Resilient Cities and Structures 3 (2024) 103–113

Contents lists available at ScienceDirect

Resilient Cities and Structures

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

Review Article

Incorporating extreme event attribution into climate change adaptation for civil infrastructure: Methods, benefits, and research needs

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ARTICLE INFO

Keywords:
Climate change
Extreme weather and climate events
Extreme event attribution
Infrastructure adaptation
Uncertainties

ABSTRACT

In the last decade, the detection and attribution science that links climate change to extreme weather and climate events has emerged as a growing field of research with an increasing body of literature. This paper overviews the methods for extreme event attribution (EEA) and discusses the new insights that EEA provides for infrastructure adaptation. We found that EEA can inform stakeholders about current climate risk, support vulnerability-based and hazard-based adaptations, assist in the development of cost-effective adaptation strategies, and enhance justice and equity in the allocation of adaptation resources. As engineering practice shifts from a retrospective approach to a proactive, forward-looking risk management strategy, EEA can be used together with climate projections to enhance the comprehensiveness of decision making, including planning and preparing for unprecedented extreme events. Additionally, attribution assessment can be more useful for adaptation planning when the exposure and vulnerability of communities to past events are analyzed, and future changes in the probability of extreme events are evaluated. Given large uncertainties inherent in event attribution and climate projections, future research should examine the sensitivity of engineering design to climate model uncertainties, and adapt engineering practice, including building codes, to uncertain future conditions. While this study focuses on adaptation planning, EEA can also be a useful tool for informing and enhancing decisions related to climate mitigation.

1. Introduction

High-cost weather and climate disasters have doubled over the past four decades across the United States due to a combination of increased exposure, vulnerability, and frequency of extreme events [1]. Extreme weather and climate events are usually caused by natural climate variability, but changes in anthropogenic forcing, such as increased greenhouse gas concentrations, also contribute to the shifts in the frequency, intensity, spatial extent, duration, and timing of weather and climate extremes [2,3]. This forcing may also result in unprecedented extreme events. For example, the heatwave that impacted the Pacific Northwest area of the United States and Canada in June 2021 was as rare as a 1-in-1000-year event in today's climate. Researchers estimated that climate change increased the likelihood of such an event by 150 times [4], which was approximately a four standard deviation event [5]. Similarly, the heatwave in the United Kingdom led to unprecedented temperatures above 40ºC during July 18-19, 2022, which was found unlikely to occur without human-induced climate change [6].

Extreme event attribution (EEA) is a developing field of research that examines how human-induced changes in the global climate system affect the probability and characteristics of extreme events [7]. It brings a new perspective into climate-change attribution as existing studies are largely focused on long-term changes in climate variables, such as mean temperature, precipitation, sea level, and sea ice, rather than changes in extremes [7–9]. However, attribution of extremes is more challenging than attribution of means because (1) the influence of climate change is more difficult to detect due to the fact that extreme events are modulated by natural climate variability [10,11]; (2) there is insufficient knowledge on how dynamical atmospheric processes, such as the large-scale circulation, respond to increased greenhouse gases, resulting in low confidence and large uncertainty in modeling extreme precipitation and storms [12–15]; (3) the cause-and-effect chains for extremes

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https://doi.org/10.1016/j.rcns.2024.03.002
Received 2 October 2023; Received in revised form 8 March 2024; Accepted 9 March 2024
Available online 20 March 2024

