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ORIGINAL PAPER

The national risk index: establishing a nationwide baseline for natural hazard risk in the US

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Abstract
The National Risk Index developed by the Federal Emergency Management Agency provides a relative measurement of community-level natural hazard risk across 50 US states and Washington, DC. The Index leverages authoritative nationwide datasets and multiplies values for exposure, annualized frequency, and historic loss ratio to derive expected annual loss estimates for 18 hazard types and combines this metric with Social Vulnerability and Community Resilience scores to generate Risk Index scores for every Census tract and county. Scores provide a holistic and comparable measure of risk across the US. Risk scores and underlying data are summarized in a custom web application. Geographical and statistical processing techniques were used to reconcile incompatibilities between the spatial and temporal collection of input datasets. The index was developed using a multidisciplinary and collaborative approach and input from subject matter experts across disciplines and target users. The National Risk Index builds upon previous efforts to develop a multi-hazard risk measurement for a large geography by expanding the number of hazard types considered, applying extensive geoprocessing techniques to combine diverse datasets, and combining traditional risk factors with the community risk factors of social vulnerability and community resilience for an enhanced nationwide picture of risk.

Keywords National risk index · Natural hazards · Risk methodology · Multi-hazard · Expected annual loss

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1 Introduction

Between 1980 and 2020, the USA experienced 285 weather and climate disasters where overall damage costs reached at least $1 billion, with a cumulative cost exceeding $1.875 trillion US dollars (Smith 2021). During the same period, there were 1963 major disaster declarations (Federal Emergency Management Agency [FEMA] 2021a). Through internal programs like Hazard Mitigation Planning, the National Flood Insurance Program, the National Earthquake Hazard Reduction Program, the Dam Safety Program, Building Resilient Infrastructure and Communities, and others, FEMA increases risk awareness and encourages mitigation actions that reduce the impacts of natural hazards. However, community participation in these programs requires completion of risk assessments (FEMA 2013) that can be expensive, duplicative, and inconsistent. To increase access to baseline risk assessment information, FEMA developed the National Risk Index to quantify the risk of natural hazards nationwide.

The quality and completeness of risk assessments vary dramatically based on the availability of data and analytical resources. Many assessments focus on only one or a small subset of natural hazards, use generalized nationwide datasets, or do not consider critical social and economic inequities. Examples of these assessments include Coleman and Dixon (2014), Ewert et al. (2018), National Oceanic and Atmospheric Administration (NOAA) (2016), Widen (2016), and Dillon (2020). Despite these efforts, there is still a need for the federal government and nonfederal partners in the US to have consistent "assessments that address long-term risks, prioritize risk-based investments, discourage risky behaviors, and appropriately recognize the risk" (FEMA 2019, p. 12).

The complex challenges associated with quantifying and communicating multi-hazard risk at a national scale are well-established (Kappes et al. 2012; Marzocchi et al. 2012). Differences in the spatial and temporal resolution of data and the scale and mechanism of impacts for each hazard have driven analytical constraints on the number of hazards, the geographic or temporal scope, the types of exposures, or the level of quantification included in many multi-hazard risk assessment efforts (Lundberg and Willis 2015; Eshrati et al. 2015; Grunthal et al. 2006). Extensive geographical and statistical processing techniques are required to reconcile incompatibilities between the spatial and temporal collection of input datasets. While the product of frequency, exposure, and vulnerability is widely accepted as a foundational definition of risk (Ward et al. 2020), the single risk metrics generated by this probabilistic approach are also acknowledged to oversimplify the risk information present in a full probability versus loss curve for a given hazard or multiple interacting hazards (Kaplan and Garrick 1981, United Nations Office for Disaster Risk Reduction [UNISDR] 2019). Multi-hazard, large-scale risk assessment challenges are deepened by the separation between scientific communities for individual hazards, a challenge the National Risk Index addressed through collaborative, interdisciplinary working groups composed of over 80 subject matter experts from a variety of hazard and risk-related fields.

FEMA's National Risk Index builds on previous efforts and frameworks, including the FEMA Multi-Hazard Identification and Risk Assessment (FEMA 1997), World Bank Natural Disaster Hotspots (Dilley et al. 2005), the United Nations Disaster Risk Index (Peduzzi et al. 2009), the World Atlas of Natural Disaster Risk (Shi et al. 2015), and the United Nations Disaster Risk Reduction Framework (UNISDR 2019). The National Risk Index expands the number of hazards considered, applies geoprocessing techniques that allow comparisons across census jurisdictions and hazard types, and combines traditional risk

Fig. 1 Generalized national risk index risk equation

$$\text{Risk} = \frac{\text{Expected Annual Loss} \times \text{Social Vulnerability}}{\text{Community Resilience}}$$

factors with social vulnerability and community resilience for an enhanced profile of risk. Social vulnerability and community resilience are foundational drivers of disaster impacts and should be fundamental considerations in any comprehensive risk assessment (Cutter et al. 2003, 2010; Lavell et al. 2012). However, few efforts have combined social vulnerability and community resilience indicators with quantifiable expected annual loss (EAL).

The National Risk Index is designed to serve as a nationwide, comparable measure of community risk for all counties and Census tracts in US states and the District of Columbia, calculated within and across 18 significant natural hazard types. The results are based on widely accepted risk quantification methods and authoritative datasets available at a national scale. The National Risk Index defines risk as the product of EAL and social vulnerability divided by community resilience, where EAL is the product of natural hazard annualized frequency, exposure, and historic loss ratio (HLR). The results include EAL estimates in US dollars and relative measures of normalized risk for every county and Census tract. Fundamentally, these definitions are consistent with other risk models and international natural hazard risk modeling guidelines that estimate EAL as a function of frequency and severity (UNISDR 2017). In this index, the severity factor is further refined into the exposure and HLR factors.

The results and input data are summarized in an interactive web application with an iteratively designed user experience (UX), consisting of map displays and reports that help users identify, visualize, and prioritize communities at risk for natural hazards. County and Census tract composite scores—as well as scores for individual hazard types, social vulnerability, and community resilience—can be downloaded through the web application (https://fema.gov/nri) for use in local analysis.

2 Methodology

Traditionally, risk is quantified in terms of expected losses using metrics such as average annual losses and probable maximum losses. Risk metrics are calculated considering hazard frequencies, damage probabilities, and consequence exposure (Di Mauro 2014). The National Risk Index approach expands on the traditional expression of risk solely as expected annual losses by accounting for the likelihood of adverse impacts based on a community's comparative social vulnerability and community resilience. Figure 1 shows the generalized risk equation. The components of this equation are explored in detail in subsequent sections.

See the National Risk Index: Technical Documentation for more information on the detailed methodology used by the Index (FEMA 2021b).

