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From local knowledge to global patterns: a cross-cultural study of the dimensions of hazards and adaptive capacity

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ABSTRACT

Understanding the human impacts of environmental hazards is a growing concern. While there is a plethora of research on climate adaptation, the literature is highly fragmented, and empirical studies are rarely carried out with global samples. This lack of comparative work limits our ability to understand general patterns in how societies adapt, thereby impeding effective policy and practice at a wider scale. To fill this gap, we outline a global comparative approach to the study of hazards that uses ethnographic data. The approach operationalizes five ecological dimensions of environmental hazards, including event type, frequency, onset speed, predictability, and severity, and investigates how they relate across a world-wide sample of 132 nonindustrial societies with significant variation in time and space. We then utilize this approach to explore how specific ecological dimensions might influence the adaptive capacity of societies to respond to events. Findings uncover generalizable patterns that exist across our global sample, suggesting that predictability enhances adaptive capacity, while temporal factors that promote uncertainty (including slow onset speed, longer event duration, and unpredictability) limit the success of adaptation efforts.

1. Introduction

Understanding the human impacts of environmental hazards is a growing concern. Both observed and projected changes indicate that many hazards such as floods and droughts, as well as outbreaks of pests and disease, are becoming more frequent and more intense [1,2]. Numerous ethnographic case studies describe how the local context shapes how and which hazards cause destruction and harm [3,4]. As important as these studies are, the literature is highly fragmented, and empirical research is rarely carried out with representative global samples [5]. Perhaps because such global studies are lacking, our general knowledge about hazards is driven by meteorological measures and climate models, which do not capture local experiences of risk and harm [6]. To address this gap, we outline a global comparative approach to the study of hazards that uses ethnographic data. Our cross-cultural method operationalizes

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and measures key ecological dimensions of hazards across a world-wide sample of 132 societies with significant variation in time and space (Fig. 1). This approach enables us to "scale up" local ethnographic findings to the global level to look for patterned distributions and relationships that can reveal generalizable findings. We then utilize our data to explore how specific ecological dimensions of hazards might mediate the adaptive capacity of societies to respond to them. These findings offer important insights to guide present and future climate adaptation efforts.

While environmental hazards are common elements in human societies, the way events unfold in a specific social context is complex. Much of what we know about this process derives from anthropologists, sociologists, geographers, and other ethnographers who engage in long-term fieldwork in research communities and use methods such as interviews and participant observation to understand and document everyday life. This *emic* perspective foregrounds the lived experience of local people and focuses on their beliefs, values, and practices. Descriptions of current and past hazards are routine components of ethnographies since these phenomena affect the activities, relations, and wellbeing of the community. As a result, ethnographies can offer an insider perspective on how hazards unfold and the significance of events on lives and livelihoods. Using a cross-cultural sample from the ethnographic record enables us to systematically investigate this variability at the global scale [7].

Cross-cultural samples comprised largely of nonindustrial societies provide a number of advantages: 1) they maximize cultural variation because such samples include a broad range of societies that vary widely in subsistence (from hunter-gatherers to intensive agriculturalists) and societal complexity (including small-scale bands, tribes, chiefdoms, and states); 2) being representative of Earth's biogeographies, they include wide variation in the human experience of environmental hazards; and 3) while climate change may be accelerating, climate-related hazards are not new and the ethnographic record may suggest ways that societies have adapted and could adapt in the future. Indeed, we are now rediscovering that people living in earlier times had adaptive responses, such as Indigenous fire management, that we can benefit from today [8]. Of course, it may be argued that the holistic data that anthropologically trained observers collect on hazards may not match the level of detail of data collected by those trained specifically to study disasters. It is true that most ethnographers, and particularly earlier ethnographers, did not set out to study hazards, just as most did not set out to study just one very specific aspect of culture or social life. While it is plausible that ethnographies may overlook some hazards, these are more likely to be relatively inconsequential events. Important events are typically remembered and are more likely to have generated responses that attempt to mitigate the potential impacts of future occurrences. Using ethnographic documents as source materials, cross-cultural researchers have uncovered thousands of patterns based on significant relationships involving almost all aspects of social life. As we discuss in section 2, earlier cross-cultural research has found significant relationships between hazards and certain cultural features, which are presumably adaptive responses to these environmental shocks.

A cross-cultural approach to hazards can help to address current gaps in our knowledge surrounding climate adaptation and resilience. Similar to ethnographies, most studies on adaptive capacity to climate change focus on a specific group; investigating the characteristics and capabilities that determine a community's ability to respond to stresses and shocks [9]. While these case studies provide invaluable data on the local context, there is a lack of research that systematically compares experiences and outcomes across cases to uncover more generalized findings [5]. In the absence of broader empirical results, general theory on adaptive capacity is often extracted from specific case studies to inform public policy decisions and models of resilience and risk reduction [10]. To advance knowledge, we need an approach that allows us to uncover more general patterns across the human experience of hazards [11,12]. We argue that the ecological dimensions of hazards (such as an event's onset speed, predictability, or severity) represent some of the experiential dynamics that set parameters for social response. Understanding and accounting for variation in these types of event qualities is considered key to reducing contemporary disaster risk, e.g., Refs. [13–15]. Our historical analysis of variation in ecological dimensions enables us to assess how the specific characteristics of hazard events relate to a society's ability to adapt. Such retrospective

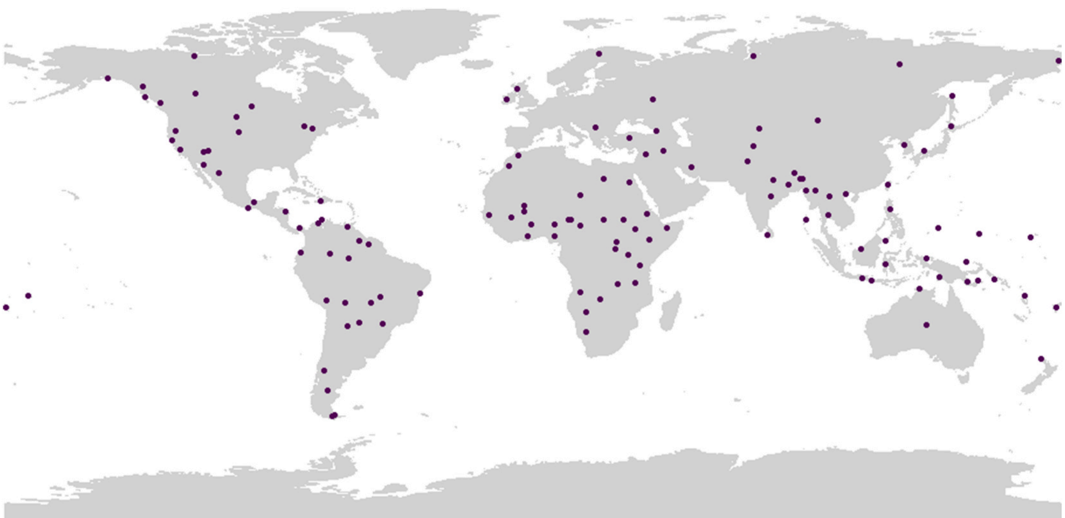

Fig. 1. Map of societies in our sample.

studies can form the basis of knowledge for mitigating future disasters [16] by providing generalizable knowledge that can inform and support the development of more effective frameworks for disaster risk reduction.

In what follows, we begin by outlining our global comparative approach to the study of hazards using ethnographic data. This framework identifies five ecological dimensions that emerge from the disaster literature. We then proceed with a description of our methods, detailing how we operationalize each dimension, compile datasets, and perform statistical analyses. Subsequent sections discuss the global experience of hazards based upon our ethnographic data.

2. Conceptual basis for the research

The data reported herein were collected as part of two larger, multi-year cross-cultural projects that aim to understand how cultures adapt and enhance resilience to environmental shocks. The first project coded the type and frequency of severe, food destroying hazards for a sample of 98 societies, finding that some aspects of hazards are broadly predictive of cultural traits. Drought, for example, predicts communal property systems [17] as well as the belief that gods control the weather [18,19]. Other studies found that food destroying hazards predict beyond-household sharing [20], exclusionary political governance [21], and warfare [22]. Related research has also explored social responses to hazards, finding that the onset speed and type of an event condition the strategies that societies use to respond [23]. In the second project, described here, we present a much more expansive coding that includes all reported environmental hazard events and their ecological dimensions. We believe that advancing our understanding of these qualities is necessary to understanding human responses, impacts, and recovery trajectories [24]. Our review of the disaster literature reveals five ecological dimensions that are commonly described within ethnographic and theoretical research on hazards. Each is described below. Details of how we operationalize each measure are provided in section 3.2.

