 2.1 (Terminology), Section 2.2 (Interrelation types) and Section 2.3 (Models). Numbers and size of circles correspond to number of references.

illustrate in Fig. 2:

(i) *Terminology* subgroup, comprises those 85 references that contain terms related to multi-hazard: {(multi-hazard*) OR [compound AND (event* OR flooding OR extreme*)]}. This sub group will be used to analyse the terminology around multi-hazard in Section 2.1.
(ii) *Interrelation type* subgroup, comprises 4 references that classify different types of interrelations between natural hazards and we will use in Section 2.2 to define five types of interrelations between hazards that will be used in this paper.
(iii) *Models* subgroup, comprises 70 references that examine interrelations between natural hazards in a quantitative way, focusing on possible interrelations between 14 natural hazards that we selected following different criteria. This is discussed further in Section 2.3.

2.1. Terminology in the context of multi-hazard, compound hazard, and hazard interrelations

Multiple hazards have been studied in different contexts and by different research communities (e.g., Kappes et al., 2012b; Leonard et al., 2014; Hao et al., 2018). In the introduction we referred to some sources that are widely used (e.g., UNISDR, 2017) that define compound hazard as a sub-group of the term 'multi-hazard'. However, from Fig. 1, as we explored our literature, two broad streams of studies were found: those using the word multi-hazard and others using the word compound hazard (with some overlap). There was a loose correlation of study foci with the words used, with multi-hazard tending toward those studies to do with solid earth and surface process hazards, and compound hazard to do with those hazard related studies in hydrometeorology. We will below develop the terminology around these approaches, focussing on these two streams, multi-hazard and compound hazard.

The terms multi-hazard and compound hazard have a broad range of inter-linked and overlapping definitions, of which we give a couple of examples here. For example, a multi-hazard approach accounts for different probabilities and intensities of multiple hazards (Eshrati et al., 2015). A general definition for a compound hazard events has been given by the IPCC SREX (Seneviratne et al., 2012) and also given and discussed by Leonard et al. (2014, p. 115) as "an extreme impact that depends on multiple statistically dependent variables or events". Eshrati et al. (2014) distinguished between compound hazard and multi-hazard, stating the following (p. 79):

> *"While compound hazards are characterized as 'several elements acting together above their respective damage threshold', multi-hazard are characterized as 'elements of quite different kinds coinciding accidentally, or more often, following one another with damaging force'"* .

Hewitt and Burton (1971) and more recently Kappes et al. (2012a, 2012b) and Eshrati et al. (2014) highlighted that the terms multi-hazard and compound hazard correspond to the two main mechanisms to

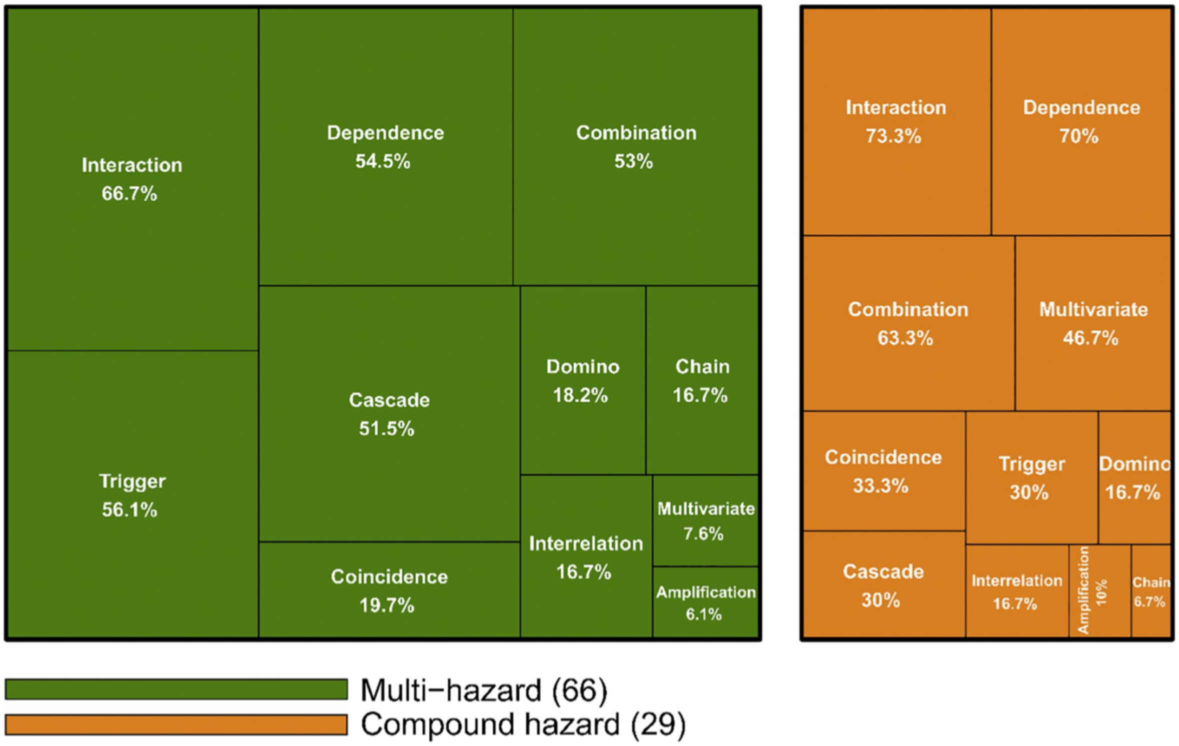

Fig. 3. Treemap of multi-hazard and compound hazard terminology used in 85 sources to describe and quantify hazard relationships. This treemap chart shows the proportion of use of terminology used in our multi-hazard literature database. Terms are grouped in two literature streams which correspond to "multi-hazard" (green, 66 references) and "compound hazard" (orange, 29 references), noting that ten of the references have both words so are included (repeated) in the green and orange parts. Each of the 85 sources within the two terminology streams of multi-hazard and compound hazard were examined for word use, with in some cases a given reference using greater than one of the words (sum of all values is > 100%). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

characterize hazard interrelations.

Previous studies have highlighted the abundance of terms to qualify hazard interrelations (e.g., Kappes et al., 2012b; van Westen and Greiving, 2017). The profusion of terminologies and definitions makes it hard to find a generally accepted definition of a multi-hazard. Moreover, some terms are linked and part of the same conceptual framework. Here we did an extensive review of the available literature to find patterns in the use of particular terms to define hazard interrelations within the context of multi-hazard and compound hazard.

To offer a better understanding of the terminology around multi-hazard and compound hazard, we first listed terms that are used to represent hazard interrelations. To do this we relied on previous reviews on multi-hazard which already gathered terms to describe relations between hazards (Kappes et al., 2012b; Gill and Malamud, 2014; Leonard et al., 2014; van Westen and Greiving, 2017; Pescaroli and Alexander, 2018). Selected terms are displayed in Fig. 3.

For the 146 references in our literature database we searched each of the documents for those containing the keywords {(multi-hazard*) OR [compound AND (hazard* OR extreme* OR event* OR risk*)]}. We performed this selection using the software Mendeley™ which performs word searches within the entire PDF file of each reference. Among the 146 sources in our database, 85 (59%) fulfiled these conditions. By doing this selection we include different sources aiming to deal with the broad issue of multi-hazard. Among these 85 sources, 66 (77%) contain the word "multi-hazard" and 29 (35%) the word "compound" (of these 66 and 29 sources, ten of them contain both terms). The term multi hazard is more frequently used than compound hazard. In our literature database, the term "compound AND (event OR extreme OR hazard)" was first mentioned in 2012 (Lavell et al., 2012), while the use of the term "multi-hazard" is more established (first mention in 2002) (van Westen et al., 2002). Moreover, as was discussed above, these terms are complementary to defining hazard interrelationships.

Our next step was to study the distribution of terms used to define hazard interrelations among these two terminology streams (multi-hazard and compound hazard). Terms we looked for in both streams include the following: cascade, chain, interaction, interrelation, dependence, combination, multivariate, domino, trigger, coincidence, amplification. As discussed in the introduction to Section 2.1, these words were selected from previous works on multiple hazards (Kappes et al., 2012b; van van Westen and Greiving, 2017; Pescaroli and Alexander, 2018) and were considered the most relevant. Fig. 3 displays the results of this analysis in a treemap, with the green (left) representing percentage results of those interrelationship terms within multi-hazard (MH) and orange (right) those within the compound hazard (CH).

From Fig. 3 we can see that the terms "interaction", "dependence" and "combination" are the most widely used in both frameworks (each term is used in 53–73% of all references in the MH or CH frameworks). The terms "trigger" and "cascade" are more often used within the MH framework (trigger: 56% in MH vs. 30% in CH; cascade 52% in MH vs 30% in CH). This contrasts with the terms "multivariate" and "coincidence" which are more associated with the CH terminology stream (multivariate: 8% MH vs 47% CH; coincidence: 20% MH vs 33% CH). This highlights the differences between the multi-hazard (MH) and compound hazard (CH) streams, and how they do not refer to the same physical processes. Differences in terminology has to do with disciplines and the modelling methods to quantify interrelations as will be shown in Section 3.

Fig. 3 also shows that the term "interrelation" is equally used (17%, i.e. one in six references) for both MH and CH. We consider interrelation to be a neutral term, equally used in both MH and CH. This analysis of the terminology shows that (i) some authors refers to compound hazard events as distinct from multi-hazard, and that (ii) authors who refer to compound hazard events do not always choose the same terms to define hazard interrelations.

2.2. Interrelationships between hazards

After defining two different terminology streams (multi-hazard and compound hazard) and analysing the terminology around hazard interrelations (Section 2.1), in this section we review different ways of classifying hazard interrelations, using the terminology previously presented.

Some authors classify hazard interrelations for different purposes. Gill and Malamud (2014) defined four interrelation types which they built on a critical review of > 200 references, including many case studies. Decker and Brinkman (2015) defined three different interrelation types between natural and human-made hazards in the context of the project ASAMPSA_E (Advanced Safety Assessment Methodologies: Extended PSA) focusing on hazards posing potential threats to nuclear installations and their possible correlations. Liu et al. (2016) did a systemic classification of hazard interrelations based on characteristics of the hazard-forming environment defining four different types which they expressed in probabilistic terms. Finally, van van Westen and Greiving (2017) consider four types of hazard relationships based on previous research. The interrelation types within each of the four references are given in Table 1.

In these four references that examined interrelationship classifications (Table 1), the same processes are described in different ways with different terms. Moreover, it is possible to find bridges in between these classifications. For example, *triggering interaction* (A1) is equivalent to *causally connected hazard* (B1), *series relationship* (C4) and *cascading hazard* (D4). From these different classifications we can highlight five different interrelation types: *independence, triggering, change conditions, compound hazard, mutual exclusion*. These are summarized in Table 2 along with the reference and interrelation type from Table 1 given.