2.1 Selection of natural hazards

The 18 hazard types included in the National Risk Index (see Fig. 1) were chosen based on a comprehensive review of hazard risk profiles from available 2016 State Hazard Mitigation Plans. For a hazard type to be included in the index, it had to be profiled by at least half of the State Hazard Mitigation Plans or be considered a significant regional hazard, which is defined as a hazard geographically limited in occurrence but contributing significantly to a region's risk profile, such as hurricane or volcanic activity. Working groups of hazard identification and risk assessment experts helped identify the best available, nationwide datasets for each hazard type. No man-made hazards, such as dam or levee failure, were included, and the subsidence hazard was excluded due to lack of available data.

2.2 Expected annual loss

The objective was to generate accurate, comparable EAL values for all communities (county and Census tract) for each of the 18 hazard types they are susceptible to and a composite EAL, which is the cumulative EAL for all hazard types. There were major challenges to achieving this objective, including, but not limited to:

- The nature of hazard types differs significantly, impacting communities with varying frequencies, severities, durations, and geographic extents.
- Hazard types contribute orders of magnitude different levels of losses. For example, average annual losses in the US from 1996 to 2019 in the Spatial Hazard Events and Losses Database of the United States (SHELDUS) from Hurricanes were $12.4 billion versus $4 million for Tsunamis (Arizona State University Center for Emergency Management and Homeland Security [ASU CEMHS] 2020).
- Hazard occurrence can result in a wide range of consequence types (e.g., injuries, fatalities, property damage, crop and livestock damage, and lifeline disruption).
- Available source datasets characterizing historic or expected hazard occurrences vary across hazard types in format, quality, period of record, geographic scope, and resolution.

To address these challenges, the team developed an overarching analytical framework; however, methods specific to hazard types were developed to address and model the variance in hazard nature, magnitude of losses, consequence types, and source data. This approach was unique and iteratively constructed for the specific needs of a national, multi-hazard risk assessment for communities. Characterization of the hazard type in terms of how it would be represented within the model was dependent on how the hazard type's occurrences were documented in the source data and how historic losses were reported. To ensure consistent EAL results across hazard types, the team ensured alignment among the annualized frequency, exposure, and HLR factors.

Losses were estimated in three consequence types: building, population, and agriculture (crop and livestock). Each hazard type was modeled to have losses in one or more of these consequence types. Impacts to buildings and population were estimated for all hazard types except drought, which only estimated agriculture losses. Additionally, agriculture losses were estimated for those hazard types where agriculture losses contributed greater than 1% of the total historic reported losses (see Fig. 2).

EAL was computed for each hazard type by evaluating the applicable losses in each relevant consequence type. All losses were quantified as an annual dollar amount. While building and agriculture losses were monetary in the source data, impacts on population were monetized into a population equivalence factor by taking fatality estimates from the source data and applying a $7.6 million Value of Statistical Life (VSL) (Zhou et al. 2020; FEMA 2009) and adjusting for inflation to 2020 dollars using the Consumer Price Index Inflation calculator (US Bureau of Labor Statistics [BLS] 2021).EAL was

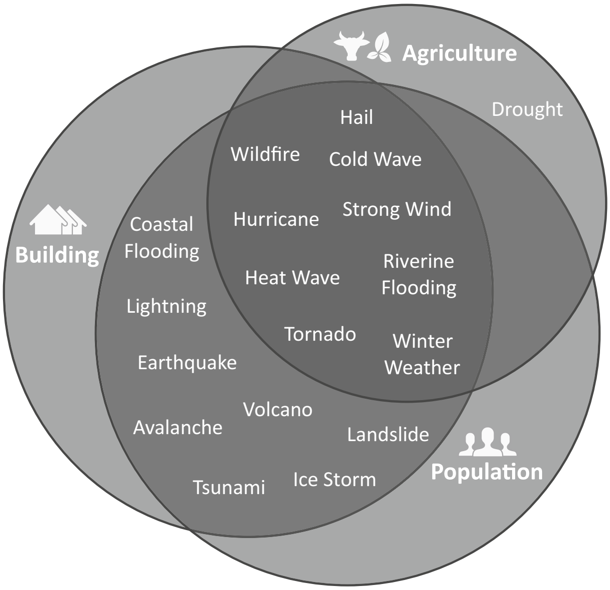


Fig. 2 Consequence types evaluated for each hazard type

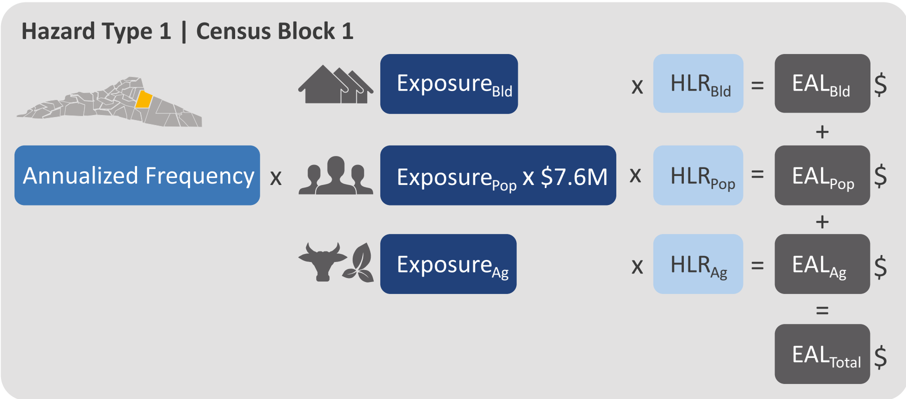


Fig. 3 Hazard type-specific calculations for consequence type and total EALs

calculated using hazard type-specific annualized frequency and consequence type-specific exposure and HLR factors using the method shown in Fig. 3. Monetization of the population consequences enabled the calculation of a total EAL, which considers all relevant consequence types for the hazard type. (Note: Each EAL factor is explored in detail in subsequent sections.)

For each community, all relevant hazard type EALs were added up to estimate composite EALs for total consequences and each of the three consequence types. Composite EALs represent the expected monetized losses from all hazard types. Hazard types with large EAL values contribute more significantly to the composite EAL than those with lower EAL values. A few hazard types often contribute most of the loss to the composite value of a community. For example, $1.35 billion of the $1.43 billion composite EAL for Los Angeles County, CA, came from Earthquake, while $73 million came from Wildfire.