2.1. Event type

Event type is a general category that defines a particular hazard phenomenon in relation to the physical mechanism by which it occurs (e.g. Ref. [25]). For example, the event type of “flood” can be described as an overflow of water beyond its regular confines. Type is the dimension most commonly used to describe a hazard in the literature. While the exact definition of a type may vary by social or disciplinary context, phenomena described as the same type are often categorized together and assumed to have shared features.

2.2. Speed of onset

A hazard event can also be categorized as having either a slow or fast onset [25]. Speed of onset indicates the rapidity with which an event occurs or the amount of time between detection of a hazard and its effect on the community [26]. Slow onset hazards such as droughts unfold gradually and are therefore more uncertain and ambiguous, whereas fast onset hazards, such as hurricanes and wildfires, are “immediate, direct, and clearly visible” [27]. In psychological terms, the former are more abstract, and the latter are more concrete [28]. While the onset speed of certain hazard types is definitional, other types exhibit variability. For example, a flash flood would be considered fast onset, while slow onset floods are characterized by water accumulating over the course of weeks or months.

2.3. Frequency

Frequency describes how often events occur within a given period of time. The concept is typically used in risk assessments, where the probability of future events is estimated given the temporal frequency of past recurrences (e.g. Ref. [29]). Frequency is most commonly used in reference to a specific type of event (i.e. the frequency of earthquakes), although there are some studies that examine the frequency of natural disturbances in general (e.g. Ref. [30]). Studies may use an exact count of events to determine frequency, however in historical cases precise documentation of hazards is often unavailable. Ethnographic descriptions, for example, may include reference to dated events, but they most-typically rely on general terms to describe frequency, especially for hazards that tend to recur (e.g., “a strong gale may arise at any moment” or “annual floods occur during the spring”).

2.4. Predictability

The predictability of a hazard describes its patterning within a social context. Highly predictable events are those that people expect to occur in a typical way. Often these expectations coincide with seasonality or other cyclical changes in the local climate [16]. Hurricanes, for example, usually occur during a specific time of year. The same is often true of flooding. In other cases, people know to anticipate particular hazards based on the presence or absence of other environmental conditions. For instance, the Rwala Bedouin of Jordan and Saudi Arabia know that “when the locusts swarm in vast numbers, one can safely predict drought” [31]. In contrast, unpredictable hazards are those that do not follow a pattern that is discernible to the local population.

2.5. Severity

Severity is the relative impact of a hazard on a society. The concept arises out of the distinction in the literature between a hazard and a disaster. While all environments generate disturbances that have the ability to cause negative impacts, humans structure their vulnerability to these phenomena with their decisions and use of the environment. A disaster only transpires when a hazard fulfills this potential for destruction and harm [32]. These event outcomes are frequently used as a proxy for adaptive capacity, with successful adaptation revealed through lessened severity of impacts [33]. We conceptualize severity as an emic measure of an event's destructive power within the local context, which differs from an objective or meteorological measurement of the physical elements of an event. The severity of a hazard can also vary by the type of resources that it destroys. In our review of the literature, the most common categories described include damage to the food supply, human lives, and the built environment. Losses to other livelihoods beyond subsistence (such as destruction of cash crops or sources of wage labor) is another important category.

3. Methods

3.1. Sample

Our starting sample comprises a total of 132 societies (Table S1), all included in *eHRAF World Cultures* (*eHRAF*), a database of ethnographic materials that are subject-indexed at the paragraph level by anthropologically-trained analysts. *eHRAF* holds over 365 culture collections and includes three different samples considered appropriate for hypothesis-testing: the Standard Cross-Cultural Sample (SCCS) [34], the Probability Sample Files (PSF) [35], and HRAF's Simple Random Sample (SRS) drawn from over 2,000 societies [36]. Each of these samples has been specifically designed to facilitate comparative, cross-cultural analysis of largely nonindustrial and subsistence-based societies on a wide diversity of topics. As explained shortly, our 132 societies are chosen from these three samples while *eHRAF* provides the searchable ethnographic materials. Our current sample of 132 cases builds upon a previous sample of 98 cases from our first project (mentioned above in section 2). The 98 cases comprise all those from the SCCS that could be more reliably coded for food destroying natural hazards. Aiming to add an additional 35 societies to our new sample, we added cases from the 60-culture Probability Sample Files not already in the SCCS and supplemented this with three additional cases chosen randomly from the SRS. For a culture to be included in our sample, the case had to have sufficient information to enable the coding of environmental hazards. This includes cases of *absence* in which the ethnographer either: 1) explicitly mentions a lack of hazards, or 2) provides ample information on related topics such as climate, topography, geology, or general disasters that indicates that hazards would have been mentioned if they had occurred. The two main samples (SCCS, PSF) both aim to maximize cultural variation and minimize cultural/linguistic/historical relatedness by choosing only one society from a designated culture area. Additionally, for each society, we use a specific time frame and place focus, known as the "ethnographic present" (EP), to minimize measurement error [7, pp. 76–78]. This framework enables cross-cultural researchers to identify data from ethnographic sources, known as "principal authorities, " that provide a synchronic "snapshot" for each culture in the sample. For the SCCS, we have used the time and place foci specified by the sample creators [34], and for the PSF and SRS cases, which do not specify a time or place focus, we have used the foci provided by the *Ethnographic Atlas* [37]. For the three societies without a designated ethnographic present, coders assigned one based on the process outlined in Table S2. Table S1 contains metadata for each society including its case number, ID in our dataset, identifier (OWC) for *eHRAF World Cultures*, the EP, and the place focus.

3.2. Data collection and coding

We developed a coding scheme based on standard practices for creating scales and coding ethnographic data [7]. To collect hazard data for each case, coders searched *eHRAF World Cultures* using the search command: "cultures:" [name of culture here]" AND subjects: ("disasters" OR "climate" OR "topography and geology" OR "gratification and control of hunger"). Coders filtered by "Document Level Samples," which limited the results to the principal authorities. There were certain cases for which searches were expanded beyond the principal authorities; this process is documented in Table S2. Coders read the relevant passages contained in the search results and used this data to code all reported hazard events that occurred within 90 years prior to the ethnographic present. This 90-year period was subdivided into three 30-year time frames, each of which was meant to approximate the length of one social generation. A description of the coding process follows; Table S3 provides all coding instructions for each variable in the dataset. A second coding was performed on 16% of cases, which determined inter-coder reliability to be high (at 89% agreement).

3.2.1. Dating events

The ethnographic record includes some hazard events with exact dates, but many more non-dated events, which are typically described in ethnographies as general or recurrent hazards. These non-dated events comprise 95% of our coded observations (see Table S6). While dated events tend to be major shocks, non-dated events usually emerge from descriptions of the local climate and/or subsistence practices and describe the regular, patterned conditions of everyday life. Common examples of non-dated events include: "extreme rainstorms are normal during the monsoon season," or "droughts occur here every 5–6 years." Dated events were recorded by their start year (variable H.2.a.) and end year (variable H.2.b.), while non-dated events were coded as "general" (GEN) for these variables. Each event was then assigned to one or more of the three time frames within the 90-year coding period (variable H.3.). These include the ethnographic present to 30 years prior, 31–60 years prior, and 61–90 years prior (hereby referred to as time30, time60, and time90, respectively). Dated events were assigned to the time frame corresponding to their start date (variable H.2.a.), while non-dated (GEN) events could be assigned to multiple time frames depending on the pattern of their recurrence. To capture this recurrence in the dataset, we reproduced observations for GEN events using an ordinal scale to approximate frequency in number of rows (see Table S4 for a full description of the method including examples).

3.2.2. Event type

Coding focused on events that have climate-related and/or environmental mechanisms.[1] Coders iteratively developed the list of hazard types as they collected data, ultimately identifying a grand total of 31 event types (variable H.5.) (see Table S5). While some types do overlap in certain attributes, we endeavored to differentiate types by their particular physical phenomena. For example, the event types of hurricane and windstorm both involve high-speed winds, but hurricanes also involve high rainfall, while windstorms do not. Similarly, extreme precipitation events may or may not cause flooding. We did, however, ultimately decide to consolidate four event types that all describe livestock and agricultural pests and disease, as this wider category aligns with common classifications used in the literature (e.g. Ref. [2]). The combined category of pests and disease (P&D) contains the subtypes of livestock epidemics, locust infestations, pest animals, and plant diseases. This reduced the total number of hazard types to 28.

3.2.3. Frequency

We measure frequency by counting dated events and approximating the count of non-dated (GEN) events (see section 3.2.1.). One event occurrence is equal to one row in the dataset.