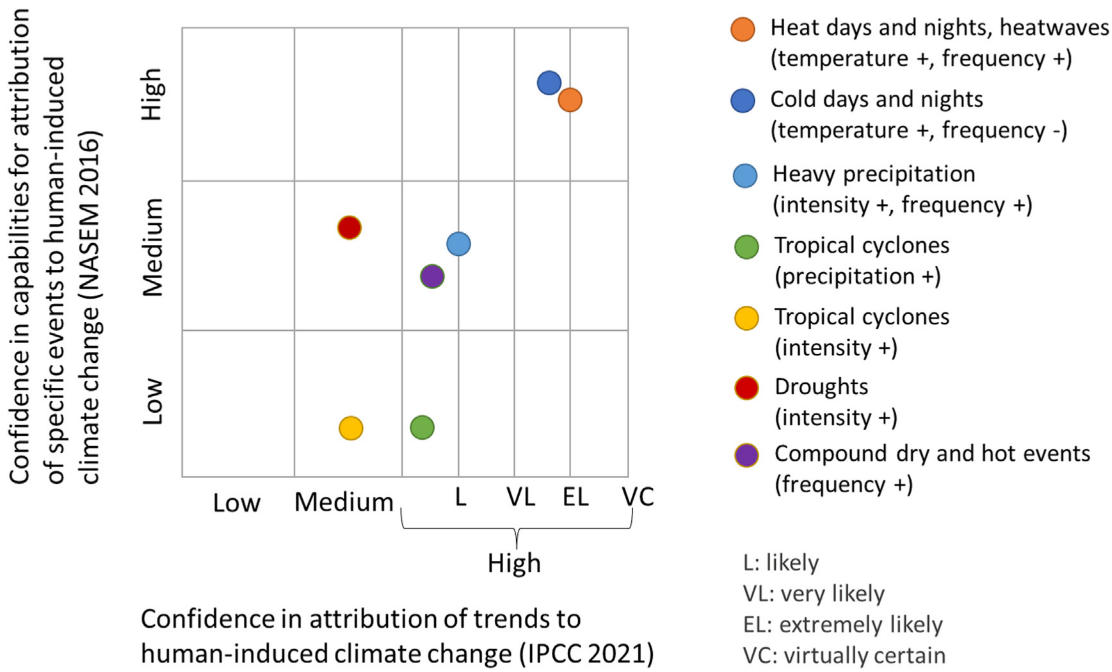

Fig. 1. Confidence in attribution of extreme events to anthropogenic climate change on global scale. "+" represents an increasing trend, and "-" represents a decreasing trend.

are nonlinear and may include instantaneous and delayed effects, which makes it difficult to quantify anthropogenic influence on the change of extreme events [9,16].

The motivations for EEA include understanding the influence of anthropogenic climate change on extreme events; convincing policymakers, stakeholders, and general public of the reality of human-induced climate change; pursuing legal liability for damages caused by past extreme events; and supporting evidence-based adaptation planning and decision making [17–27]. There has been extensive literature review on attribution methods [7,8,28–30], attribution results [2,3,9,31], and implications of EEA for climate litigation and climate policies [9,17–20,22,32,33]. However, few studies connect EEA to climate adaptation for civil infrastructure [18,26,29]. Critical infrastructure, such as energy, transportation, water and waste water, and telecommunication systems, is vulnerable to extreme event impacts because the failure in one sector can trigger cascading repercussions throughout the broader infrastructure network, leading to widespread disruptions [34,35]. The interdependence among energy, transportation, water, and communication systems further amplifies the potential for extensive disruptions when the functionality of an essential component is compromised [28,34–36]. The interplay of within-system and between-system dependences highlights the need for resilient and adaptive infrastructure planning and management [34,35].

This study provides new insights for incorporating EEA into infrastructure adaptation planning. Infrastructure planning is the process of identifying, evaluating, and prioritizing infrastructure projects that are necessary to support the growth and development of a community [37–39]. It involves the development of long-term plans for the construction, maintenance, and improvement of infrastructure systems [37]. Section 2 of this paper reviews the current state of event attribution practice. Note that this is not an exhaustive review, as this has been covered by numerous studies. Section 3 elaborates attribution methods. Section 4 discusses the state of adaptation practice with a focus on building codes, and proposes a method to incorporate EEA into risk assessment and decision-making processes. This section also outlines the benefits of using EEA in adaptation planning, and delineates the limitations of attribution analyses and future research needs. Section 5 summarizes and concludes this study.