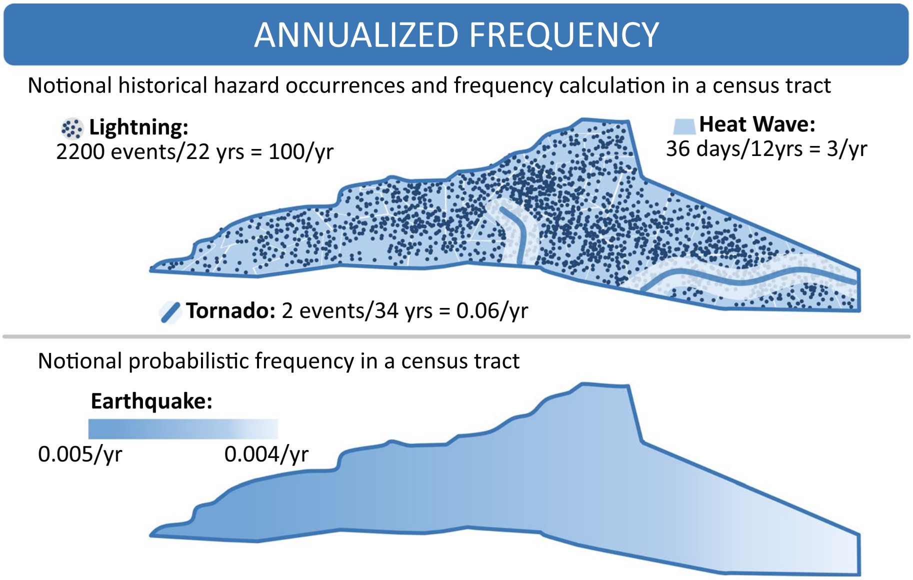


Fig. 4 Annualized frequency overview

2.2.1 Annualized frequency

Natural hazard annualized frequency is defined as the expected frequency or probability of a hazard occurrence per year. Annualized frequency is derived either from the number of recorded hazard occurrences each year over a given period or the modeled probability of a hazard occurrence each year for a given community (Fig. 4).

There were several challenges in maintaining a consistent framework when estimating frequency across hazard types, including:

- Available source datasets vary significantly across hazard types in format (e.g., points, polygons, raster), quality, period of record, and geographic scope (e.g., continental US only).
- Hazard occurrences not only cause losses over different durations (e.g., Earthquake losses take seconds, Hurricane losses take days, and Drought losses may accumulate over months), but also vary in their geographic extent (e.g., Lightning strikes impact point locations, tornadoes impact paths, and hurricanes can impact multiple states).
- Some hazard types occur frequently (e.g., Lightning), while others are rare (e.g., Tsunami).
- Some hazard types can occur in places where they have not yet been recorded.

Annualized frequency estimates for the collection of hazard types were derived from multiple authoritative data sources. The team developed a set of techniques to address the challenges for all hazard types that were combined into a tailored approach based on the unique characteristics of each hazard type and its source data. The team had to determine the geographic extent at which event counts should be aggregated to develop representative frequency estimates for a community for each hazard type. For select hazard types, frequency was modeled at the subtype level, for example by the tornado Enhanced Fujita (EF) scale.

To account for different hazard occurrence durations, frequency units were designated for each hazard. For hazard types with shorter durations (generally less than one day), historical event *counts* were used as the units for annualized frequency (i.e., events per year). For longer duration hazard types (generally more than one day), historical event *days* were used as the units for annualized frequency (i.e., event-days per year). This distinction in characterizing the frequency basis was important to ensure alignment with the calculation of the HLR, which is discussed later.

For Wildfire, Earthquake, and select Coastal Flooding subtypes, the best available source data were geocoded probabilistic statistics and return period data that were used to compute an annualized frequency. Table 3 in the Appendix identifies the source datasets and approach that was used for each hazard type.

To address challenges with geographic extent, rarity of occurrence, and potential to occur in places where hazards have not yet been recorded, the team developed three major solutions, a combination of which is used for each hazard type:

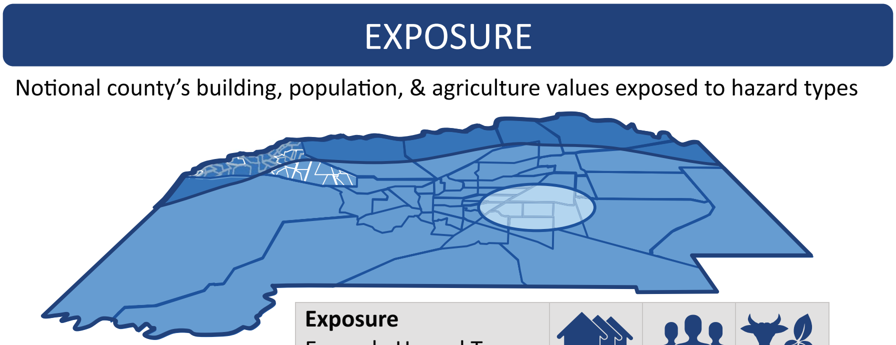
- *Hazard Occurrence Buffering* Hazard types with widespread and/or unpredictable locations were buffered using expert-determined distances to smooth the representative areas of hazard occurrence. Hazard types using this approach include Hail, Hurricane, Strong Wind, Tornado, and Tsunami.
- *Geographic Grid Aggregation* The team applied a 49-by-49 km fishnet grid[1] covering the US and counted the number of hazard occurrences (events or event-days) within each cell. Communities within the cell either inherited the count or an area apportionment of the cell count. When communities intersected multiple cells, an area-weighted count was applied. Hazard types using this approach include Hail, Hurricane, Ice Storm, Strong Wind, and Tornado. For select hazards, counts were scaled to prevent overestimation at the community level.
- *Minimum Annual Frequency* A minimum annual frequency was assigned to communities that have not experienced a hazard occurrence recorded by the source data but were determined to be at some risk. Appropriate minimum values were identified by hazard-type subject matter experts. The estimated values are low given that historic occurrences had not been recorded over the period of record. Hazard types using this approach include Avalanche, Hurricane, Ice Storm, Landslide, Riverine Flooding, Tornado, and Tsunami.

Table 3 in the Appendix summarizes the data sources and the hazard occurrence basis used to estimate annualized frequency for each of the hazard types.

2.2.2 Exposure

Exposure is defined as the representative value of buildings, population (or population equivalence), or agriculture (crop and livestock) in a community exposed to a natural hazard occurrence (see Fig. 5). Each hazard type is associated with a footprint or exposure area in which the hazard can occur and cause loss. Exposure differs across hazard types;

[1] The 49-by-49 km fishnet cell size was chosen to approximate the average area of a county.



Exposure Example Hazard Type			
Widespread Heat Wave	$250B	1.3M	$720M
Susceptible area Riverine Flooding	$90B	300K	$120M
Representative area EF2&3 Tornado	$10B	80K	$150M

Fig. 5 Exposure overview

so, the team developed three ways to define exposure: (1) widespread, (2) susceptible area, or (3) representative area or values (see Fig. 5 for examples of each). Table 3 in Appendix identifies which approach was used for each hazard type.

A widespread exposure area was used for those hazard types that either impact large, multi-county areas (e.g., Drought) or could happen anywhere in the county with similar likelihood (e.g., Strong Wind). Susceptible area exposures were used for those hazard types where there is a distinct footprint where the hazard type can occur, such as flood zones along a river or areas in proximity to a volcano.