3.2.4. Onset

Onset speed (H.7.) is coded as a categorical variable with two modes: slow (1) for events that emerge gradually and fast (2) for events that are relatively immediate.

3.2.5. Predictability

Predictability (H.8.) is an ordinal variable with three positions. Unpredictable events (1) do not follow a discernible pattern. Moderately predictable events (2) have a moderate pattern, such as a hazard that occurs sporadically but only during a particular time of year (such as hurricanes). Very predictable events (3) closely follow a pattern (such as reliable annual flooding).

3.2.6. Severity

Because hazards can impact distinct aspects of a society, we developed a series of five ordinal variables (four sub-measures and a general measure) to code for severity on a 4-point scale with intermediate scores (i.e., 1.5, 2.5, and 3.5) allowed. The sub-measures include impacts to: food resources (H.9.a.); other livelihood resources, such as export crops or sources of wage labor (H.9.b.); human lives (H.9.c.); and infrastructure, such as dwellings, draught animals, or landesque capital (H.9.d.). For each severity sub-measure, coders used the event description and general context provided by the ethnographic data to gauge the level of negative impact that the hazard had upon the group. A minimum score of 1 indicates that the hazard had no discernible negative impact,[2] while a maximum of 4 means that most/all people experienced a loss and/or most/all resources were lost. Events coded 3 (half of the community experienced a loss and/or half of resources were lost) and above are considered severe (see Table S3 for the complete coding scale). For an example of how coders operationalized severity, we offer Gluckman's [38], p. 4 account of the Lozi of the Zambezi River plain in western Zambia. Gluckman describes how a delay in the start of the rainy season "may cause crop-failure." However, he also notes that these conditions "would affect only certain Lozi gardens" because of the abundant rivers and pans, which ensure that "the [p]lain never languishes completely for lack of water." Because the description indicates that the overall destruction of the food supply was relatively low, this event was coded 2 (very few people experienced a loss and/or very few resources were lost) for destruction of food resources (variable H.9.a.). The overall severity measure (H.10.) codes for either the highest score across the sub-measures or, in rare cases where descriptions lack specific information about what was destroyed, it provides a general assessment of impacts. Only five events in the sample have an overall severity score (H.10.), but no scores for specific impacts (H.9.a.-d.). This means that H.10. is not an independent measure but is driven by the rankings for the severity sub-measures (H.9.a.-d.).

3.3. Analyses

We utilized the resulting dataset of hazard events to perform a variety of descriptive and exploratory analyses. We calculate descriptive statistics in R to analyze variability within and across the ecological dimensions. We also use Spearman's correlation matrices to discern relationships between the ecological dimensions of onset, predictability, and severity.[3] To deal with the possibility that hazards clustered within societies may not be completely independent, we supplement our Spearman's analysis with generalized estimating equation (GEE) models [39].

Most of our statistical analyses omit several types of observations. These include events that are coded as 1 (absent), 2 (threat only, but no actual event), or NA (not enough information) for variable H.12. (Occurrence of Event). See Table S3 for a complete description of codes. We also exclude events that occurred in time90, due to the sparse coverage for this period (described further in section 4 below). The only exception to these exclusions is Table S6, which provides summary statistics for the entire dataset. To determine

[1] Human pathogens were not included as hazards. Human-induced disasters, such as wild species collapse caused by over-hunting, were also not coded.

[2] The code of 0.5 was used to distinguish events for which the source provides enough detail to infer (but does not explicitly state that) there was no damage. All 0.5 codes were treated as 1 for statistical analysis.

[3] Because the ecological dimension of frequency requires a unit of analysis, we explore this dimension at different levels, such as the frequency of a certain type of event across the sample or the total number of events within a society.

whether it was appropriate to report correlations between dimensions across the entire 60-year research interval, we performed Spearman's analyses for the three subsets of the data (time30+time60; time30; time60) and compared them to assess potential variation. The results indicate minimal differences between the subsets (see Tables S12b and S13b for further detail); therefore our analysis focuses on correlations for the complete 60-year research interval. In addition, seven societies in our sample had no coded observations and are therefore not represented in the dataset. An additional seven societies had no occurred events for time30 or time60. We include these societies for sample-level analyses (such as the map) by utilizing a data frame in R. In all analyses for variable H.9.a. (food destroying severity), we group events coded 0.5 (inferred no impact) in the category for code 1 (no impact).

The reader will notice variation in sample sizes by variable and analysis. This is because not all events could be coded for all variables (see Table S7). For example, when an ethnographer describes a pest infestation, but does not provide adequate information to make a reasonable coding decision as to the event's onset speed (H.7.), the event would be coded as NA (not enough information) for this variable (see Table S3 for a description of codes). Our analysis below also draws upon ethnographic examples from cases within our sample. In addition to its name, each society is identified by its ID and ethnographic present (EP) date in parentheses, information which can be cross-referenced with Table S1.

4. Results: describing the ecological dimensions of hazards

Before proceeding with analysis of the dimensions, it is important to describe some basic elements of the sample (see Fig. 2 and Table S6) that contextualize our descriptive results and provide insights into the possibilities and limitations of utilizing the ethnographic record to understand hazards and their impacts on human societies. Coding identified a total of 4,664 observations across our sample of 132 societies. This includes a total of 4,618 occurred events spanning the complete 90-year coding interval. The remaining 46 observations represent events with unknown frequency and threats. Of the 4,618 occurred events, 95% do not have an exact date of occurrence (referred to below and in the dataset as GEN). A major reason for the low number of dated events is that many of the hazards described by ethnographers recur (such as annual rains or floods) and are therefore not discussed as specific occurrences but rather general patterns. A compounding factor is that, at the time of the ethnographic present, most cultures in our sample did not have written calendars and, therefore, precise dates of events were not obtainable from the ethnographic record. Grouping observations by 30-year time frames indicates a gradual decrease in coverage of hazards as we go back in time. This trend highlights another limit of the ethnographic record, which is largely based upon descriptions of current conditions and the living memory of community members. Unless documentation of events is contained in written records, much of the knowledge about hazards appears to be gradually lost over time. While time30 and time60 time frames have relatively similar coverage, there is a 91% drop in the number of events recorded in time90 (compared to time60). Although it is conceivable, though very unlikely, that the earliest time frame had fewer events for most cultures, it is more plausible that this distribution indicates that, in general, cultural memory and thus ethnographic data appears to provide high quality information on hazards for up to two generations prior to the ethnographic present. Because the event coverage is so sparse in time90, we have limited all subsequent analyses to include only events that occurred within 60 years of the EP (time30 and time60 time frames), which comprise a total of 4,426 observations, or 95% of the dataset.

4.1. Event type

Analysis of hazard type (variable H.5.) reveals high diversity across the sample. Out of a total of 28 hazard types, flood and drought are the two most common types of events, with the combined category for livestock and agricultural pests and disease (P&D) third (Table 1). Yet together, the three top types comprise less than half of all occurred events (see Table S5). Moreover, very few of the event types co-occur in the same society. The median society in the sample experiences only two types of events. Further, only five types of hazards occur in 15 or more societies, including drought, flood, pests and disease, great storm/extreme precipitation, and wind (see Table S5). Spearman's correlations between pairs of these types yields only one significant correlation, which is a weak negative relationship between drought and flood (Spearman's = −0.21, $p < 0.04$).

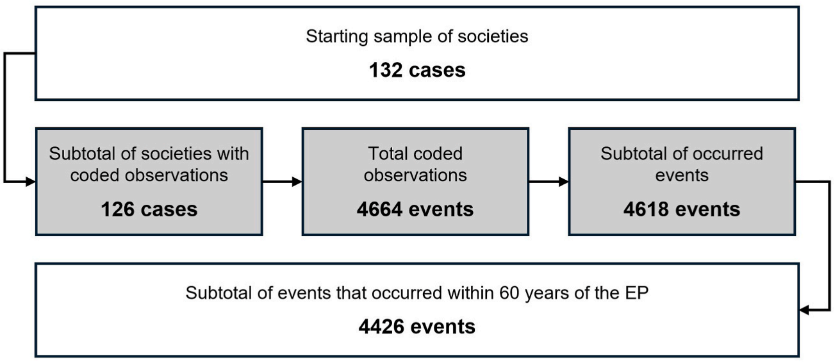

Fig. 2. Flowchart delineating the number of cases and observations used in analyses.

Table 1
Types and frequency of events by society.