Here we described in detail each of these five interrelation types, along with case-study examples of each interrelation type:

Table 2
Five interrelation types as synthesized from the four references (A to D) presented in Table 1 and used in this review.

Interrelation type	*A.*Gill and Malamud (2014)	*B.*Decker and Brinkman (2015)	*C.*Liu et al. *(2016)*	*D.*van Westen and Greiving (2017)
I. Independence	✓	✓	✓	✓
II. Triggering	✓	✓	✓	✓
III. Change condition	✓			✓
IV. Compound hazard		✓	✓	✓
V. Mutual exclusion	✓		✓	

- I. Independence (A4, B3, C1, D1): Coincidence between hazards can occur. It implies a spatial and temporal overlapping of the impact of two hazards without any dependence or triggering relationship. It is equivalent to the independent relationship in Liu et al. (2016) and van Westen and Greiving (2017) and the spatial-temporal coincidence in Gill and Malamud (2014). An example is the 2010, Pacaya volcanic eruption and tropical storm Agatha which hit the Pacific coastline of Guatemala almost simultaneously, leading to exacerbated damages due to ash blocking drainage system of rainfall triggering lahars (Gill and Malamud, 2014). We also include in this category cases where two hazards impact the same area, independently, at different times (e.g., cyclone occurring few weeks after an earthquake).
- II. Triggering (Cascading) (A1, B1, C4, D4): Implies a primary and a secondary hazard. As explained by Gill and Malamud (2014), any natural hazard might trigger zero, one or more secondary natural hazards (Tarvainen et al., 2006; De Pippo et al., 2008; Kappes et al., 2012a, 2012b; Marzocchi et al., 2012). The secondary natural hazard might be identical or different from the primary hazard. As an example, an earthquake might trigger landslides, which can trigger a flood, resulting in a hazard cascade (Catane et al., 2012).
- III. Change conditions (A2, D3): This relates to one hazard altering the disposition of a second hazard by changing environmental conditions. This phenomenon has been discussed in previous papers (Kappes et al., 2010; Catane et al., 2012). One of the reasons is its variable temporal scale, for example, a wildfire might denude an area of vegetation and harden the soil thus amplifying the strength of floods through increasing over ground flow and result in a debris flow (Cannon et al., 2008). A wildfire can have a non-negligible influence on soil infiltration up to one year after its occurrence (Shakesby and Doerr, 2006). For example, in Las Conchas in New Mexico in 2011, a wildfire charred > 150,000 acres leading to an increased flood one month later (FEMA, 2012). There is a similar issue with river flooding amplified by landslides (Costa and Schuster, 1988).
- IV. Compound hazard (association) (B2, C3, D2): In this interrelation different hazards are the result of the same "primary event", or large scale processes (Mazas and Hamm, 2017) which are not necessarily hazards. In this case there is not a primary and a secondary hazard as the different hazards occur simultaneously. As an

Table 1
Four different interrelation classifications for natural hazards from different sources. Each reference has a letter (A, B, C, D) and each interrelation type has a number (1, 2, 3, 4).

Article	Interrelation type
A. Gill and Malamud (2014)	*(A1) Interactions where a hazard is triggered*: One hazard triggers one (or more) other hazard(s).
	(A2) Interactions where the probability of a hazard is increased: One hazard changes environmental parameters that moves toward a change in the likelihood of another hazard.
	(A3) Interactions where the probability of a hazard is decreased: One hazard alters the frequency or magnitude of another.
	(A4) Events involving the spatial and temporal coincidence of natural hazards: Two hazards are independent and occur simultaneously by coincidence.
B. Decker and Brinkman (2015)	*(B1) Causally connected hazards:* When one hazard may cause another hazard; or when one hazard is a prerequisite for a correlated hazard.
	(B2) Associated hazards: Hazards which are probable to occur at the same time due to common root causes.
	(B3) Combinations of independent phenomena: Two hazards are independent.
C. Liu et al. (2016)	*(C1) Independent relationship*: Two hazards are independent.
	(C2) Mutex relationship: Two hazards cannot occur together; their trigger factors are mutually exclusive.
	(C3) Parallel relationship: Two hazards depend on the same trigger factors.
	(C4) Series relationship: One hazards triggers another hazard.
D. van Westen and Greiving (2017)	*(D1) Independent events*: Two hazards are independent.
	(D2) Coupled events: Two hazards are triggered by the same triggering event.
	(D3) One hazard changes the conditions for the next.
	(D4) Domino or cascading hazard: One hazard causes the next.

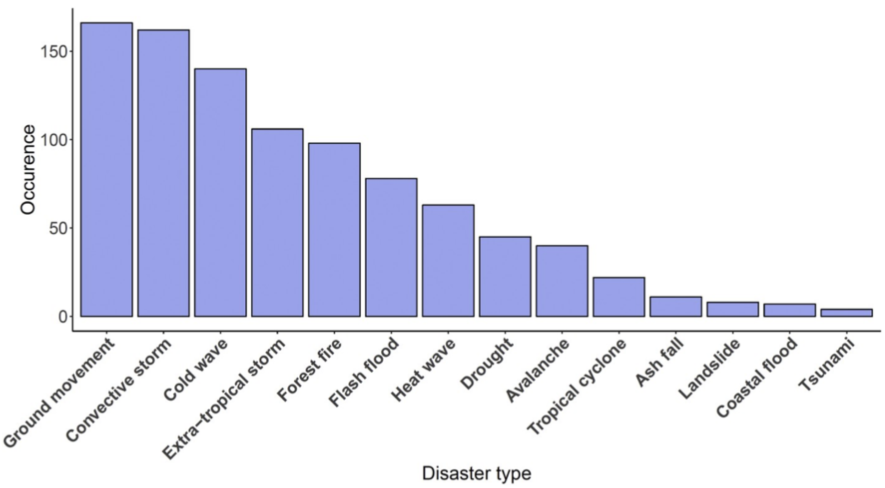

Fig. 4. Occurrences of 14 disaster types in Europe in the period 1900–2018. Data from CRED (2018).

example, the co-occurrence of river flooding and sea surge could be the result of the same large-scale process (tropical cyclone, mid-latitude cyclone) (Bevacqua et al., 2017; Dowdy and Catto, 2017). The two hazards are considered as dependent and form a multi-hazard event called compound flooding (Klerk et al., 2015; van den Hurk et al., 2015; Wahl et al., 2015; Moftakhari et al., 2017). Depending on the scale we focus on this dependence can be almost instantaneous or lagged. Therefore, Klerk et al. (2015) found a statistical dependence between extreme discharge on the Rhine river and extreme sea level at its outlet into the North Sea, but with a 6 days lag time. This can be explained by the size of the Rhine catchment. Moreover, some other dependences are spatially and temporally closer, such as the dependency between lightning activity and hail occurrence (Lang and Rutledge, 2002; Carey et al., 2003).

- V. Mutual exclusion (negative dependence) (A3, C2): Two natural hazards can also exhibit negative dependence or be mutually exclusive. There is limited literature because a negative dependence of two hazards does not lead to an increased impact, which is the case for positive dependence. There are many examples of hazards that show negative dependence, often hydrometeorological (e.g., heavy rain and fire). However, such negative dependence is often on a particular spatial and/or temporal scale. For example, within a tropical cyclone both extreme wind and lightning are likely to occur but Molinari et al. (1999) shown that the extremes of these two hazards occur in different part of the cyclone. On the scale of the whole cyclone, those two hazards are positively dependent, but on a narrower scale they appear to not occur in an extreme way together.

We will use these five interrelation types (independence, triggering, change condition, compound hazard, mutual exclusion) in the rest of this paper. Moreover, a focus has been put on triggering (type II), change condition (type III) and compound hazard (type IV) in Section 4.2 as these interrelations are of greater interest compared to independence and mutual exclusion (Kappes et al., 2012a; Gill and Malamud, 2014; Decker and Brinkman, 2015; Mignan et al., 2016).

2.3. Natural hazard interrelations models database

To select relevant hazards for our analysis we first referred to previous reviews on hazard interrelationships (Gill and Malamud, 2014; Decker and Brinkman, 2015) where they give qualitative information about natural hazard interrelations with matrices. Gill and Malamud (2014) present a matrix of potential interactions between 21 different natural hazards while the one realized for the ASAMPSA_E project by Decker and Brinkman (2015) contains 70 natural hazards (many subcategories of those given by Gill and Malamud, 2014).

We use three selection criteria for the natural hazards we choose to focus on, such that they would be a diverse and representative range. These selection criteria loosely informed our list of 14 natural hazards and were as follows: (i) those hazards that caused past recorded impact (disasters) in Europe; (ii) hazards prone to have interrelations with at least one other natural hazard; (iii) hazards that can be quantified with one (or a small set) of environmental variables. The hazards and categories we use further below are not exclusive, and other studies might choose other hazards to focus on, or classify a given hazard type into two different (more relevant) types.

Our first criteria that helped to loosely inform our final list of diverse hazard types is past recorded impact to Europe. To do this we used the Emergency Events Database (EM-DAT) a record of disasters maintained by the Centre for Research on the Epidemiology of Disasters (CRED, 2018). EM-DAT contains data on the occurrence and effect of over 14,600 disasters (as of 2018) in the world from 1900 to present. There are several criteria for a disaster to be included in the dataset, including ≥10 people died or ≥100 people affected or declaration of state of emergency or a call for international assistance (CRED, 2018) Despite its recognition, the quality of this disaster database faces biases (e.g., threshold biases, spatial aggregations) discussed by Jonkman (2005) and Gall et al. (2009).

With these biases in mind, we extracted disaster profiles in Europe from EM-DAT (CRED, 2018) over the period 1900 to 2018. The distribution of natural disasters from this database are displayed in Fig. 4. The corresponding natural hazards that resulted in these disasters include: earthquakes, hazards related to convective storms (lightning, extreme wind, hail, extreme rainfall, river flooding), extra-tropical cyclones (sea surge, extreme waves, coastal flooding, extreme wind, extreme rainfall), extreme temperature (heat wave, cold wave), drought, forest fires and snow avalanches.

Most of the hazards resulting in the disasters shown in Fig. 4 can be expressed with environmental variables and, as it will be shown in Section 3, are suitable for modelling. Two hazards from Fig. 4 we do not include are snow avalanches and wildfires. Snow avalanches, despite their destructive power and their relevance for Europe, are difficult to model regarding their interrelations with other hazards. Wildfires have a complex link with other hazards such as drought, extreme temperature, lightning and floods (Myers and Van Lear, 1998; Littell et al., 2016; AghaKouchak et al., 2018). However, the multiplicity of possible combinations leading to a fire outbreak are beyond the scope of this study focusing on interrelations between two hazards, so they are also excluded. From the natural disasters in Fig. 4 and our selection criteria

Table 3
A list of 14 single natural hazards considered in this paper broken up into geophysical, atmospheric and hydrologic natural hazard categories.