For Tornado, representative areas were estimated using average historic occurrence footprints for three sub-types based on the EF scale: (1) EF-scale 0 and 1; (2) EF-scale 2 and 3; and (3) EF-scale 4 and 5. These representative areas were 0.78 km^2, 13 km^2, and 79 km^2, respectively. For Avalanche, a default value was applied for building and population exposure based on an analysis of historical event occurrences.

As source data varies in its native spatial representation of each hazard type, the team translated each relevant record in the source data into a spatial polygon dataset for each hazard type. Spatial processes were then used to intersect those exposure areas with Census block or Census tract boundaries to determine exposed areas for each hazard type.

Exposure values in the National Risk Index leverage FEMA's Hazus data (version 4.2 Service Pack 1) (FEMA 2018a) for building value and population estimates at each administrative reference layer (Census block, Census tract, and county). To generate exposure value estimates, the team multiplied exposure areas, either widespread or susceptible, by building and population densities. Depending on hazard type, the calculation used either average density or developed area density. Average building and population densities were calculated by dividing the building and population values by the total area, while developed area building and population densities were calculated by dividing the building and population values by the total developed area within the administrative reference layer. For agriculture, the US Department of Agriculture (USDA) 2017 Census of Agriculture

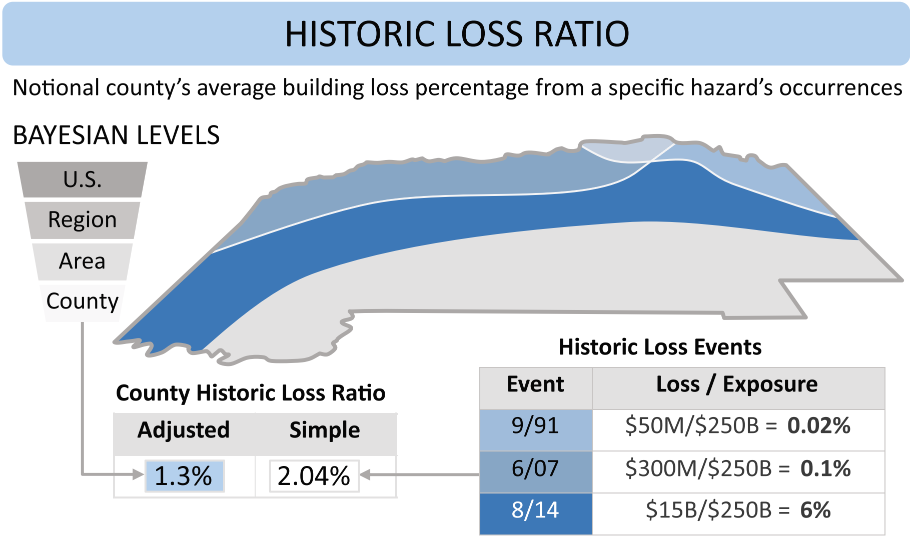


Fig. 6 HLR overview

provided an estimated dollar value of crop and livestock within each state (USDA 2019). This value was area-apportioned to each administrative reference layer. Agriculture value density was calculated by dividing the agriculture value by the total agriculture area of the administrative reference layer.

Table 3 in Appendix summarizes the relevant consequence types and the exposure area basis used to estimate exposure for each of the hazard types.

2.2.3 Historic loss ratio

HLR is a hazard- and county-specific estimate of the percentage of the exposed consequence type expected to be lost in a single hazard occurrence (see Fig. 6). This factor is developed using SHELDUS, which provides county-level data[2] for each hazard occurrence, including begin and end dates, duration, county, associated hazard and peril, property damage, crop losses, injuries, and fatalities (ASU CEMHS 2020).

As SHELDUS only records events that resulted in losses, hazard occurrences with no losses are not included in SHELDUS. Thus, because the HLR averages needed to consider all events—including those that did and did not result in losses—a number of zero-loss hazard occurrences equal to the difference between the estimated total number of occurrences and the number of occurrences that resulted in loss were added to the dataset as part of the HLR calculation process.

A county's HLR could be the simple average of loss ratios (losses divided by exposure) from past hazard occurrences. However, because there are often wide variances in loss ratios or not enough hazard occurrences for a statistically significant average, the Bayesian credibility approach (Schnieper 1995) that considers multiple geographic levels was developed. Specifically, averages and variances of the individual hazard occurrence loss ratios

[2] Note: This level of detail is more than what is publicly available on the SHELDUS website.

Fig. 7 Bayesian-adjusted HLR calculation

are calculated for each consequence type for up to four levels depending on the hazard type: (1) county, (2) surrounding area (196-by-196 km grid), (3) region, and (4) US.

The model used the average and variance values from the four levels to determine each level's weighting factor and to calculate a final, county-level Bayesian-adjusted HLR for each hazard type and consequence type using the equation in Fig. 7.

Here:

$HLR_{Building}$ is the county-level Bayesian-adjusted HLR for the building consequence type for a specific hazard type. Note: a similar formula was used to calculate population and agriculture HLRs.

$Average\ Loss\ Ratio_X$ is the average loss ratio for hazard occurrences at X level (national, regional, surrounding area, county) for the consequence type (e.g., building).

$Weight_X$ is the weighting factor for hazard occurrences at X level (national, regional, surrounding area, county) for the consequence type based on the variance of X level compared to variances at all other levels.

Figure 8 provides a representation of how loss ratios and variance impact the HLR calculation for four notional neighboring counties. In this example, the HLR for County D would be closer to County D's average, which has many occurrences of a hazard that resulted in similar loss ratios, than Counties A, B, or C, which have had few or no occurrences and greater variance in their loss ratios. The HLRs for Counties A, B, and C will receive more contribution from the higher geographic levels (e.g., surrounding area, regional, or national) due to the lack of occurrences and/or high variance in loss ratios. Not all geographic levels were used for each hazard type. Table 3 in Appendix identifies which Bayesian levels were applied to each hazard type.