	# of events	# of societies	Mean	Min	Median	Max	SD
Number of event types	4426	126[b]	2.5	0	2	9	1.8
Frequency of all events[a]	4426	126[b]	35.1	0	40	162	34.9
Drought	536	57	9.4	1	4	43	12.0
Flood	842	40	21.1	1	11.5	41	17.1
Pests and disease (P&D)	521	42	12.4	1	4	50	16.0

Note: See Table S5 for a complete list of types. Statistics for frequency of flood, drought, and P&D include only societies in which the specified event type occurred.
[a] Frequency includes a count of all dated events and an approximate count of all non-dated (GEN) events that recur.
[b] Six cases are coded NA for frequency of events.

We can better understand how types relate to each other through exploratory visualizations such as a minimum spanning tree, which represents connections across objects by identifying how types cluster and which types are more or less connected [40,41]. Here, a minimum spanning tree is useful for describing potential underlying relationships between event types in our sample. Fig. 3 visually represents these interconnections, depicting general patterns of co-occurrence of hazard types within a society. Hazard types that are more likely to co-occur are more centralized and/or clustered together, while terminal branches are less connected to other terminal branches. The top three hazard types—drought, flood, and pests and disease—cluster together, indicating that they are present together in a higher number of societies. As would be expected, hazard types that have similar climatological or geographical provenance also tend to cluster together because they also tend to co-occur in similar environmental contexts. Doldrums and hurricanes, for example, are both maritime events, while tidal waves and earthquakes both involve tectonic activity. Overall, however, it appears that there are no strong generalizable patterns to co-occurrence. Rather, across a global sample that is representative of Earth's biogeographies, it appears that the types of hazards a society encounters vary substantially from one society to another.

4.2. *Frequency*

An examination of frequency reveals high variation in the approximate number of events that societies experience. Fig. 4 visualizes the spread of the data with a histogram. Over the 60-year period for which we have adequate coverage, societies in the sample experienced between 0 and 162 events, but most societies incurred less than 50. Several outliers fall outside three standard deviations above the mean, which indicates that the median is the more-representative measure of the norm. As shown in Table 1, the median society in the sample experienced forty events, which averages to one event every 1.5 years. Comparing median frequency of events to median number of hazard types reveals a 20:1 ratio, which means that the same types of events tend to repeat through time. This pattern of recurrence remains consistent across the top three hazard types, however, there is substantial variation in frequency. Flood events tend to recur more than twice as frequently as drought or pests and disease.

4.3. *Predictability*

Findings for predictability (H.8.) build upon the results for frequency and type. Not only do societies repeatedly encounter the same types of events through time, but these recurrences also tend to follow a culturally recognized pattern. A high majority of hazard events (86%) exhibit a temporal pattern of occurrence with emic significance (see Table S9). This includes moderately predictable events (26%) that occur sporadically but only during a particular time of year, and very predictable events (60%) that have a more defined schedule. Comparison of the top three hazard types (Fig. 5) reveals that the predictability of an event varies by its type. Flood is clearly the most predictable of the top three types. Most events (96%) follow a pattern and a high majority (84%) are very predictable, meaning that they recur on a regular cycle. Ethnographies indicate that these types of floods are typically related to other climatological phenomena, such as the annual snow melt or rainy season. Similarly, most pests and disease events (83%) also follow a pattern and a majority (61%) are very predictable, such as annual fungal outbreaks or locust swarms in the dry season. In contrast, drought is the least predictable hazard type, with 26% of events coded as unpredictable. Although the majority of droughts still follow a pattern, droughts are more likely to be moderately predictable (43%) than very predictable (31%), a distribution that diverges from the trends of the sample overall. This difference in the predictability of drought compared to all other hazard types is statistically significant (Mann-Whitney U test, $z = -18.10$, $W = 683{,}000$, $p < 0.001$; see Table S10) and is reflective of wider trends that correspond to onset speed (see next sections).

4.4. *Speed of onset*

The dimension of onset (H.7.) measures the temporal emergence of an event. As shown in Table S11, fast onset hazards occur much more frequently, with more than three times as many fast events (3,073) as slow events (894) in the sample. There are also many more types of fast onset hazards. Flood is the most common type of fast hazard, but flood events comprise only 21% of the category, which includes a total of 27 event types. In contrast, the category of slow onset hazards includes 11 event types overall. Drought is the most common type of slow onset hazard and comprises a majority (60%) of events. Table S11 also shows that most types of events exhibit a strong patterning to their onset. Comparing the top three hazard types (Fig. 6) demonstrates this trend. All droughts are slow onset, while most floods (96%) and pests and disease (97%) are fast onset.

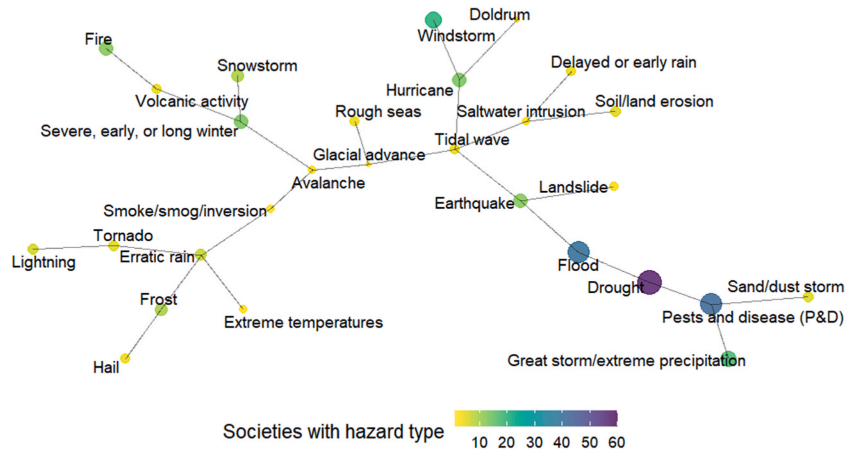

Fig. 3. Minimum spanning tree of hazard types. The figure represents relationships of hazard type co-occurrence among all 28 hazard types. Larger node size and darker color indicate that a higher number of societies experience events of that hazard type.

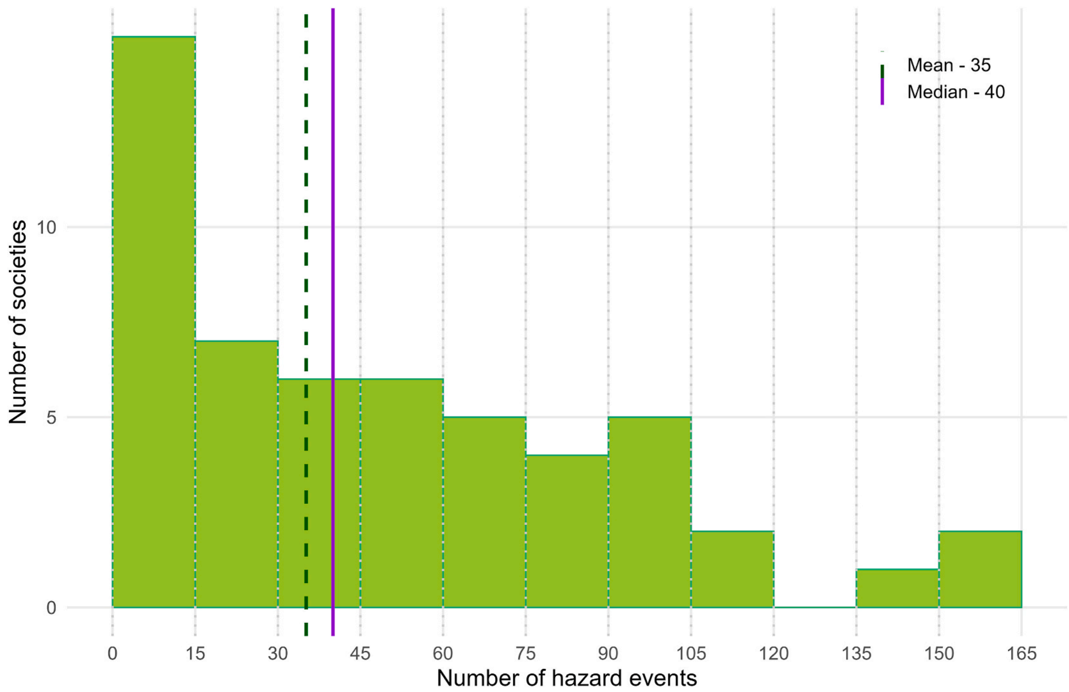

Fig. 4. Frequency of hazard events by number of societies. The histogram includes 126 societies, excluding 6 cases in the sample that are coded NA for frequency of events. Bin width was determined by the Freedman-Diaconis rule. Frequency values include a count of all dated and non-dated (GEN) events that recur. The recurrence for GEN events is approximate, therefore our frequency values are also approximate (see Table S5 for a description).