1. Geophysical	2. Atmospheric	3. Hydrological
1.1 Earthquake	2.1 Lightning	3.1 Sea surge
1.2 Landslide	2.2 Extreme rainfall	3.2 Extreme waves
1.3 Volcanic eruption	2.3 Extreme wind	3.3 River Flood
	2.4 Extreme temperature	3.4 Tsunami
	2.5 Hail	3.5 Drought
	2.6 Tornado	

we selected 14 natural hazards (Table 3).

Based on 14 natural hazards from Table 3, there are 196 interrelationship pairs possible, if each hazard can potentially interact with another hazard of the same type. For example, an earthquake might trigger a landslide, but also an earthquake can increase the probability of another earthquake occurring. In our multi-hazard literature database, 70 of the references are to do with interrelationship case studies relevant to the hazards given in Table 3. Note that there was an iterative process in our methodology for those references included in the final literature database, in that after the database was initially compiled, the hazards to be studied were decided upon (above) and then additional references to do specifically with those hazards given in Table 3 were added.

We will now use the 70 references from our multi-hazard literature database in combination with the 14 natural hazards given in Section 3 to examine in detail different methodologies for the quantification of hazard interrelationships.

3. Methodologies for quantifying hazards interrelations

This section focuses on hazard interrelation modelling and quantification, particularly for pairs of hazards. In this section, we are interested in (i) how different disciplines quantify hazard interrelations and (ii) creating a grouping of these different methods into an overall framework. Literature is used here as evidence for this task and includes 70 references (See Fig. 2 and Supplementary Material Table B) which each have an aspect of quantification between two given hazards. In Section 3.1 we give a representation of current knowledge related to hazard interrelation modelling through two matrices. In Section 3.2, the main models for quantifying hazard interrelationships are presented with examples of applications to natural hazard interrelations. Finally, in Section 3.3, the applicability of the modelling approaches to different types of hazard interrelations and categories of natural hazards are discussed.

3.1. Natural hazard interrelations matrices

We now use the 14 hazards selected in Section 2.3 and displayed in Table 3, combined with evidence from our natural hazard interrelations models database (Supplementary Material Table B), to create two hazard interrelations matrices (see Table 2 and Section 2.1 for further discussion of terminology):

(i) *cascading hazards* (Fig. 5): two hazards that occur sequentially in time where one hazard *triggers* or *changes the conditions* of another secondary hazard;
(ii) *compound hazards* (Fig. 6): two associated hazards impacting the same time and place.

These matrices (Figs. 5 and 6) display the types of interrelation between hazards (Section 2.2), and the category of model used in the literature to quantify the interrelations (we have divided these broadly into stochastic S, empirical E and mechanistic M). For example, extreme rainfall triggers or changes conditions for landslide and this interrelation has been modelled with empirical and mechanistic models. We will later (Section 3.2) give a much more detailed view and classification of the different interrelation modelling approaches.

The cascading hazards matrix presented in Fig. 5 displays relationships when one hazard triggers another (e.g., earthquake triggers a landslide) or when one hazard changes the conditions for another (e.g., earthquake increase the probability of landslide by reducing the soil cohesion). Both interrelation types imply one primary (earthquake) and one secondary hazard (landslide) as they were defined by Gill and Malamud (2014) in a matrix they constructed. In Fig. 5, the matrix hazard A is always prior (in time) to hazard B. Hazard interrelations that are not sequential are not considered and some interrelations are still debatable according to the literature. For example, the relationship between earthquake and flood is still not clear. From the $(14 \times 14) = 196$ interrelationship pairs possible in the Fig. 5 matrix, we have indicated 33 where there is a potential cascading relationship, of which 13 are both triggering & change condition (purple & green), 7 triggering (green), 5 change condition (purple), and 8 'debatable' (white). These were identified from the work of Gill and Malamud (2014), Decker and Brinkman (2015) and Mignan et al. (2014). We then looked for quantification relationships (an iterative process within the construction of our natural hazard interrelations model database) and for 12 of the cells in Fig. 5 we found quantification studies relating one hazard with another (indicated by S, E, M in the matrix), which we will discuss in greater depth in Section 3.3.

The same 14 hazards as in Fig. 5 are presented in Fig. 6, but in this case, there is no temporal or causal relationship between hazards, therefore only 105 interrelationships (cells) are possible. Every hazard might be associated with another hazard (compound hazard), but in the literature some compound interrelationships are more likely to occur. In Fig. 6, cells are identified that are: (i) (26 cells) compound (where a statistically significant dependent relationship has been identified in the literature), (ii) (11 cells) where the relationship is debatable in the literature. The remaining 68 cells (grey) have not been identified as having a definite compound hazard relationship in the literature. Although a compound hazard relationship might not exist (Fig. 6), a cascading hazard might exist (Fig. 5). Of the compound cells identified, 12 have been marked (using our interrelationship database) with a specific model approach using letters S, E, or M. When natural hazards are compound (associated or statistically dependent), they are likely to occur together because they depend on the same precursory factors. Liu et al. (2016) defined trigger factors that induce hazards and control the frequency and magnitude of hazards. Because of the statistical dependence of compound hazards (e.g., extreme wave and sea surges), they have been widely studied with stochastic models (see Section 3.2) (Hawkes et al., 2002; Dong et al., 2015; Rueda et al., 2016; Petroliagkis, 2018). Moreover, lack of data and the short time range of available records have limited the use of stochastic methods for interrelations with hazards such as lightning or hail. Empirical methods are more commonly used to acknowledge or quantify relationships (Lang and Rutledge, 2002; Price and Federmesser, 2006; Schultz et al., 2011; Iordanidou et al., 2016).

3.2. Models and classification

In this section, we present three hazard interrelation modelling approaches (stochastic, empirical, mechanistic, indicated by S, E, M in the matrices in Figs. 5 and 6) which covers the14 hazards we selected (Table 3). Here, by models, we mean statistical or numerical tools used to quantify hazard relationships. The idea behind this classification is to build a framework to clarify different quantification methods to deal with a range of hazard interrelations.

In Fig. 7 we present these three different categories of models to quantify interrelations between natural hazards and their subcategories. This categorisation was built using the 70 studies in our natural hazard interrelations model database (Supplementary Material

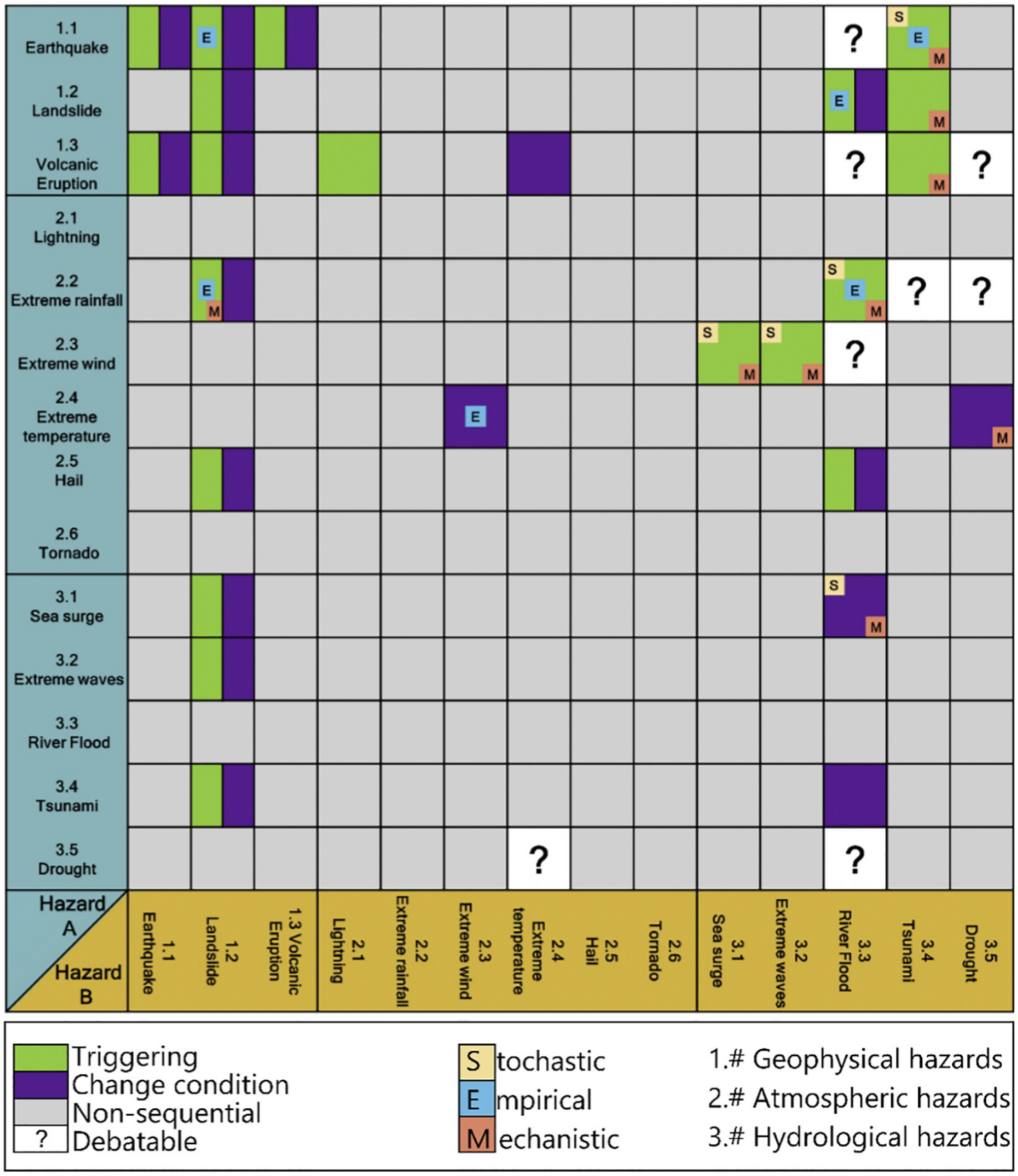

Fig. 5. Cascading hazard interrelation matrix for the considered hazards in this study. Matrix based on 70 references and the modelling approach applied. This figure shows the type of interrelations between hazards when there is a sequential effect – from hazard A to hazard B – and the modelling methods which are used for each pairs of hazards. The colours of the cells represent the interrelation types: green for triggering, purple for amplification; cells in grey represent non-sequential interrelations (see Fig. 6) and white cells (with '?') represent interrelations with debatable nature. The letters represent the interrelation type: S for stochastic, E for empirical and M for mechanistic. The numbers refer to the natural hazard category: 1.# for geophysical; 2.# for atmospheric and 3.# for hydrological. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table B). For each of the 70 studies, we pulled out the main modelling method(s) used to quantify hazard interrelationships and the types of hazards (where appropriate). We then used the overall evidence and categorized these. Our categorizations were inspired by classifications already made for hydrological models (Devia et al., 2015), dependence modelling in hydrology (Hao and Singh, 2016; Hao et al., 2018), landslide susceptibility models (Reichenbach et al., 2018) and more general overview on models in science (Frigg and Hartmann, 2012).