2.2.4 Calculation of EAL

EAL values, quantified as an annual expected dollar loss, were computed at the Census block level for each hazard type and relevant consequence type and summed to a total EAL. The Census block-level EAL values were then aggregated to the parent Census

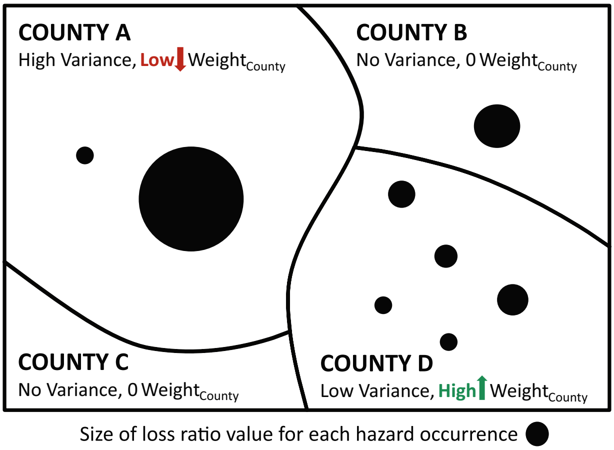


Fig. 8 Representation of how loss ratios and variance impact county weighting factors

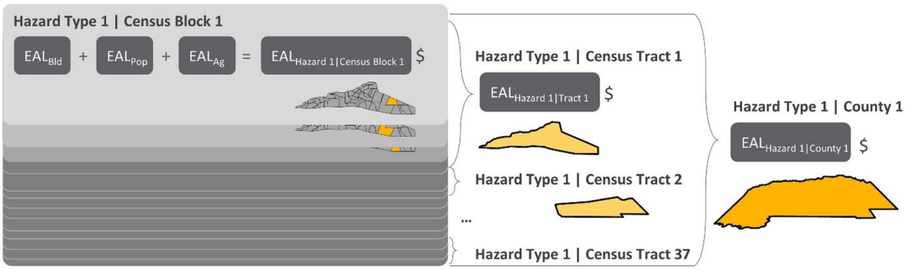


Fig. 9 Aggregation of hazard-specific census block EAL values to parent census tracts and county

Fig. 10 Aggregation of hazard-specific EAL values to composite EAL value

tract and county separately (see Fig. 9). This process was used for all hazard types except for Avalanche and Drought, which used county and Census tract, respectively, as the base EAL calculation level. For Earthquake, county and Census tract EAL values were extracted from FEMA's P-366 study data (FEMA 2017).

Additionally, a composite EAL value (for total EAL and each consequence type) was calculated by summing the EALs for the 18 hazard types for each census tract and county as shown in Fig. 10.

Table 1 Comparison of national average annual historic losses to EAL

Hazard type	Average annual historic losses	EAL	Ratio of EAL to average historic losses
Avalanche	$124 M	$56 M	0.5
Coastal flooding	$1.1 B	$1.2 B	1.1
Cold wave	$610 M	$428 M	0.7
Drought	$1.7 B	$3.3 B	2.0
Earthquake	$0.2 B	$7.2 B	**35.0**
Hail	$1.7 B	$1.3 B	0.8
Heat wave	$1.6 B	$0.9 B	0.6
Hurricane	$12.5 B	$3.7 B	**0.3**
Ice storm	$399 M	$442 M	1.1
Landslide	$212 M	$267 M	1.3
Lightning	$504 M	$500 M	1.0
Riverine flooding	$7.1 B	$4.7 B	0.7
Strong wind	$2.0 B	$1.3 B	0.6
Tornado	$3.3 B	$5.1 B	1.5
Tsunami	$4 M	$5 M	1.3
Volcano	$2 M	$117 M	**51.8**
Wildfire	$1.8 B	$1.6 B	0.9
Winter weather	$517 M	$297 M	0.6

Bolded ratios are beyond a factor of two

2.2.5 Comparing EAL to historical losses

To gauge the accuracy of EAL values, historic losses from SHELDUS for the period from 1996 to 2019 were annualized for a national loss estimate for each of the hazard types. When compared to the aggregated total EAL estimate, all hazard types, except Hurricane, Earthquake and Volcanic Activity, were within a factor of two (see Table 1). These exceptions existed because losses for those hazard types are driven by relatively few hazard occurrences. For example, from 1996 to 2019, 75% of all Hurricane consequences were caused by only seven storms. These hazard occurrences are statistical outliers where high-value urban areas were impacted by severe hazard occurrences.

Similarly, from 1996 to 2019, the US had only one earthquake that exceeded one billion dollars in property loss: the 2001 Nisqually earthquake that impacted King, Pierce, and Thurston counties in Washington (ASU CEMHS 2020). Through use of national probabilistic data, the potential for major earthquakes in other parts of the country, such as Los Angeles and San Francisco, was recognized, and the probability that outlier events might occur was included. For this reason, Earthquake EAL estimates are much higher than historic losses for the period. Pursuing the development or integration of probabilistic data for additional hazard types, such as Hurricane and Riverine Flooding, could significantly improve the risk profiles.

Despite these outliers, the relatively high level of agreement between the calculated EAL values and the historical loss records shows that the EAL estimates are well aligned with actual recorded historic losses.

2.3 Social vulnerability and community resilience

Communities are impacted differently by natural hazards. To address the inequities of disaster impacts, the National Risk Index includes *social vulnerability* as a community-specific coefficient that increases risk and *community resilience* as a community-specific coefficient that decreases risk. The use of these parameters to increase or decrease the community Risk Index scores is consistent with emerging approaches for modeling natural disaster risks (Lavell et al. 2012). The National Risk Index accounts for social vulnerability and community resilience with the University of South Carolina's Social Vulnerability Index (SoVI) and Hazards and Vulnerability Research Institute's Baseline Resilience Indicators for Communities (HVRI BRIC) index, respectively.

SoVI is a location-specific assessment that utilizes 29 socioeconomic variables contributing to a community's reduced ability to prepare for, respond to, and recover from hazards (University of South Carolina 2021a). To construct the index, SoVI converts variable values from this initial set into z-scores and applies a principal components analysis that reduces their dimensionality to a smaller set of statistically optimized components. Then SoVI implements an additive model over these components to adjust their cardinality and arrive at the final result (Cutter et al. 2003). SoVI values range from − 19.944 to 42.589 for Census tracts and from − 9.73 to 15.64 for counties.

The HVRI BRIC dataset includes a set of 49 indicators that represent six types of resilience: social, economic, community capital, institutional capacity, housing/infrastructure, and environmental (University of South Carolina 2021b). To construct the index, HVIR BRIC uses linear min/max scaling to standardize the units of each variable along an interval from 0 (less resilient) to 1 (more resilient). Then HVIR BRIC calculates the mean of these scaled values within each resilience-type and their sum determines the result (Cutter et al. 2014). HVRI BRIC values range from 2.059 to 3.233. HVRI BRIC values are only available at the county level, so each Census tract was assigned the value of its parent county.

These two indices include some related data inputs but are conceptually distinct. While SoVI examines population characteristics to understand vulnerability of individuals to disaster, HVRI BRIC incorporates measures of social, economic, and institutional resilience and community capital (Cutter et al. 2010). At the county level, SoVI and HVRI BRIC index values have low statistical correlation (Pearson's correlation coefficient of − 0.26), statistically confirming their conceptual distinction.

2.4 Risk calculation

Individual hazard-type Risk Index scores and a composite Risk Index score were calculated for each Census tract and county using the process shown in Fig. 11. These scores measured the relative risk of a community to that of all other communities at the same level (Census tract or county). EAL, SoVI, and HVRI BRIC values used different scales and units. To combine them, their unit values were independently normalized to a range of 0 (lowest possible value) to 100 (highest possible value). To achieve this range, the values of each component were rescaled using a min–max transformation, which preserves their distribution while making them easier to understand. EAL values can span several orders of magnitude between rural and urban communities. To address this, a cube root transformation was applied before min–max normalization.