4.5. Severity of impacts

Table 2 reviews variation in overall severity (H.10.) and in the four severity sub-measures (H.9.a.-d.). The overall measure indicates that a minority (16%) of events are severe, meaning they affected half or more of the community (code values of 3+). Comparison of the four severity sub-measures (H.9.a.-d.) reveals that the effect of a hazard on food supplies (H.9.a.) is the most common impact recorded in the ethnographic record. We were able to code a large majority of events (93%) for their capacity to destroy food resources. This finding is understandable, given that access to food is one of the most fundamental capabilities a society needs to survive. In contrast, sub-measures for human lives, infrastructure, and other livelihoods have higher amounts of missing data (see also Table S7). We see some possible explanations for these discrepancies. Firstly, accurately measuring the impact on human lives (H.9.c.) proved difficult for coders. Most ethnographic descriptions of deadly hazards included only vague references to human suffering or loss.

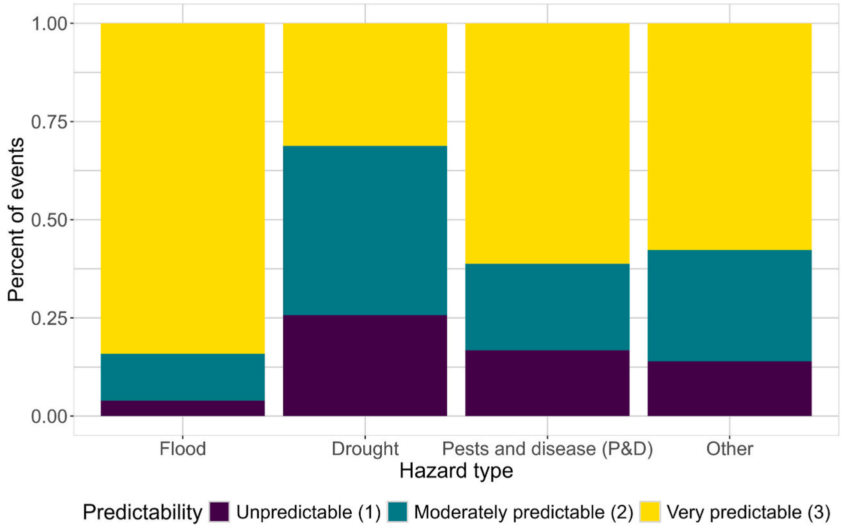

Fig. 5. Predictability by hazard type.

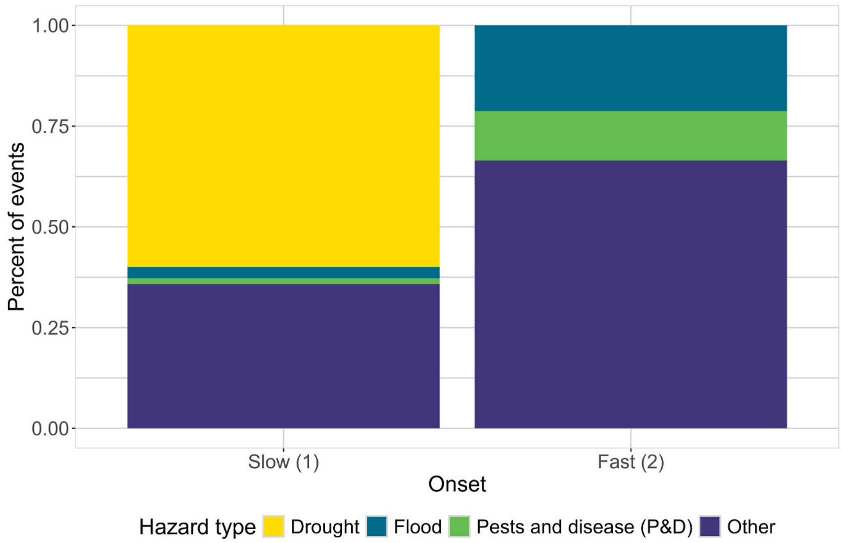

Fig. 6. Speed of onset by hazard type.

Further, when deaths were explicitly mentioned, there was often not enough population data to accurately gauge the demographic impact at the group level. During reliability testing, coders also identified a cognitive bias associating deaths with increased severity, which corresponds to ambiguity in the coding scheme. The coding instructions for severity asked coders to gauge the proportion of people that experienced a loss. While this scale worked well for other severity measures, it was unclear what exactly qualified as "a loss" in terms of human lives. Coders tended to conceptualize all households or kin groups that lost a member as experiencing a loss, even though the variable was meant to code for loss of individual lives. This resulted in a general overestimation of the proportion of deaths an event caused.[4] Regarding the remaining two sub-measures for infrastructure and other livelihoods, large levels of missing data likely mean that these measures could not be meaningfully applied to all cases. Our sample includes a wide diversity of human societies, many of which are nonindustrial and therefore simply do not have much infrastructure or other livelihood resources to lose.

[4] An example that highlights this dynamic of vague description, cognitive bias, and coding ambiguity is instructive: Makal [35] describes an unusually severe winter experienced by the Turks (ID#47; EP 1950) in 1947, which caused food and fuel shortages, blocked roads, and emaciated livestock. However, while adults "emerged from the winter with very little harm done, […] pitiless children's diseases, profiting by the cold, swept the little creatures away." This event was coded as "very severe" (4) for H.9.c., which should indicate that most/all people experienced a loss. While clearly all/most people in the village did not die, the ethnography indicates that many households lost a child and, therefore, the coder determined that many kin groups experienced the loss of a young family member.

Table 2
Severity of top hazard types - drought, flood, and pests and disease.

	1	1.5	2	2.5	3	3.5	4	Total coded	Total severe	% severe
All hazard types										
Overall severity (H.10.)	715	0	2595	324	406	19	302	4361	727	16.67
Food destroying (H.9.a.)[a]	1676	1	1621	226	323	19	246	4112	588	13.48
Other livelihoods (H.9.b.)	2138	20	203	60	58	1	47	2527	106	2.43
Human lives (H.9.c.)	1925	45	611	93	37	1	51	2763	89	2.04
Infrastructure (H.9.d.)	1943	0	888	41	77	3	52	3004	132	3.03
Drought										
Overall severity (H.10.)	0	0	198	110	102	3	106	519	211	40.66
Food destroying (H.9.a.)[a]	40	0	162	106	103	3	105	519	211	40.66
Other livelihoods (H.9.b.)	227	0	14	4	14	0	2	261	16	3.08
Human lives (H.9.c.)	219	0	10	0	10	0	17	256	27	5.20
Infrastructure (H.9.d.)	335	0	0	8	1	0	0	344	1	0.19
Flood										
Overall severity (H.10.)	124	0	631	9	56	2	18	840	76	9.05
Food destroying (H.9.a.)[a]	414	0	253	9	47	2	8	733	57	6.79
Other livelihoods (H.9.b.)	429	20	83	0	11	0	4	547	15	1.79
Human lives (H.9.c.)	448	40	112	0	4	0	0	604	4	0.48
Infrastructure (H.9.d.)	261	0	379	3	47	0	17	707	64	7.62
Pests and disease										
Overall severity (H.10.)	0	0	394	18	54	5	50	521	109	20.92
Food destroying (H.9.a.)[a]	2	1	380	10	34	5	29	461	68	13.05
Other livelihoods (H.9.b.)	317	0	48	8	18	0	28	419	46	8.83
Human lives (H.9.c.)	395	0	1	0	1	0	15	412	16	3.07
Infrastructure (H.9.d.)	369	0	60	8	0	0	2	439	2	0.38

Note: A higher number indicates higher severity.
[a] Observations originally coded 0.5 (inferred no impact) for variable H.9. a. Are merged with code 1 (no impact) in the table.

In contrast, food destruction is a measure that is highly relevant to all societies regardless of their subsistence strategy or complexity.

Comparing severity variables across the top three hazard types elucidates distinct patterns in hazard impacts. Looking at overall severity, drought is the most severe hazard type of the top three. All droughts have some impact and close to half of events (40%) are severe. Review of the severity sub-measures for drought shows that the overall severity measure is heavily driven by food destroying (H.9.a.) impacts. For the human lives sub-measure, droughts are also the most-deadly hazard type of the three, with 5% of events resulting in the death of half or more of the population.[5] Moving on, about one-fourth (21%) of pests and disease events are coded severe for the overall severity measure. Severity sub-measures indicate that pests and disease events tend to be most destructive to food resources (H.9.a., 13%) and other livelihoods (H.9.b., 9%), which includes crops and animals raised for market. The impact of pests and diseases on the latter category likely reflects common findings in the agriculture and development literature that highlight how high production intensity and lack of diversity in commercial monocultures make them more vulnerable to pests and disease [42].[6] Finally, flood is the least severe hazard of the top three types, with 90% of events coded for overall severity having little to no negative impact (codes 1–2). Severity sub-measures indicate that, when floods are severe, they tend to be food- (H.9.a., 7%) and/or infrastructure- (H.9.d., 8%) destroying.