Fig. 7 gives an overview of the main modelling methods available for different types of interrelations. Three different modelling approaches are highlighted, within which there are model families (two for each modelling approach) which are subdivided into modelling methods. In total, for the 70 references (73 pairs of natural hazards) in our database, we recorded 79 unique uses of 19 different modelling methods, of which the stochastic modelling approach had 27 (34%) uses, empirical had 31 (39%) uses, and mechanistic 21 (27%) uses. For the stochastic approach there are two families (A. multivariate and B. copula) and 7 modelling methods. For the empirical approach, there are three families (B. copula—shared with stochastic, C. dependence measures, D. regressions) and 9 methods. Finally, for the mechanistic approach there are two families (E. conceptual models, F. physical models) and 3 methods. Later in Section 3.3 we give the number of uses (out of 79) for each modelling method.

We shall now define the three main modelling approaches (stochastic, empirical, mechanistic). Because of the vast literature for each method, here we provide a concise explanation for each of the six model families in Fig. 7 with relevant linked literature and illustrate four methods with case studies.

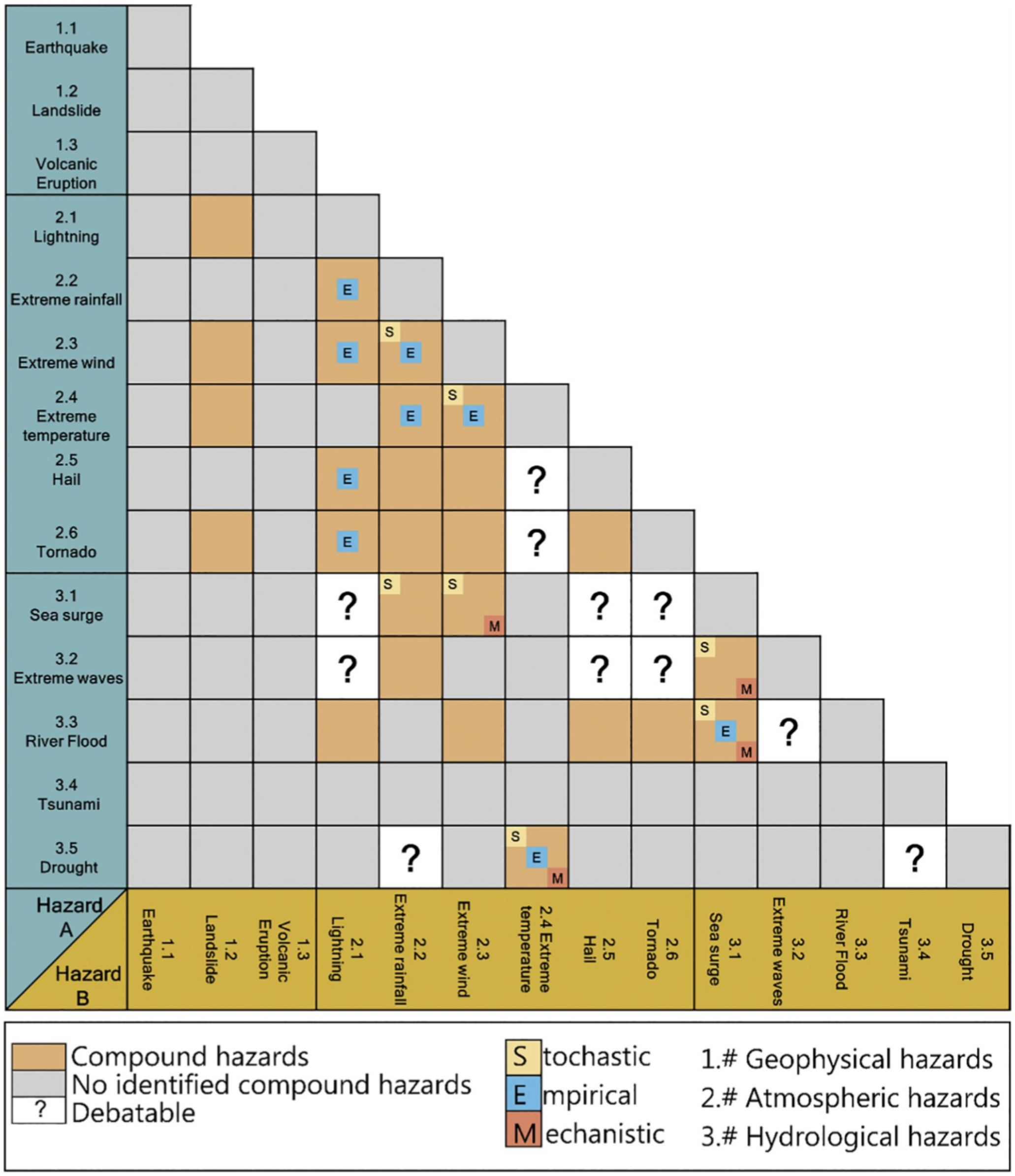

Fig. 6. Compound interrelation matrix for the considered hazards in this study. Matrix based on 70 references and the modelling approach applied. This figure shows the type of interrelations between hazards when there is a known association between hazards (compound hazards) and the modelling methods which are used for each pair of hazards. The colours of the cells represent the interrelation types: beige for known compound, light grey for no identified compound hazards (see Fig. 5 for identified cascading hazards); and white cells represent interrelations with debatable nature. The letters represent the interrelation model: S for stochastic, E for empirical and M for mechanistic. The numbers refer to the natural hazard category: 1.# for geophysical; 2.# for atmospheric and 3.# for hydrological.

3.2.1. Approach I: stochastic models

We define stochastic models as models based on samples of different variables with random behaviour (Cox and Miller, 1965). In this category, we include all the methods with generation of random data from statistical distributions. In Section 2.2 we presented different types of interrelationships between natural hazards, in case of compound events, there is usually a statistical dependency between different natural hazards. Stochastic models can model this statistical dependency between extreme environmental variables (e.g. extreme wind, extreme rainfall) (Ledford and Tawn, 1997; Yang and Zhang, 2013; Zheng et al., 2014; Ming et al., 2015). Methods presented in this category come from multivariate statistics and extreme value statistics (Gümbel, 1958, Tawn, 1988, 1990; Coles and Tawn, 1991, 1994; Nelsen, 2006; Gudendorf and Segers, 2010). One of the main strengths of these models is that they allow for extrapolation beyond the range of available data. Among stochastic models, we distinguish two model families: (i) copulas (which can also be empirical) and (ii) multivariate models (Fig. 7). The main difference between these two families is that multivariate models include marginal modelling (i.e., modelling the distribution of each separate variable) while copulas solely focus on modelling the dependence structure (Hao and Singh, 2016). Stochastic models have been particularly used to model compound hazards (Fig. 6) as they provide the joint probabilities of two hazard occurring at the same time. Conditional probability has also been used to model causal relationships (Liu et al., 2018). Stochastic models permit the estimation of joint probabilities of exceedance and return periods; these quantities are commonly required by engineers and decision makers.

3.2.1.1. *Copulas*.
In a bivariate case, a copula is a joint distribution function which defines the dependence between two variables

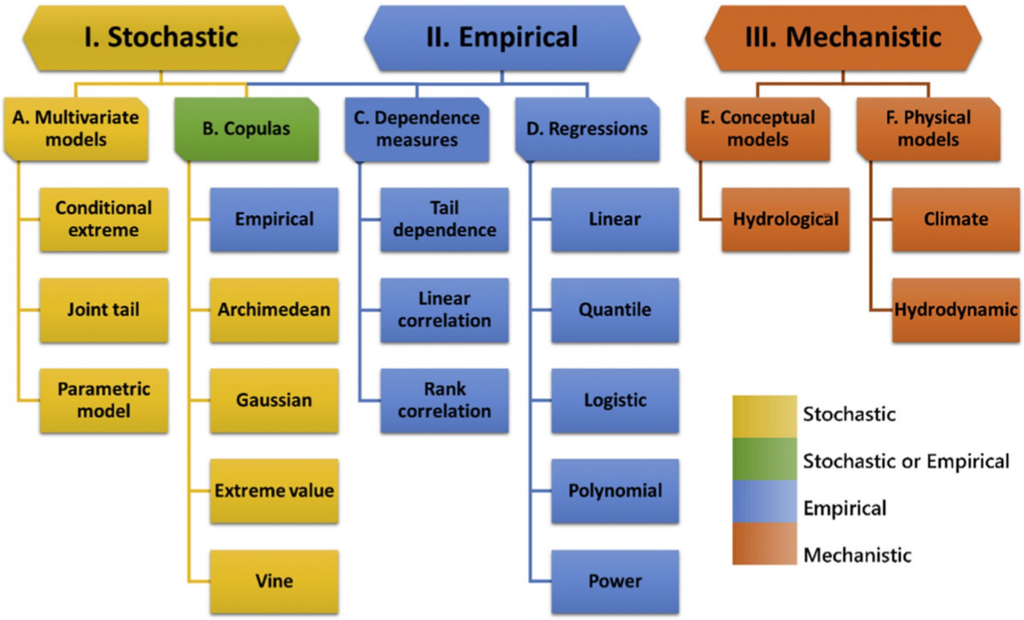

Fig. 7. Natural hazard interrelationship models: three different modelling approaches (I. stochastic, II. empirical, and III. mechanistic), six families (A. multivariate, B. copula, C. dependence measures, D. regressions, E. conceptual models and F. physical models) and 19 modelling methods. This classification is based on a review of 70 references from 1980 to 2018 (see Supplementary Material Table B1).

independently from the marginal distributions of these variables (Heffernan, 2001; Favre et al., 2004; Nelsen, 2006; Hao and Singh, 2016). See (Genest and Favre, 2007) for a good introduction to copulas. For two variables X and Y, any bivariate distribution function with marginal distribution functions $F_X(x)$ and $F_Y(y)$ and the joint cumulative distribution function $F_{X,Y}(x,y)$ can be expressed as a copula in the following form (Nelsen, 2006):

$$F_{X,Y}(x,y) = C\{F_X(x), F_Y(y)\} \tag{1}$$

where C is the copula function. Copulas are not limited to two variables and therefore eq. (1) can be extended to higher dimensions. Several classes of copula with different properties are available (Joe, 1997; Favre et al., 2004; Nelsen, 2006). Copula used in our literature database belong to one of the three following classes: Archimedean copulas, Gaussian copulas and extreme value copulas. Copula are parametric models; indeed, each copula is suitable within a given range of dependence structures. Without prior knowledge on the studied hazards,several copula with different levels of complexity needs to be fitted to the data and compared (Sadegh et al., 2017). Using a copula which does not capture adequately the dependence structure between two variables can lead to either underestimation or overestimation of the joint probability of these two variables (Ledford and Tawn, 1997; Mazas and Hamm, 2017).