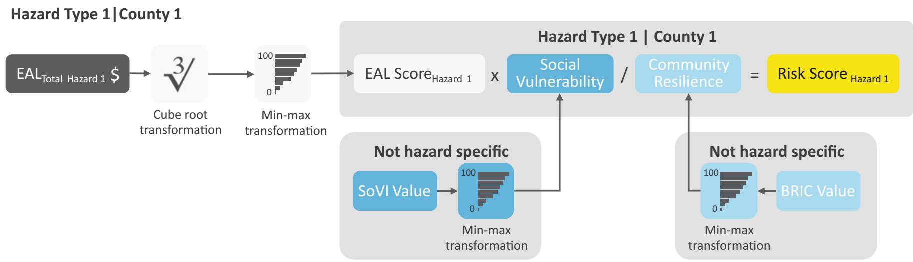


Fig. 11 Calculation of a hazard-type risk score for a county

The cube root transformation controls for this characteristic and provides scores with greater differentiation and usefulness (Hoyle 1973).

Here:

EAL Score$_{Hazard}$ is a score derived from the estimate of expected losses (building value, population equivalence, and agriculture value) each year from the hazard type.
Social Vulnerability Score is derived from an index value of demographic characteristics that measure a community's susceptibility to the adverse impacts of natural hazards.
Community Resilience Score is derived from an index value of demographic characteristics that measure a community's ability to prepare for, adapt to, withstand, and recover from natural hazards.

A composite, multi-hazard Risk Index score is calculated using the same process with the EAL$_{\text{Composite}}$ value. This represented the risk of a community for all hazard types relative to all other communities at the same level (Census tract or county).

Additionally, a five-category qualitative rating was provided that describes the nature of a community's score in comparison with all other communities at the same level, ranging from "Very Low" to "Very High." To determine the content of each rating category, an unsupervised machine learning technique known as k-means clustering or natural breaks was applied to each score: Risk Index, EAL, Social Vulnerability, and Community Resilience. For each score, this approach divided all communities into five groups such that the communities within each group were as similar as possible (minimized variance) while the groups were as different as possible (maximized variance).

Since the value ranges associated with each rating category are assessed independently for each component and score, there were no fixed numeric values for each category. For example, a county's risk score for Tsunami could be 6.2 with a rating of "Very Low," while its risk score for Riverine Flooding could be 3.3 with a rating of "Relatively Low." The rating is intended to classify a community for a specific component, relative to all other communities at the same level.

Figure 12 shows the standard color schemes for each rating category, illustrates how component ratings impact risk ratings, and provides several illustrative examples of EAL, Social Vulnerability, Community Resilience, and Risk Index scores and rating categories for ten representative counties.

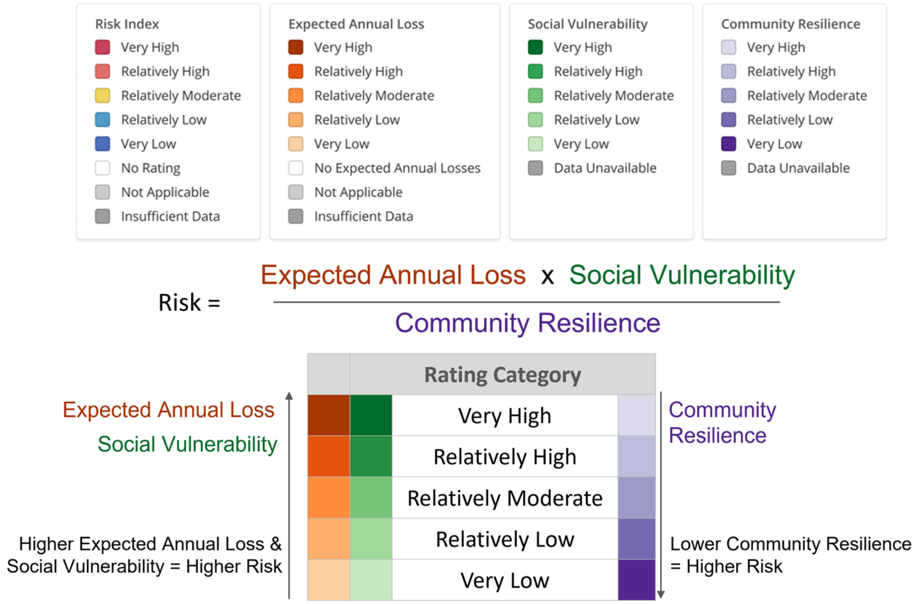


Illustration of Risk Component Scores

County	Expected Annual Loss	Social Vulnerability	Community Resilience	Risk
County 1	100	45	52	100
County 2	26	94	58	55
County 3	54	48	35	51
County 4	16	92	56	37
County 5	32	36	44	24
County 6	22	45	43	22
County 7	9	69	59	15
County 8	25	21	57	13
County 9	10	44	45	9
County 10	16	4	39	1

Fig. 12 National risk index qualitative rating legend and illustration of risk component scores

3 Results and discussion

The National Risk Index methodology produced baseline natural hazard risk assessment information; however, without a user-friendly application to view the data, it was difficult to ensure that the risk scores, ratings, and underlying data and calculations could be understood and used by the target audience. To fulfill this need, a web application was designed using a multidisciplinary and collaborative approach that adopted principles and methods from user-centered design (UCD), user experience (UX), usability, and design thinking (Rosenzweig 2015; Narang et al. 2017; Rubin and Chisnell 2008; Argyle et al. 2017; Lathrop et al. 2014; Lanter and Essinger 2017; Morgan 2016; Steuri et al. 2020). This approach facilitated an iterative design of the risk communication methods based on the latest data.

Representative target users and experts were involved throughout the web application development process to get real time feedback and insights to verify that the presentation of results in the application was understandable, useful, and simple to use, and that the application provided a positive user experience. An early investigation into the adoptability of the National Risk Index as a decision support tool found that perceived simplicity and usefulness would increase the likelihood of a local practitioner adopting it for risk management activities. Feedback also indicated that users' ability to understand the information would influence their likelihood to use it in future decision making.

Through the many meetings with potential users and experts, the team identified the results that would be useful for informing a variety of decisions, and designed the web application to present risk information and data in a way that would inform these decisions, including:

- Enhancing hazard mitigation plans.
- Encouraging community level risk communication and engagement.
- Supporting the development or enhancement of codes and standards.
- Informing long-term community recovery.
- Educating new homeowners and renters.
- Prioritizing and allocating resources.
- Identifying the need for more refined risk assessments.
- Informing the insurance and mortgage industries.
- Updating emergency operations plans.