2. State of attribution practice

The sixth assessment report of the Intergovernmental Panel on Climate Change (IPCC) [2] and the 2016 report of the National Academies of Science (NASEM) [6] all stated that the climate science community has developed a good understanding of extreme cold and heat, extreme rainfalls, and compound dry and hot events, but lower confidence for understanding droughts, extreme snow and ice, wildfires, and tropical cyclones, as shown in Fig. 1. As the climate gets warmer, the signal of climate change will likely be clearer, and hence, there will be increased confidence in attributing trends of extreme events to human-induced climate change [2].

The IPCC report [2] also suggested that the hottest temperatures may increase over continental land areas at a rate that is 1.5-2 times of global mean surface warming. Heavy precipitation events and agricultural and ecological droughts may become more frequent and intense in some regions, and this likelihood is more pronounced at higher levels of global mean warming. The maximum wind speed of extreme tropical cyclones (Category 4-5) may increase by 10 %, 13 %, and 20 %, and tropical cyclone-related precipitation may increase by 11 %, 14 %, and 28 % for global warming levels of 1.5, 2, and 4°C, respectively. Concurrent heatwaves and droughts, fire weather, and compound flooding are likely to increase as climate gets warmer (Fig. 1). Compound flooding refers to a flood with multiple drivers, such as extreme rainfall, storm surge, river flow, sea level rise, waves and tides.

Table 1 provides examples of definitions for eight types of weather and climate extremes [2,40]. It is worth noting that the results of an attribution study can be very sensitive to the event definition. Therefore, in practice, extreme events are often determined based on observed impacts on human society and ecosystems [41,42]. However, in the context of adaptation planning, defining extremes based on the probability of exceedance or the return period of an event provides a basis to evaluate the effectiveness of adaptation strategies in mitigating the impacts of climate change.

In the last decade, the science of rapid attribution has received a growing interest around the world as a way to inform the public about the links to climate change before or immediately after the occurrence of an event. The first product for rapid attribution was the Weather Risk

Table 1
Common definitions, indices, and drivers for weather and climate extremes.

Category	Definitions	Indices	Drivers
Heatwave	• Consecutive days in which maximum daily temperature is above the 90th or higher percentile of maximum daily temperature over a base period; or • Consecutive days in which daily maximum temperature is above an absolute threshold such as 35°C	Maximum and minimum daytime and nighttime temperatures; 3-day average maximum temperature; wet bulb globe temperature; heat index; number of heatwave days; warm spell duration index; combined extreme index	Large-scale meteorological pattern; land-atmosphere feedback (e.g., soil moisture, snow or ice albedo); land use change (e.g., deforestation, irrigation and crop intensification); emission of anthropogenic aerosols; the urban heat island effect
Cold wave	• Consecutive days in which maximum daily temperature is below the 10th or lower percentile of maximum daily temperature over a base period; or • A rapid fall in temperature within 24 hours and extreme low temperatures for an extended period	Maximum and minimum daytime and nighttime temperatures; number of cold wave days; snow depth; cold-degree days; wind chill index	
Extreme rainfall	• Days with precipitation above the 90th or higher percentile of local precipitation in history; or • Rainfall in 24 hours greater than a certain amount such as 100 mm	Peak rainfall; the 90th, 95th, or 99th percentile precipitation; probable maximum precipitation; maximum depth of precipitation accumulation for certain hours or days; the total precipitation accumulated from hours exceeding specified percentiles; annual exceedance probability; precipitation duration	Increase in moisture advection; decrease in atmospheric aerosols; increase in sea surface temperatures; large-scale land use change; reservoirs; irrigation; urbanization
Drought[a]	A sustained period with substantially below-average moisture conditions *The National Drought Mitigation Center* [43] *classified drought into five categories: abnormally dry, moderate drought, severe drought, extreme drought, and exceptional drought.*	Standardized precipitation-evaporation index; Palmer drought severity index; rainfall anomaly index; reconnaissance drought index; standardized precipitation evaporation index; number of consecutive dry days	Large-scale circulation pattern; global ocean-atmosphere coupled pattern; land-atmosphere feedback; precipitation deficits; soil moisture deficits; hydrological deficits; change in land cover and plant phenology
Extreme storm[b]	• Wind speed above the 90th or higher percentile of local wind in history; or • Storms that occur every 500 years	Peak wind speed; the 90th, 95th, or 99th percentile of wind speed; Saffir-Simpson hurricane wind scale	Large-scale circulation pattern (e.g., Hadley and Walker circulations, monsoon circulations); decrease in atmospheric aerosols; increase in sea surface temperatures; land use/land change impacts (e.g., surface roughness changes [44])
Flood[c]	Inundation of normally dry land *The National Weather Service* [40] *classified flood into three categories: minor flooding, moderate flooding, and major flooding.*	Peak streamflow; the 90th, 95th, or 99th percentile of daily streamflow distribution; annual maximum streamflow; number of catchments flooding simultaneously; flood synchrony scale; annual number of flood events; return period; expected number of exceedances	Land-atmosphere feedback; amount and intensity of precipitation; antecedent soil moisture; snowmelt; stream morphology; river and catchment engineering; land cover change; water regulation and management; sea level rise; waves and tides; storm surge
Compound heat and drought	Concurrent extreme heat and precipitation deficit in a region	Indices for heatwave and drought	Precipitation deficit; global warming
Fire weather or fire season	Compound hot, dry, and windy events	Forest fire danger index; Canadian fire weather index; monthly severity rating	Heat; drought; wind speed; anthropogenic ignition; biofuel abundance