3.2.1.2. Multivariate models. Despite their theoretical relation to copulas (Tawn, 1990; Heffernan, 2001), multivariate models differ from copulas as they include margins in the modelling process (i.e. marginal distributions are usually fixed for a given model). Multivariate models are usually parametric (Ledford and Tawn, 1997) or semi-parametric (Heffernan and Tawn, 2004; Hao and Singh, 2016). Among multivariate models, parametric models developed for characterization of bivariate extreme value distributions have been the most used to investigate hazard interrelations (Gumbel, 1961; Yue, 2000; Zheng et al., 2013). The conditional extreme model (Heffernan and Tawn, 2004) has the particularity of estimating the dependence structure between two variables conditioned on one being extreme. A joint tail model requires all variables to become large at the same rate; this can be problematic when looking at compound events where not all the variables are extreme (Leonard et al., 2014; Liu et al., 2016). Parametric multivariate models have the same limitations as copula models as they can typically handle only one form of extremal dependence. However, semi-parametric models such as the conditional extremes model are more data driven, offering more flexibility at the price of a higher sensitivity (e.g. leading to different results with different datasets even when modelling the same processes) (Winter, 2016).

3.2.1.3. Example of stochastic approach: estimation of the joint probability of extreme rainfall and sea surge. The interrelation between extreme rainfall and sea level is of primary interest when studying coastal flooding. Indeed, high sea levels prevents the flow of excess water due to extreme precipitations toward the open sea (Zheng et al., 2013; Klerk et al., 2015; van den Hurk et al., 2015). The quantification of the interrelations between these two hazards has previously been done using stochastic models (Fig. 6). As both hazards are related to stormy weather conditions (e.g., cyclonic systems) (Zheng et al., 2013) this interrelation has been quantified through the estimation of joint probabilities of occurrence (Lian et al., 2013; Xu et al., 2014a; Zheng et al., 2014; Klerk et al., 2015). Lian et al. (2013) looked at the joint probability of extreme rainfall and sea surge in Fuzhou City, China for the years 1952 to 2008. The dependence structure, and therefore the joint probability of rainfall and sea level exceeding extreme levels was assessed using the Gumbel copula, from the class of extreme value copulas (Fig. 7).

Lian et al. (2013) found that for their study area, 24 h extreme rainfall and high sea level were positively dependent. This implies that these two hazards are compound hazards. Fig. 8 shows the joint probability of having an event associated with different 24 h extreme rainfall return periods (5 to 50 yr) and tidal level (5 to 50 yr) established with a Gumbel copula.

In coastal engineering, the joint probability of extreme waves and sea surges has also been widely studied with different classes of copulas (Masina et al., 2015; Rueda et al., 2016; Mazas and Hamm, 2017) or multivariate models (Coles and Tawn, 1994; Hawkes, 2008; Dong et al., 2015).

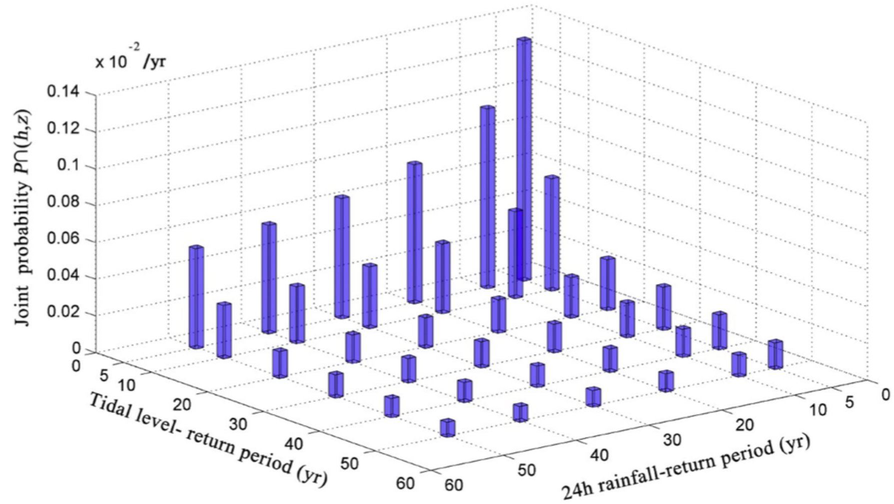

Fig. 8. Bar graph of joint probability of tidal level (sea level) and 24 h rainfall as a function of their respective return periods (figure from Lian et al., 2013).

3.2.2. Approach II: empirical models

Empirical models are based on measurements and are observation oriented. In empirical models, empirical distributions are fitted directly to the observed data. Among empirical models, we defined two families: dependence measures and regressions. The main drawback of empirical models in comparison to stochastic and mechanistic models is the impossibility to extrapolate beyond the range of the data (Zou et al., 2003).

3.2.2.1. Dependence measures. While looking at hazard relationship, a popular method is to compute dependence measure (Zheng et al., 2013; Klerk et al., 2015; Petroliagkis, 2018; Ward et al., 2018). Dependence measures aim to describe how two (or more) variables are correlated. Several dependence measures including linear correlation (Pearson) or rank correlation (Spearman, Kendall) can be used to measure the strength of the association between variables (Hashemi et al., 2015; Hao and Singh, 2016). The most popular dependence measure to quantify the dependence between two hazards is the Pearson linear correlation coefficient ρ (Zou et al., 2003):

$$\rho = \frac{\mathrm{cov}(x, y)}{\sigma_x \sigma_y} \tag{2}$$

where cov(*x*,*y*) the covariance of the two variables *x* and *y*, with associated standard deviations (respectively) σ_x and σ_y.

For an estimation of the dependence in the tails or extreme parts of the distributions, dependence measures previously presented might not be accurate and other dependence measures aremore appropriate (Hao and Singh, 2016). Dependence between variables in the joint tail domain has been widely studied in the statistics literature (e.g., Coles and Tawn, 1991; Ledford, 1996; Coles et al., 2000; Coles, 2001; Heffernan, 2001; Heffernan and Tawn, 2004; Keef et al., 2013; Zheng et al., 2014). The dependence between variables in the tails can be classified as asymptotic dependence (or asymptotic independence) and the different diagnostics and measures developed are summarized in Heffernan (2001). Two variables can therefore be asymptotically independent but also have dependence at sub asymptotic level. Dependence measure are often used as a first estimate of the potential relationship between two hazards and also support the selection process of an appropriate stochastic model (Section 3.2.1).

3.2.2.2. Regression. Regressions have been widely used to quantify interrelations between natural hazards (Costa and Schuster, 1988; Keefer, 1994; Koutroulis et al., 2012; Suppasri et al., 2012; Meng and Shen, 2014; Iordanidou et al., 2016). Regression is a statistical method to measure changes in a dependent variable in response to changes in one or several independent variables (Chen et al., 2014). There are many different types of regression models such as linear regressions, power regressions, logistic regressions or quantile regressions (Zou et al., 2003; Nelder and Baker, 2006; Chen et al., 2014; Hao et al., 2018). Linear regressions are the most commonly used to estimate relationships between natural hazards (Caine, 1980; Keefer, 2002; Koutroulis et al., 2012; Iordanidou et al., 2016; Petroliagkis, 2018) and is often associated with the Pearson linear correlation coefficient (Eq. 2). The generalized linear model framework encompasses more sophisticated types of regressions such as the logistic regressions (appropriate when the dependent variable is dichotomous) (Nelder and Baker, 2006). In situations where we are more interested in high (or low) levels for hazards (e.g. an extreme quantile as opposed to the median), quantile regression provides a better approach than linear regression (Chen et al., 2014; Hao et al., 2018). Regressions have been particularly used for cascading hazards (Fig. 5) as they include independent (primary hazard(s)) and independent (secondary hazard (s)) variables.

3.2.2.3. Example of empirical approach: two examples. Here we give two examples of empirical approaches. Our first is the *tail dependence between river flow and sea surge*. For hazard interrelation quantification, one often wants to focus on the extremes (Svensson and Jones, 2004; Dutfoy et al., 2014). Svensson and Jones (2004) used the extremal dependence measures χ and $\overline{\chi}$ introduced by Coles et al. (1999) to study the extremal dependence between sea surge, river flow and precipitation in south and west Britain (Fig. 9). These coefficients aim to measure the extremal dependence for bivariate random variables (X,Y) and assume initially that the marginal distributions of x and y are identical. The dependence measure χ is the probability of one variable being extreme given the other is extreme. The extremal dependence coefficient varies in the range [0;1] with a value of 0.0 meaning that the two variables are asymptotically independent and a value of 1.0 that they are asymptotically perfectly dependent. The dependence measure $\overline{\chi}$ estimates the level of dependence in the particular case of asymptotically independent variables.

Svensson and Jones (2004) highlighted statistically significant asymptotic dependence between river flow and daily maximum sea surge, two hazards that combine to form a compound hazard (Fig. 6). In their study, this dependence is associated with overarching meteorological events (i.e.mid latitude cyclones). These events may cause both sea surge and high river flow (via precipitation). The characteristics of the studied catchment such as size can influence the results. For large

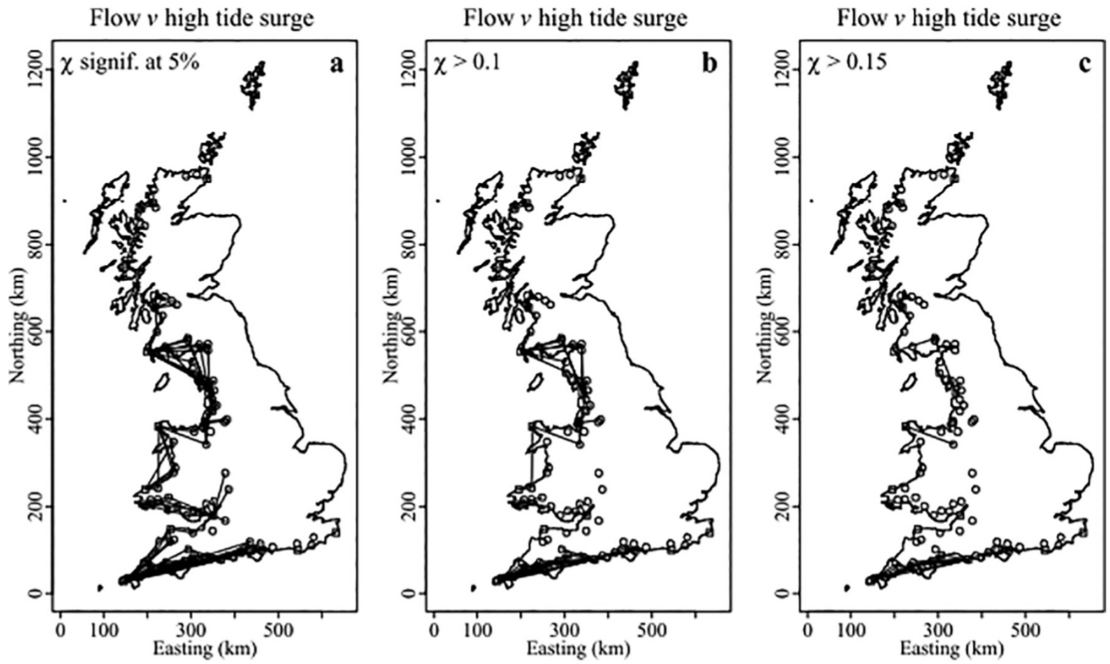

Fig. 9. Example of an empirical approach: dependence river flow and daily maximum sea surge occurring at high tide around the coastline of the UK. Lines connect neighbouring station-pairs with χ exceeding (a) the 95% significance level, (b) 0.1, and (c) 0.15 (figure from Svensson and Jones, 2004).

catchment areas, time lags can become increasingly important, which can be used to capture the interrelations between sea surge and river flooding (Svensson and Jones, 2004; Zheng et al., 2013; Klerk et al., 2015; van den Hurk et al., 2015).