It was a challenge to create a web application for the National Risk Index that was useful for practitioners and decision makers, easy for the public to understand, and able to withstand the scrutiny of academic and scientific communities. To achieve these objectives, the following features were included:

- An interactive web map using a Mercator projection[3] to visually explore the results.
- A feature to create printable reports with risk information for a single community or multiple communities to enable comparisons.
- Downloadable nationwide and state-level datasets at the county and Census tract level in tabular (csv) and spatial (shapefile and geodatabase) formats.
- Summary and technical documentation explaining the methodology, source data, and data processing methods, as well as information and guidance on use.

Feedback and other insights from potential users of the application and experts informed the presentation of scores, ratings, and underlying data in the web map and reports. Aspects of the application's presentation of risk information influenced by users and experts include:

- Qualitative rating labels.
- Presenting normalized risk scores out of their maximum (out of 100) and alongside minimum and maximum scores in the dataset.
- Presenting national and state average scores and a community's relative position when compared to the rest of the US and relevant state.
- Progressively disclosing a community's risk information by initially presenting an overview followed by the underlying data that supports the overview.

[3] The National Risk Index application presents results using a Mercator projection because it is a common, native format for web-based geographic information systems (GIS). An Albers projection is used for all geoprocessing in the calculation of risk.

Table 2 Composite and hazard-type risk index scores for several sample counties

Hazard	Los Angeles County, CA	Harris County, TX	Oklahoma County, OK	Essex County, NJ	Rolette County, ND	Juneau City and Borough, AK
Composite	100	80.6	32.5	21.9	13.3	3.9
Avalanche	7.8	NA	NA	NA	NA	11.5
Coastal flooding	2.9	20.7	NA	25.4	NA	2.9
Cold wave	NR	NR	NR	NR	70.8	NR
Drought	0.5	13.8	10.3	2.1	6.0	NR
Earthquake	100	8.1	12.6	12.4	0.5	4.2
Hail	11.1	34.1	70.7	11.8	14.8	NR
Heat wave	18.0	23.5	40.7	19.0	10.7	NR
Hurricane	NA	100	4.2	12.0	NA	NA
Ice storm	19.4	12.1	71.0	24.7	24.3	2.8
Landslide	7.6	5.9	5.0	15.3	18.4	ID
Lightning	33.4	60.9	30.5	34.3	13.2	ID
Riverine flooding	20.4	100	25.3	17.2	5.8	3.3
Strong wind	20.5	23.3	22.6	42.1	17.9	NR
Tornado	37.1	100	53.8	36.8	15.4	0.2
Tsunami	25.4	NA	NA	NA	NA	6.2
Volcano	NA	NA	NA	NA	NA	NA
Wildfire	89.6	11.8	15.0	2.5	19.2	ID
Winter weather	14.5	65.3	43.9	44.8	62.9	10.5

Depending on the specific need, users can view the scores and ratings through a variety of lenses: (1) hazard type risk or EAL rankings within a community, (2) community risk or EAL rankings within a hazard type, and (3) community risk or EAL rankings across all hazard types. Example results are included Table 2. Figure 13 contains the national maps for the composite EAL and Risk Index ratings for both counties and Census tracts from the National Risk Index November 2021 release (version 1.18.1).

Table 2 compares the composite and hazard type-specific Risk Index scores and ratings for six counties with differing profiles. Communities will not have risk scores for select hazards based on the reasons below:

- *Insufficient Data* (*ID*) Hazard, social vulnerability, or community resilience source data are not available.
- *Not Applicable* (*NA*) Community is not considered at risk for hazard type.
- *No Rating* (*NR*) EAL, and therefore risk, is zero.

Risk Index scores represent risk to the entire community relative to all other communities at the same level; thus, communities with higher exposure (i.e., more to lose) will often rank higher. For example, Los Angeles and Harris County are the two highest risk counties, but they are also ranked 1 and 3 respectively in both total population and building value, which means they have a very high exposure compared to smaller and less populated counties. The risk scores are not per

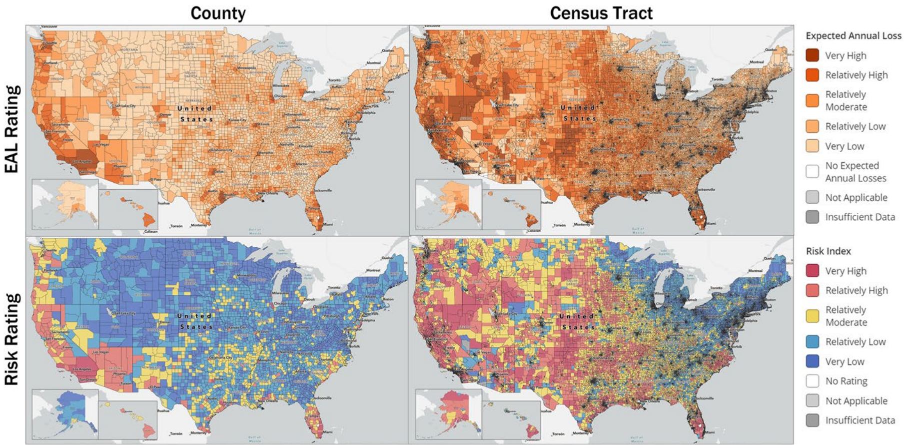


Fig. 13 Composite EAL and risk index ratings for census tracts and counties

capita measures. However, the web application provides data for download so that users can calculate a per capita or exposure-adjusted measure based on their needs.

The Risk Index results are not predictive; rather they provide comparisons between communities and hazard types largely based on historical event data. To evaluate the accuracy of results, the team conducted review sessions with more than 40 experts from federal partner agencies and academia with expertise spanning multiple facets of risk methodology and communication, specific hazard types, and source data. Experts reviewed multiple iterations of individual hazard type and composite Risk Index results as well as the EAL, Social Vulnerability, and Community Resilience scores. Expert feedback from these sessions was iteratively incorporated into the final version.

Partners and contributors supported development of the Index by providing source data, insights into datasets, and data limitations, including any methodology decisions made in their preparation. Subject matter experts identified and helped troubleshoot potential reporting biases, such as more frequent hazard occurrence reporting in urban vs. rural areas, inconsistencies in scores, and risk information for certain communities that did not align with other studies. Reviewers identified anomalies in data and provided explanations for them based on source data knowledge and experience with historic data values.

4 Conclusion

The development of the National Risk Index is a significant and meaningful first step toward establishing a baseline or minimal standard national level, multi-hazard, and multi-component measurement of natural hazard risk. Through application of best-available, national-level datasets with reliable periods of record for common hazard types found in State Hazard Mitigation Plans, the National Risk Index establishes hazard type-specific approaches using common and novel analytical techniques. The techniques are generally applied at the Census block level to integrate data for 18 hazard types, manage geographic and temporal constraints, and account for multiple consequence types. The National Risk Index uses an accepted method to calculate EAL dollars and normalized EAL scores at multiple levels of geography for each individual hazard type. Combining

EAL scores with Social Vulnerability and Community Resilience components emphasizes the importance of both natural hazard and community risk factors in any complete risk assessment. The resulting normalized Risk Index scores offer both a comparable measure of natural hazard risk at regional and national scales and a reliable resource at the community level.