4.6. Interactions across dimensions: assessing adaptive capacity

Investigating the interactions across ecological dimensions demonstrate how the specific features of events interact. Here, we focus our discussion on examining how the dimensions of predictability and onset relate to the five severity measures (Table 3). To explore these relationships, we apply two complementary approaches that each address a different stage of data analysis. First, we used nonparametric Spearman's rank correlations[7] as an initial exploratory tool to identify the presence and strength of monotonic associations between variables. Once these basic associations had been established, we then used generalized estimating equation (GEE) models[8] to formally evaluate population-level patterns while accounting for the fact that hazards are grouped within societies. Adding

[5] As described in the previous paragraph, this statistic may overestimate the actual proportion of lives lost.

[6] While the negative impacts of commercial monocultures are typically associated with the post-1950s development era, many cultures in our sample were exposed to the effects of markets before this time. For example, both the Haitians (ID#160; EP 1935) and the Fellahin of Egypt (ID#43; EP 1950) were engaged in export cotton production prior to their respective EP, and both industries experienced major problems with insect pests. Intensive livestock herding (often for subsistence and market) is another common correlate of pests and disease hazards in the sample.

[7] All the variables meet two of the three assumptions of the Spearman's rank correlation coefficient test: the data are ordinal and observations are paired. To assess whether the relationship between each pair of variables is monotonic, we used scatterplots and a loess application to visualize the trend in the data. Analysis determined that the relationships are almost all monotonic (see Figs. S1 and S2).

[8] Generalized estimating equations assume clustered/correlated responses, a specified within-cluster covariance structure, and a linear relationship between the link-transformed response and its predictors. All variables meet at least two of these assumptions, with only mild violations of linearity under the identity link. Onset (variable H.7.) satisfies all these assumptions.

Table 3
Significant correlations across predictability, onset, and severity.

Ecological Dimension	Severity variable	rho	p-value	# of events
Predictability (H.8.)				
	Overall severity (H.10.)	−0.35	<0.001	4343
	Food destroying (H.9.a.)[a]	−0.32	<0.001	4097
	Other livelihoods (H.9.b.)[b]	−0.07	<0.001	2523
	Human lives (H.9.c.)	−0.17	<0.001	2751
	Infrastructure (H.9.d.)	−0.03	0.06	2991
Onset (H.7.)				
	Overall severity (H.10.)	−0.33	<0.001	3902
	Food destroying (H.9.a.)[a]	−0.45	<0.001	3694
	Droughts omitted	*−0.29*	*< 0.001*	*3175*
	Infrastructure (H.9.d.)	0.27	<0.001	2549

Note: Correlations performed using Spearman's correlation matrices. Higher scores for onset are faster; higher scores for predictability are more predictable. For a complete table of correlations, see Table S12a. For a comparison of correlations by time frame, see Table S12b. All but one of the relationships between variables are monotonic and therefore meet this assumption of the Spearman's rank correlation coefficient test. See Fig. S1 for visualizations.
[a] Observations coded 0.5 (inferred absent) were merged with code 1 (absent) prior to analysis for this table.
[b] Non-monotonic relationship.

GEE models enables us to evaluate whether the associations between predictability/onset and severity variables hold across societies, while controlling for the possible non-independence of observations within each society (e.g., a large number of events in a small number of societies may produce significant correlations but not reflect general patterns across cases). We also draw on data from some of our ethnographic case studies of the two most common types of hazards—drought and flood—to contextualize our wider findings.

4.6.1. Predictability and severity

The correlations in Table 3 between predictability and severity indicate that when events are more predictable, that is, when they follow a locally recognized pattern, they tend to be less destructive. More specifically, there are significant negative correlations between predictability and four of the five severity variables (infrastructure severity is marginally significant). Note that two of the correlations–overall severity and food destroying severity–are modest in size; the other three correlations are very weak (one is nonmonotonic). The strongest of these bivariate correlations are reinforced by findings from the generalized estimating equation (GEE) models presented in Table S12c. Consistent with Table 3, GEE results show that greater predictability remains significantly and negatively associated with overall severity ($\beta = -0.42$, $p < 0.001$, $n = 4343$) and food-destroying severity ($\beta = -0.47$, $p \leq 0.001$, $n = 4097$). Other severity categories (other livelihoods, human lives, and infrastructure) had weak and nonsignificant effects, echoing the small and/or marginal Spearman's rho correlations.

A closer look at the top three hazard types offers additional insights. Table S13a indicates that Spearman's correlations between predictability and severity by hazard type are much more robust. For example, regarding drought, the four significant negative correlations range from −0.43 to −0.62. The negative relationship between predictability and loss to infrastructure is significant for floods. Of the 15 correlations in Table S13a, only three are nonsignificant. GEE models (Table S13c) reinforce the results of the Spearman's correlations for drought and pests and disease (P&D). Both hazard types remain significantly and negatively associated with the same four of five severity variables. For flood, GEE models support two of the four significant Spearman's correlations, including a significant relationship with food destroying severity ($\beta = -0.48$, $p = 0.02$, $n = 732$) and a marginally significant relationship with overall severity ($\beta = -0.45$, $p = 0.07$, $n = 838$).[9] The loss of significant relationships with infrastructure and human lives severity highlights important differences in method and how they correspond to internal variation within our data for flood events. Review of our dataset indicates that the frequency of flood events follows a bimodal distribution. The majority of floods tend to recur quite frequently (typically seasonally). These events are clustered in specific societies, they are highly predictable by definition, and they tend to be very low severity. In contrast, non-seasonal floods tend to be much less predictable and have a greater potential to be severe. While there are much fewer occurrences of these types of events, they are also more dispersed across our sample of societies. The lack of significant associations in the GEE model for destruction of infrastructure and human lives likely reflects the uneven distribution of these impacts across societies rather than undermining the broader relationships between predictability and hazard severity observed in the Spearman's correlations.

Our finding that increased predictability tends to lessen impacts suggests a link between event patterning and cultural adaptation. This supports common findings in the literature (e.g. Refs. [10,43]) which indicate that societies that experience destructive hazards often respond by changing their existing relations and practices–adaptations that are meant to boost their adaptive capacity to cope with future stresses and shocks. Moreover, as pointed out by Pelling [33], p. 14, outcomes are often used as a proxy for gauging adaptive capacity, with successful adaptation revealed through lessened severity of events. In sum, it appears that being able to

[9] Because overall severity is not an independent measure, but reflects the highest value across the four severity sub-measures (see section 3.2.6.), the marginal significance of this relationship in the GEE model reflects the loss of significant relationships with infrastructure and human lives severity (which we contextualize in the remainder of the paragraph).

anticipate an event helps a society prepare for it and increases local capacity to develop strategies of mitigation and response. Our results indicate that this relationship has demonstrable effects on impacts, as more predictable events tend to destroy significantly fewer material resources and lives.

A closer look at floods exemplifies this dynamic. Floods are the most predictable among the top three of our hazard types, with 96% of events exhibiting a locally recognized pattern (see Table S9). Review of our ethnographic data sources indicate that the high predictability of floods often corresponds to distinctive features of the hazard type: temporal and spatial patterning. Floods often correspond to seasonal shifts, such as monsoon seasons or the annual snow melt. In addition, floods are typically spatially selective. Events tend to occur in identifiable places such as river valleys and other low-lying areas. These common features facilitate predictability, as familiarity with the local environment enables a society to gauge both when and where flooding will occur. This higher predictability, in turn, enables effective planning and adaptation.

Review of our ethnographic data reveals that societies with predictable flooding adapt specifically by modifying their land use strategies and infrastructure to avoid flood-prone areas during times of risk. Mobile societies, such as the Tehuelche (ID#185; EP 1870) of Patagonia, know to avoid camping in river basins during the spring snow melt, when rivers are subject to "great floods" [44], p. 290. Similarly, sedentary groups avoid placing permanent settlements in areas with predictable flooding. For example, the Amhara (ID#37; EP 1953) of Ethiopia's highland plateau build settlements on or near hilltops to avoid being flooded during their short, wet season, a time of year when 80% of the region's rain falls [45], p. 28. Adaptations to flood also include the development of technology, such as structures built on stilts or raised platforms, and infrastructure to block, channel, or store water and prevent damage. Previous cross-cultural research has found that these types of proactive adaptations are the most common cultural responses to flood [23]. The Amhara, for example, utilize terrace farming to prevent erosion and landslides. They also build canals to store and channel water to agricultural fields [45], p. 43. This capability to capture flood waters enables complementary agricultural adaptations that increase productivity by extending production into the long dry season [46]. In this way, the management of flood waters can also function to turn a potentially destructive hazard into a valuable resource; integrated environmental solutions that are a common feature of intensive agricultural systems [47].