Our second empirical approach example is one that is widely studied in terms of interrelations between hazards, *extreme rainfall and landslides* (e.g., Caine, 1980; Glade, 2000; Guzzetti et al., 2007). According to our review, the quantification of rainfall-triggered landslides (triggering relationship, Section 2.3) has been mostly done through empirical models (Fig. 5). Guzzetti et al. (2007) (among others) expressed this interrelation through a regression between rainfall intensity I (mm h^{-1}) and rainfall duration D (h) which gives a threshold for landslide triggering. This relationship is of the form of (Glade, 2000):

$$I = C \times D^{\alpha} \tag{3}$$

with, C and α constants.

As shown in Fig. 10, this relationship varies depending on the region concerned, one of main limitation of this approach. The triggering threshold also depends on other parameters such as past history of landslide occurrence, soil type, slope, and antecedent conditions. This last aspect has been addressed by Glade (2000) in New Zealand.

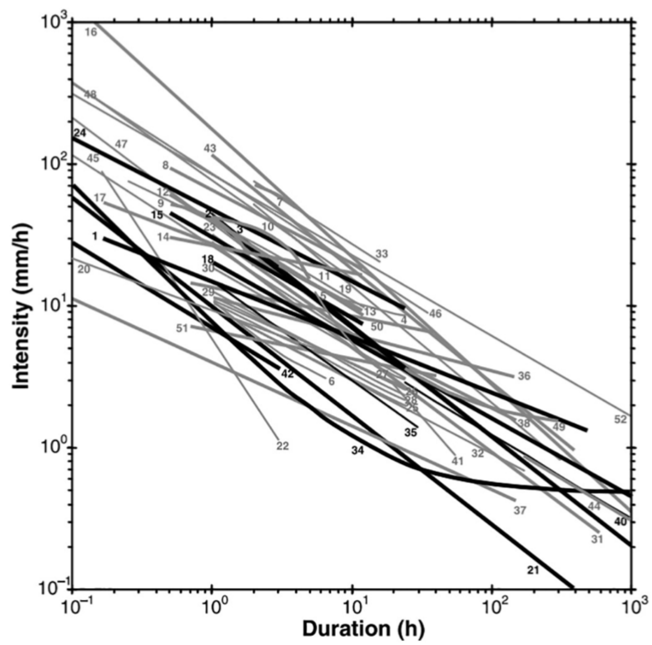

Fig. 10. Intensity-duration relationship for landslide triggering in New Zealand (from Guzzetti et al., 2007).

3.2.3. Approach III: mechanistic models

Mechanistic models are mathematically idealized representation of real phenomena (Devia et al., 2015). They are based upon physical processes and mechanisms that rule the considered system operations. Usually mechanistic models are applied on water bodies (Booij et al., 1996; Geist et al., 2009; Luger and Harris, 2010; Dutykh et al., 2011), as the equations coming from fluid mechanics can be used. Mechanistic models are divided into two families: conceptual models and physical models.

3.2.3.1. Conceptual models. Conceptual models are widely used in hydrology (Nash and Sutcliffe, 1970; Devia et al., 2015). In hydrology, conceptual models aim to describe all the components of hydrological processes with various interconnected reservoirs which represent the components of the flow of a river (e.g., infiltration, runoff, snow pack). Conceptual models need a large amount of input data (usually rainfall and temperature records) to assess different parameters through calibration. Examples of hydrological conceptual models include GR (Coron et al., 2017), HBV, TOPMODEL and MORDOR (Devia et al., 2015).

3.2.3.2. Physical models. Physical models aim to simulate the behaviour of different systems such as the atmosphere (Tinti et al., 2003), the ocean (Klerk et al., 2015), the climate (Kašpar et al., 2017) and hydrological systems (Devia et al., 2015; Bout et al., 2018). Based

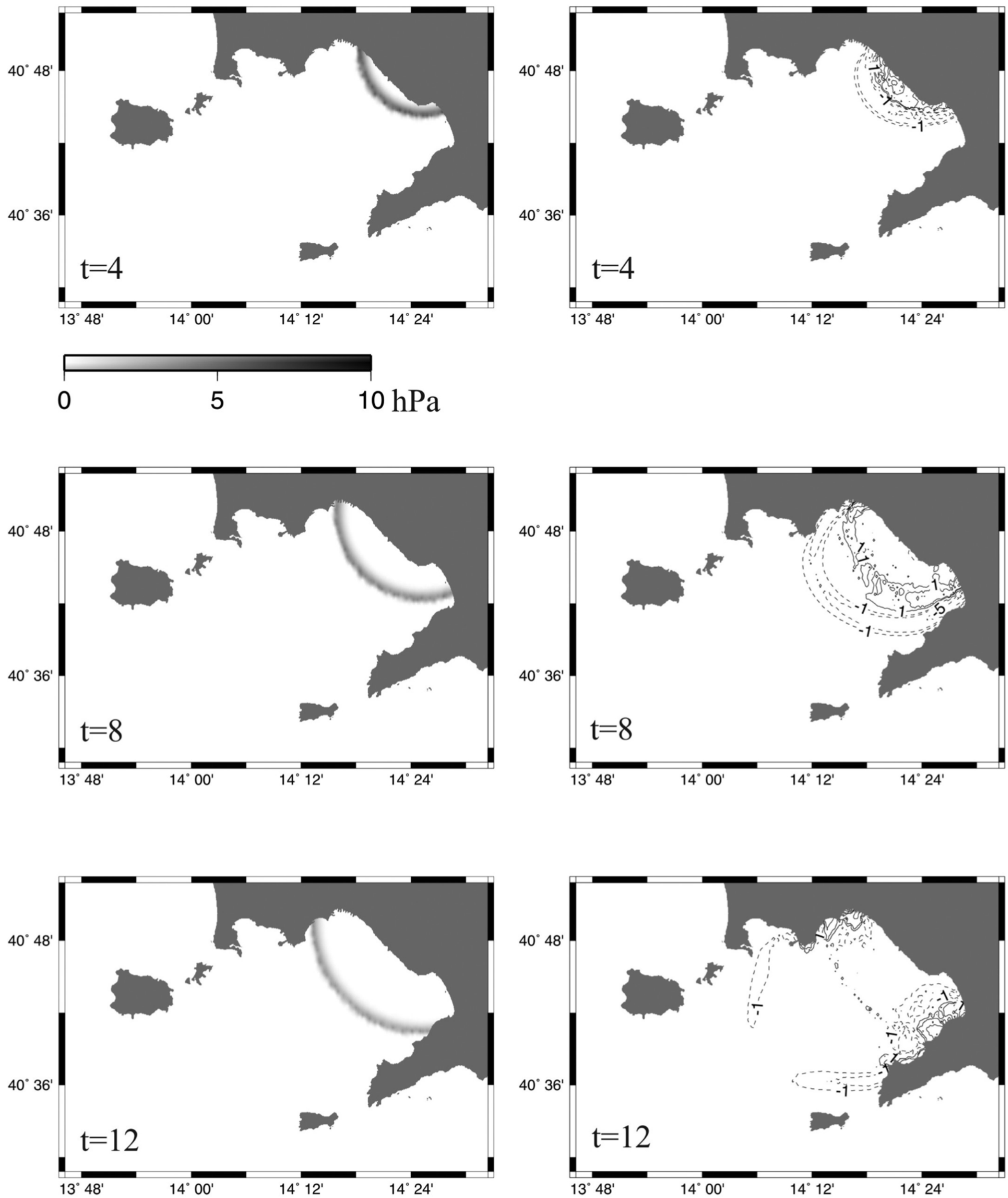

Fig. 11. Pressure pulse field (on the left) computed at different times, given in minutes. Water elevation fields (on the right) computed at the same instant. Time is measured from tsunami origin time and not from beginning of eruption. Contour lines labels are in cm. Positive/negative elevation curves are solid/dashed lines (figure from Tinti et al., 2003).