The innovative approach would not have been possible without cross-disciplinary collaboration and the invaluable contributions from experts. Although the National Risk Index relies on nationally available input datasets to derive comparable risk scores, each data source was corroborated by hazard identification and risk assessment experts. Contributors brought insights from geoprocessing, actuarial science, data science, UX design, web application development, risk assessment, and mitigation planning. Periodic expert evaluation validated the vision and value of the Index, while offering crucial insights to refine and continually improve its methodology, including anticipated source data updates and identified opportunities to improve or supplement datasets.

While an important first step, there are several limitations that could be addressed in subsequent enhancements, including expanding coverage to US territories, integration of new data sources to enhance hazard representation, use of probabilistic models as they become available, modeling potential impacts of climate change, and expanding to consider other equity-related factors.

Overall, the National Risk Index provides opportunities to broaden our understanding of risk distribution at the regional and national level, and can help communities prioritize risk assessment needs, including data collection to fill information gaps or for more detailed analyses. It is a single data repository for 18 hazard types, social vulnerability, and community resilience, including the EAL dollar values used to calculate EAL scores, which are useful to local hazard mitigation planning efforts. The National Risk Index application serves as a risk communication resource and a decision-making support tool by enabling users to identify the highest risk hazard type for a community, the hazard type with the highest potential for negative impacts, or the communities with the highest potential for negative impacts. Leveraging its public availability, the team will solicit feedback from users to identify improvements and enhancements to the index and application (e.g., alternate risk metrics like per capita EAL). Additionally, the team will explore ways that the national results can be supplemented with local datasets to better inform local decisions. Lastly, the National Risk Index is also intended to inspire the risk assessment community to pursue new and innovative products to supplement the National Risk Index and further support risk reduction.

Appendix: Hazard methodology summary

Table 3 summarizes key facets of the modeling approaches for annualized frequency, exposure, and HLR that were applied to each of the hazard types.

Table 3 EAL factor methodology summary for each hazard type

Hazard type	Annualized frequency		Exposure				HLR			
	Data source	Hazard occurrence basis	Consequence types			Exposure area	Bayesian levels			
			Building	Population	Agriculture		County	Area	Region	US
Avalanche	ASU CEMHS (2020)	Event	✓	✓		*Representative exposure*	✓			✓
Coastal flooding	FEMA (2018b), NOAA 2018), NHC 2018a), NHC 2018b)	Event	✓	✓		*Susceptible Area*: Developed area in coastal flood footprints	✓	✓	✓	
Cold wave	NWS (2018), ISU (2018)	Event day	✓	✓	✓	*Widespread*: Average hazard occurrence size	✓	✓	✓	✓
Drought	NDMC (2018)	Event day			✓	*Widespread*: Average hazard occurrence size	✓	✓	✓	
Earthquake	FEMA (2017)	Event Probabilistic	✓	✓		Expected annual loss and exposure from FEMA 366 study	✓	✓		✓
Hail	NWS (2017a)	Event	✓	✓	✓	*Widespread*: County/Census tract area	✓	✓	✓	✓
Heat wave	NWS (2018), ISU (2018)	Event day	✓	✓	✓	*Widespread*: Average hazard occurrence size	✓	✓	✓	✓
Hurricane	NHC (2018b)	Event	✓	✓	✓	*Widespread*: Average hazard occurrence size	✓	✓	✓	
Ice storm	USACE (2014)	Event day	✓	✓		*Widespread*: Average hazard occurrence size	✓	✓	✓	✓
Landslide	NASA (2021)	Event	✓	✓		*Susceptible area*: Landslide susceptible area	✓			
Lightning	NCEI (2017)	Event	✓	✓		*Widespread*: County/Census tract area	✓	✓		✓
Riverine Flooding	NCEI (2020)	Event day	✓	✓	✓	*Susceptible area*: 1% annual chance floodplain	✓		✓	
Strong wind	NWS (2017b)	Event	✓	✓	✓	*Widespread*: County/Census tract area	✓	✓	✓	✓

Table 3 (continued)

Hazard type	Annualized frequency		Exposure				HLR			
	Data source	Hazard occurrence basis	Consequence types			Exposure area	Bayesian levels			
			Building	Population	Agriculture		County	Area	Region	US
Tornado	NWS (2020)	Event	✓	✓	✓	*Representative Exposure*: Average historical damage size by sub-type	✓	✓	✓	✓
Tsunami	(NCEI 2018)	Event	✓	✓		*Susceptible area*: Inundation zone area	✓	✓	✓	✓
Volcanic activity	GVP (2013)	Event	✓	✓		*Susceptible area*: 100-km buffer around active volcano locations	✓	✓		✓
Wildfire	Short et al. (2016)	Event Probabilistic	✓	✓	✓	*Susceptible area*: Areas where modeled flame length > 8'	✓	✓		✓
Winter weather	NWS (2018), ISU (2018)	Event day	✓	✓	✓	*Widespread*: Average hazard occurrence size	✓	✓	✓	

Author contributions Conceptualization was done by CZ, JR, and JB. Risk methodology was done by CZ, MM, EG, and JB. Source data processing and risk methodology implementation were done by EG and MM. Manuscript writing—Original draft preparation were done by MM and EG. Manuscript writing—Review and editing were done by CZ, JR, MM, EG, NR, and JB. Application design and risk communication were done by CZ, NR, and JB. Project management was done by CZ and NR.

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Data availability Access the latest National Risk Index at: https://fema.gov/nri. Explore the latest National Risk Index data using the National Risk Index map (https://hazards.fema.gov/nri/map). The latest National Risk Index data can be downloaded from https://hazards.fema.gov/nri/data-resources. Archived National Risk Index datasets can be made available upon request by emailing FEMA-NRI@fema.dhs.gov.

Code availability Code was used for National Risk Index source data processing and application development. All code is proprietary to FEMA and cannot be shared openly.

Declarations

Conflict of interest Casey Zuzak and Jesse Rozelle (FEMA) received support from Compass PTS JV, a joint venture that includes ABS Group and CDM Smith, Inc., and FACTOR, Inc. as a subcontractor. Authors from ABS Group (Matthew Mowrer), CDM Smith, Inc. (Nicholas Ranalli), and FACTOR, Inc. (Emily Goodenough) have and continue to provide production and technical services to FEMA under federal contract awards. Authors from ABS Group, CDM Smith, Inc. and FACTOR, Inc. are consultants to FEMA and were paid for the services provided to FEMA for the National Risk Index and this submitted manuscript. Jordan Burns was affiliated with FEMA while supporting and contributing to the National Risk Index but is now a researcher at the National Renewable Energy Laboratory.

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