The predictability of floods can also be leveraged to help cultures lower the severity of less predictable hazards such as drought. For example, the intensive wet rice farmers of Okayama prefecture in Japan (ID#117; EP 1950) inhabit an area that is prone to both flood and drought. Water management adaptations have developed over centuries of public works projects designed to "prevent drought [and] work also against inundation" with technologies including water gates, canals, and dikes as well as irrigation systems, reservoirs and water storage ponds [48], p. 126. This sophisticated use of flood waters enables farmers to build diverse agricultural systems, cultivating wet rice paddies at the same time as fruit orchards that benefit from the dry, sunny weather [48], p. 21.

4.6.2. Onset, severity, and predictability

The correlations between onset and severity shown in Table 3 suggest that the speed at which an event emerges conditions the seriousness of its impacts. Results with overall severity (H.10.) indicate that, in general, slow onset hazards tend to be more severe than fast onset hazards (Spearman's $= -0.33$, $p < 0.001$, $n = 3902$). However, analysis of the four severity sub-measures produces two significant correlations of varying directionality, revealing that slow and fast hazards have distinct destructive capabilities. First, we find a significant positive relationship between onset speed and infrastructure severity (H.9. c.) (Spearman's $= 0.27$, $p < 0.001$, $n = 2549$), indicating that fast onset hazards tend to have more negative impacts upon the built environment. As described in section 4.4., fast onset hazards is a diverse category comprising a total of 27 hazard types including flood (20%), windstorm (12%) and pests and disease (12%) (see Table S11). Infrastructure, such as dwellings, ships, draught animals, and irrigation systems, appears to be especially vulnerable to these types of hazards. In contrast, there is a significant negative relationship between onset and food destroying severity (H.9.a.) (Spearman's $= -0.45$, $p < 0.001$, $n = 3694$), indicating that slow onset hazards destroy more food. The correlation remains significant even after removing droughts (Spearman's $= -0.29$, $p < 0.001$, $n = 3175$), which comprise 60% of slow onset events. Generalized estimating equation (GEE) results (Table S12c) reinforce our findings related to the effects of slow-onset hazards. In models predicting severity as a function of onset, both overall severity ($\beta = -0.73$, $p < 0.001$, $n = 3902$) and food-destroying severity ($\beta = -0.90$, $p < 0.001$, $n = 3694$) were inversely related to fast-onset. As with our Spearman's correlations, the latter relationship persisted after excluding drought events ($\beta = = 0.59$, $p < 0.001$, $n = 3175$). GEE results also indicate a significant negative relationship between infrastructure severity and onset ($\beta = = 0.20$, $p = 0.01$, $n = 2549$).

Our findings that slow onset hazards are more destructive in general, and especially to food resources, align with broader patterns supported by our data that link uncertain event temporalities to increased severity of impacts. The concept of temporality describes how a hazard event relates to the process time. This includes time as both an objective measure that is countable in increments (such as seconds, weeks, or years) and as a psychological process that structures how humans perceive, experience, and remember events [49]. Events with *uncertain* temporalities are those that exhibit higher variability and indeterminacy in these domains (c.f. [50]). The dimension of onset operationalizes the temporality of event emergence as either fast or slow. By definition, slow onset events are more uncertain; droughts and other slow onset hazards like severe winters, soil erosion, and certain forms of pests and disease "unfold gradually and are therefore more uncertain and ambiguous." Our dataset enables us to measure two additional domains of temporality, including the dimension of predictability and also event duration, defined as the time that passes between the initial impact of a hazard and when its direct physical manifestations ultimately subside [26]. Analysis suggests that the uncertainty associated with slow onset hazards can be compounded by each of these two temporal domains.

First, correlations between onset and predictability reveal that the occurrence of slow onset events tends to be less predictable (Spearman's $= 0.30$, $p < 0.001$, $n = 3954$; see Table S12a). This inability, in many cases, to predict when or if an event will occur is an important temporal factor that increases the uncertainty surrounding slow onset events. Second, analysis of event duration indicates

Table 4
Annual duration of dated events by onset.

Onset	# of events	Duration				
		Mean	Min	Median	Max	SD
Fast (H.7. = 2)	110	0.05	0	0	2	0.27
Slow (H.7. = 1)	73	4.52	0	0	114	19.05
Droughts only	49	1.14	0	0	11	2.40
Droughts removed	24	11.42	0	0	114	32.40

Note: Event duration (how long an event ultimately lasts) is distinct from but also connected to the dimension of onset (the speed at which an event emerges). It is only possible to ascertain a rough estimate of event duration for the subset of events in our sample (194/4 %) that have defined start/end dates. We compute event duration by subtracting the event end year (H.2.b.) from its start year (H.2.a.). Events that have the same start/end year, therefore, have an event duration of zero.

that slow onset hazards tend to be both longer and more variable in their length. We were only able to measure duration for the subset of 194 events in our 60-year research interval that could be dated by start and end year. Although these measures are not exact, analyzing start and end years in reference to onset (H.7.) indicates that a slow onset speed tends to correspond to a longer event duration (Table 4). Events with longer duration include, for example, droughts that emerge slowly but also persist for years or instances of soil erosion that lead to gradual land loss over decades.[10] It makes sense that the longer a society lives under hazard conditions, the greater the strain and the longer it takes to begin the recovery process. For example, new crops cannot grow until a drought ends, food reserves dwindle as a severe winter endures, a persistent cattle plague gradually diminishes the integrity of a herd.

In addition, comparing standard deviations indicates that slow onset hazards also have significantly higher variability in duration, implying that the duration of slow onset events is much more uncertain. Understanding the human experience of slow onset hazards is therefore not just a matter of the speed at which these events unfold, but also the unpredictable patterning of their occurrence, their longer timespan, and the subsequent variability in how long they will ultimately last. Together, these temporal dynamics of uncertainty appear particularly damaging to food supplies. This finding provides statistical support to previously untested hypotheses that have emerged from past cross-cultural studies of adaptation to severe food destroying hazards [17–22], many of which posit that it is the uncertainty of these events that drives the cultural responses that emerge.

The differences we have identified between impacts of fast and slow onset events correspond to differences in the types of adaptations that societies use to respond to them. Previous cross-cultural research by Pierro et al. [23] has found that technological adaptations are the most common responses to fast onset hazards, whereas religious strategies are the most common responses to slow onset hazards. Looking specifically at drought, which is the most common slow onset hazard, Pierro et al. [23] found that the three most-frequently used strategies all involve appeals to supernatural forces, including rituals during the event, sacrifices, and preventative rituals. However, the presence of religious rituals does not preclude pragmatic responses. Indeed, the next three most frequently used coping mechanisms are migration, livelihood diversification, and irrigation techniques. In general, societies with religious coping mechanisms are more likely (albeit with marginal significance) to also have pragmatic coping mechanisms. Still, the primacy of religious responses to slow onset hazards likely relates to their high severity and temporal uncertainty. Human awareness of the temporal properties of events influence behavior and cognition, thereby driving emotions such as anticipation or fear and informing plans for the future [49]. Anthropological theory posits that religion often functions to relieve anxiety caused by the uncertainty of life, including natural forces beyond human control (see Ref. [19] for a review). Through rituals and sacrifices, humans try to engender hope within a community and also influence the supernatural agents or forces perceived to be responsible for hazard events, thereby attempting to prevent or end their suffering. The longer an event endures and the more extensive the impacts, the greater the need to relieve anxiety and assert control. Likewise, preventative rituals may help to allay worries that arise due to the unpredictability of slow onset events. In addition, slow onset hazards are also more likely to result in erosive responses that deplete resources and compromise the resilience of a household or community [23], p. 7.