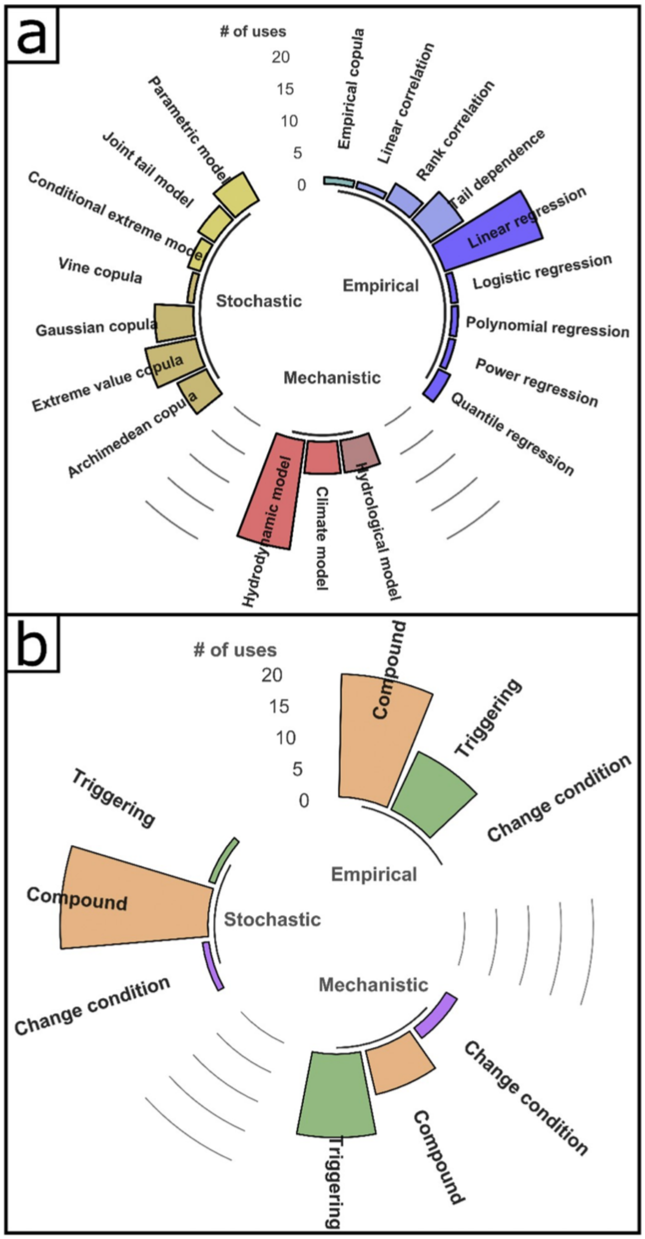

Fig. 12. Circular barplot for each of the three modelling approaches (stochastic, empirical, and mechanistic): (a) the modelling method uses from Fig. 7 (out of 79 model method uses); (b) three interrelation types frequency (triggering, compound, change condition). Data based on our interrelationship database (Supplementary Material Table B1). Colour groupings used approximate those given in Figs. 5 to 7.

on our literature database, physical models tend to use fluid mechanics, heat transfer equations or thermodynamic laws. In hydrology, the processes of water movement are represented by finite difference equations (Silvestro et al., 2016). To model mechanistically extreme hydrological events, an extensive amount of data (e.g., soil moisture content, initial water depth, topography, topology, dimensions of river network) are required (Dietrich et al., 2010; Bout et al., 2018). This massive need for data is the main drawback of physically based hydrological models compared to conceptual models (Devia et al., 2015). Hydrodynamic models are based on the shallow water equation which are usually 1D or 2D with the modelled domain often represented with triangular meshes (Tinti et al., 2003; Wang et al.,

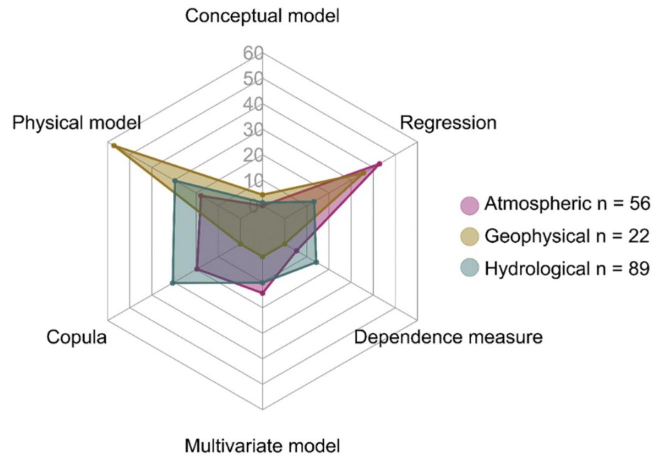

Fig. 13. Radar chart of the use (in %) within each model family by hazard groups. Percentages are out of the number of instances within each natural hazard category (given in legend).

2012; Silva-Araya et al., 2018). This modelled domain can be discretized by numerical methods such as finite elements or finite volumes (Geist et al., 2009). Physical models can overcome many weaknesses of the empirical or stochastic models because they use parameters which have physical meaning. However, they are often computationally intensive (Geist et al., 2009; Luger and Harris, 2010; Borgonovo et al., 2012).

3.2.3.3. Example of mechanistic approach: volcanic eruption triggering a Tsunami. Here we give an example of a mechanistic approach, that of a volcanic eruption triggering a tsunami. Hydrodynamic or hydraulic models based on shallow water equations are suitable to model hazard interrelations within bodies of water (sea, lake and river) (e.g., Pelinovsky and Poplavsky, 1996; Kumbier et al., 2018). Tsunami characteristics allow the use of shallow-water equations to model the propagation and intensity of a tsunami wave given the characteristics of an earthquake or a submarine landslide (Geist et al., 2009; Luger and Harris, 2010). Various studies have been conducted to develop operational code for the numerical modelling of tsunamis (e.g., Pelinovsky and Poplavsky, 1996; Dutykh et al., 2011). Numerical models are also used to assess the effect of tsunamis generated by continental slope slides on particular shorelines (Geist et al., 2009) or to better understand the effect of past tsunamis on particular areas (Power et al., 2017).

Tinti et al. (2003) provides a thorough example of the mechanistic approach, using a hydrodynamic model to assess the interrelation between a volcanic eruption (here a pyroclastic flow) and tsunamis in the Gulf of Naples. From historical eruptions, Vesuvius can produce explosive eruptions with large volume of pyroclastic flows. Tinti et al. (2003) considered two processes that could trigger a tsunami from pyroclastic flows: (i) the penetration of dense flows into the water, which is comparable to a landslide-induced tsunami; (ii) the overpressure pulse generated by light pyroclastic flow travelling on the sea surface over long distances. To estimate the influence of a pyroclastic flow, Tinti et al. (2003) estimated the pressure pulse that could be produced by a large Vesuvian eruption and propagated it over the whole Gulf of Napoli (Fig. 11). Using the non-linear shallow water and equations they found that the potential amplitude of a tsunami triggered by pyroclastic flows in the Gulf of Naples remains small (with the largest waves having an amplitude around 70 cm on the coastline), even including uncertainties around the set of parameters.

3.3. Hazards, models and interrelations

In Section 3.2 we defined three different modelling approaches for hazard interrelations quantification (stochastic, empirical, mechanistic) along with associated modelling families and methods. We will now focus on the links between these modelling approaches/families/methods with the previously defined hazard categories (atmospheric, geophysical, hydrological) and three of the five interrelation types (change condition, compound, triggering). Within the three modelling approaches presented in Section 3.2, some modelling methods are more popular for hazard interrelation studies (i.e., they occurred more frequently in our hazard interrelationship model database, Supplementary Material).

Fig. 12a shows the number of uses of modelling methods among the 70 natural hazard interrelations studies (79 uses overall: stochastic 27 uses; empirical 31 uses; mechanistic 21 uses), with 6 of our 70 references using more than one modelling methods. There are different reasons for a given reference having more than one use: (i) the same modelling method has been applied to different hazard combinations (Carey et al., 2003; van den Hurk et al., 2015); (ii) different modelling methods are compared using the same hazard combination (Zheng et al., 2014; Sadegh et al., 2017); (iii) different modelling methods are combined for a given hazard combination (Dietrich et al., 2010; van den Hurk et al., 2015; Petroliagkis, 2018).

Fig. 12a shows that among the 70 references (79 uses) for hazard interrelationship modelling:

- Stochastic modelling approach: *extreme copulas* method are the most prevalent (30% of stochastic modelling uses, 8 occurrences out of 27. This is explained by the fact that among the 14 hazards selected in this review, several are the extreme occurrence of environmental variables (e.g. extreme temperature).
- Empirical modelling approach: *linear regressions* methods are the most prevalent (51% of empirical modelling uses, 16 occurrences out of 31). This is probably due to their relative ease of use and interpretation.
- Mechanistic modelling approach: *hydrodynamic models* are the most prevalent (81% of mechanistic modelling uses, 17 occurrences out of 21). Hydrodynamic models are relevant in describing many different types of hazard interrelations (e.g., river flooding, coastal flooding, compound flooding, tsunami).

Fig. 12b shows the frequency of the three interrelation types (triggering, compound, change condition) (total of 77 uses in our hazard interrelationship database) as a function of the three modelling approaches (stochastic, empirical, mechanistic). The reason for one reference having more than one use are analogous to the ones mentioned above. We find from Fig. 12b:

- Stochastic modelling approach: the *compound* interrelation type is by far the most prevalent (22 out of 25 uses, 90%). Stochastic models presented in this study do not capture temporal effects or feedback loops, even if the use of lag times or conditional probabilities can overcome this limitation (van den Hurk et al., 2015; Hao et al., 2017; Liu et al., 2016). However, as compound hazards are two (or more) hazards that act together on a given region and time (Section 2.2), stochastic models are particularly relevant for these as can be seen in Fig. 12b.
- Empirical modelling approach: the *compound* interrelation type (20 out of 30 uses, 67%) is twice as prevalent as the *triggering* interrelation type (10 out of 30, 33%). The relative simplicity of empirical models offers a way to obtain quantitative assessment of a hazard interrelation when mechanistic models (next) cannot be applied.
- Mechanistic modelling approach: the *triggering* interrelation type (13 out of 22 uses, 59%) is more prevalent than *compound* (7 out of 22) and *change condition* (2 out of 22) types. The complexity and level of precision of mechanistic models allows one to represent a broad range of interrelations including amplification or triggering effects.

Within our three modelling approaches, we defined six families, two for the stochastic and mechanistic approaches and three for the empirical approach (one of which being shared with the stochastic approach). In Fig. 13, we consider the modelling family as a function of the category of hazard studied (atmospheric, geophysical, hydrological). We start with the 70 references in our interrelationship database. Of these, 68 references have one pair of hazards discussed, and two sources have 3 (Carey et al., 2003) and 2 (van den Hurk et al., 2015) different hazard combinations. For the 73 hazard combinations in our database, we then paired each natural hazard with the family of model used in the reference. For example, Bout et al. (2018) examine interaction of rainfall (atmospheric natural hazard category) and landslides (geophysical hazard category) using a hydrodynamic model (physical model family) and Bevacqua et al. (2017) examine sea surge (hydrological hazard category) and river flooding (also hydrological hazard category) using vine copulas (copula model family). Therefore, we would count 1 x physical model in the atmospheric hazard category, 1 x physical model family in the geophysical hazard category, and 2 x copula model family in the hydrological hazard category. In Fig. 13, there are 56 instances for atmospheric, 22 for geophysical and 89 for hydrological natural hazard categories. We then count the percentage of instances within each natural hazard category as a function of the six model families on a radar chart.

From Fig. 13 we find:

- For *atmospheric hazards* the regression modelling family is largely dominant (43%) in our interrelation database. This can be explained by the complexity of modelling interrelations between atmospheric hazards such as hail, lightning or wind and the lack of robust or large enough datasets for some of these hazards (Webb, 2016).
- *Geophysical hazards* are predominantly either physical models (57%) or regression model (36%). Physical models are favoured when the resources are sufficient (data quantity, computational power) but regressions can be applied with lower quantities of data.
- *Hydrological hazards* have been studied with every model family in this review. Copulas (31%) and physical models (30%) are the most popular as they can provide results from a wide range of scenarios and extrapolate beyond the observations.

In Section 3, we reviewed the use of 19 different modelling methods for the quantification of interrelations between 14 different natural hazards. We will now discuss some of the results presented in Sections 2 and 3.

4. Discussion and conclusions

The study of multi-hazard is a relatively new field (Kappes et al., 2012b; Gill and Malamud, 2014; Pescaroli and Alexander, 2018; Terzi et al., 2019) and still not unified in its terminologies and approaches. The aim of this critical review article has been to use grey- and peer-review literature to critically identify and compare current research in quantifying (natural) hazard interrelations. In this critical review article we aspire to add to others in the multi-hazard community who have reviewed and identified relevant modelling approaches to quantify different kinds of interrelations between hazards and risks (e.g., Liu et al., 2015; Gallina et al., 2016; Hao and Singh, 2016; Terzi et al., 2019). By doing an extensive review, including a broad range of natural hazards involving different time and space scales, we have aimed to contribute to a better understanding on the state-of-the-art regarding hazard interrelations quantification and offer a clear view on weaknesses and strength of several methods in different contexts. For this purpose, a natural hazard interrelationship literature database of 146 sources (Supplementary Material) was created and used to explore the following: (Section 2.1) *terminology* surrounding multi-hazard interrelations; (Section 2.3) *quantification models* for interrelations between hazards. This section will discuss the five following themes: (a) the diversity of modelling methods for quantifying hazard interrelations; (b) some of the main drivers in modelling method selection for hazard interrelations quantification; (c) limitations (uncertainties) of the modelling methods; (d) limitations of the present review; (e) perspectives for extending this interrelationship classification to more than two hazards.

4.1. The diversity of modelling methods for quantifying hazard interrelations

In this paper we have focussed on the quantification of interrelations between two (vs. three or more) hazards, for 14 different natural hazards. We used matrices (Figs. 5 and 6) to display our findings, similar to other studies (e.g, Gill and Malamud, 2014; Decker and Brinkman, 2015). We used these matrices to display the use of different modelling approaches (stochastic, empirical, mechanistic) for hazard interrelations quantification. The wide variety of modelling approaches reviewed highlights the lack of a unified framework for multi-hazard quantification. Indeed, this variety is not surprising, given the range of natural hazards considered in this study (Table 1) across geophysical, atmospheric and hydrological categories. Different types of hazard interrelations that extend across varying spatial and temporal scales require a panoply of modelling methods, and a coupling between these models (Leonard et al., 2014). The difficulty to model all hazard interrelations in the same manner is highlighted in Section 3, where two matrices are displayed (for 14 natural hazards) to present (i) cascading hazards (Fig. 5) and (ii) compound hazards (Fig. 6). Later, we summarize (Figs. 7 and 12) the 19 modelling methods that are most prominently used in the literature across 14 natural hazards for quantifying the interrelationships between these hazards. The figures and database (Supplementary Material) are a resource that can be consulted by the reader to be more aware of (i) those modelling methods (including reference to specific literature) currently directly being done for a given hazard interrelationship pair, (ii) other potential modelling methods that are being applied across all hazards studied here. For example, the interrelation between drought and extreme temperature have been studied with empirical (quantile regression) and stochastic methods (Gaussian copula) (Meng and Shen, 2014; Serinaldi, 2016), but it might also be studied using other methods in the database such as conditional extreme models or other types of regression depending the needs.

4.2. Some of the main drivers in modelling method selection for hazard interrelations quantification

It is not the purpose of this study to rank modelling methods in general. Nevertheless, we can argue from Section 3.3 some approaches or even models seem more applicable to given interrelation types or hazard categories and hazard types. Indeed, relationships where one hazard triggers or changes the conditions for another imply causality, which is not undertaken by the stochastic models reviewed in this work. Similarly, interrelations between compound (associated) hazards cannot be modelled with regression models which implies that one parameter (hazard) is influencing the other (causality). For example, interrelations of any geophysical hazard with any hazard category (geophysical, atmospheric, hydrological) are mostly quantified with physical models or regressions while interrelations of a hydrological hazard with any hazard category are mostly studied with copulas or physical models. As most of the hazard interrelations studies in our database are case studies, model choice is conditioned by the studied area, the hazards studied or the quality of the data available. But the choice of a quantification method when studying interrelations between hazards goes beyond the previously cited constraints; the context and the purpose of the study play an important role. For example, a study with engineering purposes might be more prone to use multivariate model to extrapolate beyond the range of observations while a study focusing on the impact of a particular hazard interrelation might favour a physical model.

4.3. Limitations (uncertainties) of the modelling methods

There are many limitations for the 19 modelling methods discussed here, with one of the major ones being data quality. Empirical models are more sensitive to data quality because they are data driven. In stochastic modelling approaches, additional uncertainties come from the different assumption made (e.g., statistical distribution choice, dependence model selection). In the case of mechanistic models, data are also central to calibrate and validate the model, and other uncertainties arise from some assumptions and simplifications inherent to the model.

4.4. Limitations of the present review

One of the limitations of the model classification presented in this review is that it is designed for interrelations between two hazards. Multi-hazard modelling becomes effectively more complicated when going to higher dimensions (i.e., more than two). Empirical models such as regression accept multiple parameters. This can be useful to create a hazard index or indicators for multiple hazard risk (Marzocchi et al., 2012; Nadim et al., 2013; van Westen and Greiving, 2017). Mechanistic models can represent the behaviour of several environmental variables. But, their scales often do not correspond to the needs of a multi-hazard study (Leonard et al., 2014). Regarding stochastic models, most of the parametric copulas in use for bivariate hazard models lack flexibility when going to higher dimensionality (Bevacqua et al., 2017; Hao et al., 2018). In addition, the variability of the dependencies among the difference pairs of hazards makes it harder to model (Bevacqua et al., 2017). A multivariate extreme model such as the conditional extreme model are suitable for high dimension (Heffernan and Tawn, 2004); although, this model has not been tested for high dimensional multi-hazard modelling yet. The present review does not cover all the possible methods for quantifying natural hazard interrelations. Methods such as agent-based modelling or event trees could have been included, but these latter are weak in addressing uncertainties (Terzi et al., 2019) and their relevance is limited when dealing with a low number of variables. The physical phenomena behind natural hazards can offer better insight or better characterization of the interrelation, particularly for meteorological hazards. These events have been sketched in the literature and are mostly considered as predictors or triggering factors (Liu et al., 2016; Bevacqua et al., 2017).Other limitations of this review include those inherent in any critical and systematic review (e.g., see discussion in Gill and Malamud, 2014; Reichenbach et al., 2018, for inherent weaknesses), such as potentially not having covered all relevant literature to 'capture' the current use of models relevant for quantifying hazard interrelations. We believe, though, that our review methodology (Section 2) is robust enough to capture not all literature, but the majority of modelling methods and approaches currently in use for the 14 hazards we explored in this review paper.

4.5. Perspectives for extending this interrelationship classification to more than two hazards

To address the challenge of extending our classification to a high number of variables, recent research conducted suggest pair-copula construction (PCC) (Bevacqua et al., 2017; Liu et al., 2016) and network approaches (Nadim et al., 2013; Leonard et al., 2014; Gill and Malamud, 2016; Liu et al., 2017) to model multi-hazard events. PCC are also called vine copula (Bedford and Cooke, 2002; Hashemi et al., 2016; Bevacqua et al., 2017; Liu et al., 2016). The decomposition which the vine copula framework allows one to select different bivariate copulas for each pairs of variables, providing a great flexibility in dependence modelling (Brechmann and Schepsmeier, 2013; Hao and Singh, 2016). Among the network approaches, Bayesian networks are very promising with an increasing use not only in multi-hazard risk assessment studies but also in dependability analysis, risk analysis and maintenance studies (Gutierrez et al., 2011; Duval et al., 2012; Weber et al., 2012; Poelhekke et al., 2016; Kwag and Gupta, 2017; Sperotto et al., 2017). Bayesian networks have lots of benefits when dealing with a great number of variables, particularly their versality and their capacity to model both dependability and causality relationships (Weber et al., 2012). Moreover, Bayesian networks are not originally designed to deal with continuous variables (Sperotto et al., 2017) and that is why these were not discussed in Section 3. Non-parametric Bayesian networks which associate the structure of Bayesian network and copulas (Hanea, 2010; Hanea et al., 2010, 2015) represent one way to overcome this limitation. For example, this method has been used to study multiple dependence between river discharge and storm surge in the USA during a hurricane (Couasnon et al., 2018). The association of copulas and Bayesian networks is a dynamic area of study and different approaches have already been developed with very few applications to natural hazards (Hanea, 2010; Elidan, 2010; Bauer and Czado, 2016; Pircalabelu et al., 2017).

In conclusion, we have used our literature database composed of 146 references to identify trends for hazard interrelation. We first highlight trends in terminology to define hazard interrelations from these group hazard interrelations into five hazard interrelationship types: triggering, change condition, compound, independence and mutually exclusive). Our critical review focuses on 14 different natural hazards from three hazard categories (atmospheric, geophysical, hydrological) and the possible interrelations that can occur between these. From the 14×14 possible hazard interrelation couples within our set of hazards, we find quantification methods applications to 24 different interrelations. Two matrices are created to illustrate this in practice, one for cascading hazards (temporal order in the multi-hazard event) and one for compound hazards (two or more hazards acting together). We then identify three modelling approaches (stochastic, empirical, mechanistic) including 19 modelling methods to quantify hazard interrelations between two hazards for 14 hazards. We then synthesize results of our classification of quantification methods for hazard interrelationships and propose an outlook on the modelling approaches used regarding the category of the hazards studied and the type of the interrelation between these latter. In this context, using an appropriate modelling method combined with a better understanding of physical phenomena leading to hazards interrelations (multi-hazard events), might be one of the keys toward efficient hazard interrelation quantifications.

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Appendix A. Supplementary data

Supplementary material which is a database of 146 references related to this article can be found at https://doi.org/10.1016/j.earscirev.2019.102881 and consists of the following:

- Table A1. Multihazard Database. 146 multi-hazard references (rows) with 14 attributes (columns) for each reference, including citation information, keywords, hazards studied, and then information about the modelling method (if appropriate).
- Table A2. Multihazard Database Structure. Detailed metadata information describing Table A1.
- Table B1. Interrelations Database. A subset of 70 of the references from Table A1 consisting of 73 rows of information (due to different hazard combinations for two references) with 14 attributes (columns) for each reference, including citation information, studied region, hazard A and B type and category in the interrelationship that is quantified, modelling approach, family and model, interrelationship type.
- Table B2. Interrelations Database Structure. Detailed metadata information describing Table B1.

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