Together, these cross-cultural research findings suggest that the temporal dynamics surrounding slow onset events have a greater potential to push societies beyond their material capacity to successfully adapt and remain in their current form. While societies implement a number of strategies to respond, the dynamics of severity and temporal uncertainty may ultimately force reorganization of societal structures and processes. Review of our ethnographic data for the Teda (ID#40; EP 1950), who live in the Tibesti Massif of northern Chad, illustrates how extended drought can exceed the limits of cultural adaptation. The Tibesti Massif has an arid climate, and droughts are both common and unpredictable. Cline [51], p. 24 A describes how life among the Teda is highly attuned to water scarcity, with subsistence strategies coordinated across larger family units. While some family members practice nomadic pastoralism, others tend permanent gardens in the valleys, where farmers utilize irrigation channels, ridging, and soil amendment strategies to regulate water use. The pastoralists, meanwhile, follow a pattern of seasonal migration during which they spend the majority of the year herding goats and camels in the western pasture lands—while also maintaining date palm groves in luxuriant oases where they stay for several months to tend and harvest the trees. Herders dig large wells along their routes to tap underground water reserves, infrastructure that they position within the landscape to avoid detection and use by strangers.

[10] Fast onset events can also have long durations, such as a fast onset livestock disease that becomes endemic. However, this combination appears to be very uncommon. Only five dated events in our dataset (2.6 % of dated events) had event durations over a year.

Despite such elaborate adaptations, however, ethnographies indicate that in the decades preceding the ethnographic present for the Teda (1950), the region experienced cycles of worsening drought that resulted in severe negative impacts on the population. Over the 60-year research interval, the Teda suffered five very severe multi-year droughts amounting to a total of 28 years living under drought conditions [51–53]. During this time, famine was frequent as were sacrifices to encourage rain [54], p. 132. As desperation grew, families were forced to abandon their gardens and "draw on other sources — either by trading and raiding in the grain-growing lands to the south, or by commercial undertakings [or] by taking their flocks to better pastures in regions outside Tibesti" [51], p. 23 A.

5. Conclusion

In this study, we have outlined a new global comparative approach to the ethnographic study of hazards. In so doing, we have identified and analyzed five ecological dimensions of hazards, which include event type, frequency, predictability, onset, and severity. Descriptive analyses of these dimensions offer generalizable insights regarding the human experience of environmental hazards. To summarize our findings:

- The types of hazards a society encounters (1) vary substantially from one society to another, and (2) tend to repeat through time.
- The tendency for repetition coincides with predictability. While a majority of hazard events are predictable, the predictability of an event varies by its type. Droughts are significantly less predictable than other types of hazards.
- Fast onset events occur more frequently than slow onset events.
- The speed at which an event emerges conditions its impacts. Slow onset hazards tend to be more severe and destroy more food, whereas fast onset hazards have more negative impacts on infrastructure.
- The severity of an event's impact varies by its type. Of the top three hazard types, droughts and pests and disease are the most likely to be severe whereas most floods have little to no negative impact.
- The specific kinds of impacts of an event vary by its type. Of the top three hazard types, droughts are the most destructive to food resources and human lives, pests and disease events tend to impact food resources and other livelihoods, and floods tend to be food- and/or infrastructure-destroying.
- Hazards that are more predictable tend to be less severe. The more predictable a hazard is, the lower the severity of its impacts on food resources, human lives, infrastructure, and other livelihoods.

By scaling up the richness of the ethnographic record to a global sample, we have uncovered some generalizable and predictable patterns that exist across societies; insights that can inform climate adaptation and climate change policy. Today, many scholars argue that disaster risk is defined by its systemic nature: compounding and interrelated threats across environmental, socioeconomic, and political spheres often render individual events more complex and unpredictable [55]. The need to understand the complex disruptions characterized by cascading and compounding dynamics has become a core element of the cross-disciplinary approach to resilience [56]. We believe that the research presented here complements and supports these efforts. While systems thinking provides a comprehensive view of understanding complexity and fostering resilience, it also reinforces the need to develop a more thorough understanding of the basic variability of hazards that works to promote such complexity. The five ecological dimensions that we identify and investigate (event type, frequency, onset speed, predictability, and severity) are key elements of the complexity of hazard variability. Indeed, researchers have identified significant limitations of risk reduction models that don't take these dimensions into account e.g., Refs. [13–15]. Our findings advance knowledge of these ecological dimensions and how they influence the parameters for social response, thereby providing new insights that can be leveraged to inform broader models.

In addition, current climate adaptation efforts focus on identifying components for building adaptive capacity as well as on developing these components to work toward progressive risk reduction [33], pp. 14–5. Our analysis has identified two such components for building adaptive capacity. First, consider the predictability of hazards. As we noted earlier, in general, hazards that are more predictable tend to have less severe impacts on food resources, infrastructure, human lives, and other livelihoods. We suggested that lower severity is likely a result of societies having developed prior solutions after experiencing the same types of events and observing patterns. This patterning enables preparedness and the development of adaptations that lessen future impacts. While it is true that environments are becoming less predictable with the unfolding of climate change [1], it is also likely that "most changes will occur gradually [by] stretching the boundaries of previous extremes" [11, p. 653]. As extremes increase, building access to weather and climate forecasting that integrates local knowledge of hazards could be a way to bolster predictability and empower local communities (c.f. [57]). While better access to information would enhance the ability of communities to prepare, ethnographies also demonstrate that it is imperative for people to have the capacity to leverage their knowledge of local environments to adapt to new conditions in sustainable ways. Success requires investment of material and social resources in infrastructure as well as in culturally relevant expertise. This emphasis on local knowledge and practice, however, does not imply that solutions from other cultures are irrelevant. Indeed, the ethnographic record is replete with examples of cultures integrating and benefitting from the creative solutions of other groups.

Our second major finding is the significance of the temporality of events and impacts. While our analysis uncovered an important link between patterning and preparation, there are also elements of hazards that can impede effective response. Our data indicate that outcomes worsen when events exhibit slow onset speed, longer and/or more variable event duration, and more unpredictability. While each of these elements promotes uncertainty, they also tend to co-occur, patterns that should inform models of disaster risk reduction. Such compounding temporal factors may present significant barriers that impede the success of adaptation efforts. In this context, it may be useful to focus on building new institutional approaches to preparedness in the face of uncertainty. This could include the creation of organizations that are intentionally designed for uncertain environments [58] and/or the development of proactive funding mechanisms based on the potential for critical need [55]. It is also important to exercise caution when operationalizing these findings as policy positions. The significant difference in the severity of floods and droughts, for example, does not imply that resources should be diverted away from flood adaptation. Rather, our analysis shows that a main reason why floods tend to be less damaging is because attention has been paid to building proactive responses to them, such as mindful land-use patterns and the development and maintenance of complex infrastructure. Because patterns of climate change are increasing the co-occurrence of wet and dry extremes [49], an integrated approach to water management could help societies adapt to both flood and drought.

This study also suggests useful directions for future research and practice. Our findings demonstrate that the cross-cultural comparison of ethnographic data can uncover generalizable patterns that advance our understanding of the social context of hazards. This scientific knowledge offers a human-centered perspective to policy makers, one that is based upon local experiences of risk and harm. It is important to note, however, that our sample includes nonindustrial societies, many of which are described before substantial involvement with global capitalism and the interconnected world system. Therefore, it would be important to compare our results with a sample of more recently-described and interconnected communities. In doing so, researchers could draw upon the vast literature of contemporary case studies on disaster recovery and climate adaptation; an endeavor that would effectively respond to important critiques regarding the lack of comparative work within the field e.g., Refs. [5,11,12]. We suspect that adaptation to hazards would be more difficult for groups embedded within larger political and economic systems in which local communities have less control over decisions. As many contemporary case studies demonstrate, effective adaptation—even for very predictable events—is often impeded by geopolitical factors [59], social norms [60], and a global market logic that prioritizes profit and political expediency [61,62]. Here, cross-country comparisons would also be warranted, especially as countries vary in the degree to which they are able to assist individuals and communities in mitigating climate change.

CRediT authorship contribution statement

Samantha K. King: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Cynthiann Heckelsmiller:** Writing – review & editing, Methodology, Investigation. **Carol R. Ember:** Writing – review & editing, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Eric C. Jones:** Writing – review & editing, Supervision, Formal analysis, Conceptualization. **Sebastian Wang Gaouette:** Writing – review & editing, Visualization, Validation, Methodology, Data curation. **Anj Lee Droe:** Writing – review & editing, Methodology, Data curation. **Danielle Russell:** Writing – review & editing, Methodology, Data curation. **Jacqueline Heitmann:** Writing – review & editing, Validation, Methodology, Data curation. **Isana Raja:** Writing – review & editing, Data curation. **Michele Gelfand:** Writing – review & editing, Formal analysis, Conceptualization.

Reproducibility

Data files and R scripts are available on Open Science Framework at https://osf.io/q8euw. R Version 4.4.1 was used to calculate statistics.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijdrr.2025.105950.

Data availability

Data files and R scripts are available on Open Science Framework at https://osf.io/q8euw.

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