[a] Droughts include meteorological droughts (due to precipitation deficits), agriculture droughts (due to soil moisture deficits), ecological droughts (due to water stress in plants), and hydrological droughts (due to water shortage in streams or storages).
[b] Storms include tropical cyclones, extratropical cyclones, and severe convective storms (e.g., thunderstorms).
[c] Floods include pluvial floods, flash floods, river floods, groundwater floods, surge floods, and coastal floods.

Attribution Forecast (WRAF) system, which generated monthly forecasts for extreme hot, cold, wet, and dry conditions across 58 territorial regions, and assessed the change in the likelihood of extreme conditions from the year 2009 to 2017 [45]. In 2015, the World Weather Attribution (WWA) group developed a protocol to deliver rapid attribution service worldwide [41,42]. This effort focuses on highly impactful events and takes into account the exposure and vulnerability of population and infrastructure [46].

Similar attribution protocols have since been initiated, but with more regional focuses. For example, New Zealand launched a project known as the Extreme Weather Event Real-time Attribution Machine in 2018, aiming to provide a national attribution service for heat and precipitation extremes within days of occurrence of the events [47,48]. The National Oceanic and Atmospheric Administration (NOAA) funded a project in 2021, intended to create a prototype rapid event attribution system for temperature-related and drought extremes in the United States and outlying territories [49]. The Australian Bureau of Meteorology has started to build a real-time Event Explainer system with a focus on regional heatwaves, and other extremes such as high-intensity rainfalls and fire weather conditions could be incorporated into the system at a later stage [50]. Results from rapid attribution can help communities to prepare for future extreme events by improving understanding of the physical drivers of these events and the health and societal impacts of these events at the community level [51–53].

However, rapid and operational attribution methods tend to use a limited number of peer-reviewed methods to ensure confidence in their results [7,9]. “Slow” attribution is often conducted afterward to update attribution statements and evaluate the robustness of rapid attribution [49]. A notable reference for “slow” attribution is the annual report of the Bulletin of the American Meteorological Society, which collects attribution studies for weather events that occurred in the past years [54]. Nevertheless, the WWA studies that have undergone peer-review have remained largely unchanged, implying that the rapid analysis can be an acceptable and useful method for event attribution [55,56].

Compound event attribution also has received a growing research interest, as many weather and climate related catastrophes are inherently of a combined nature [2,57]. Compound events are defined as the combination of multiple drivers and/or hazards that contributes to societal or environmental risk [2]. The drivers are not necessary to be extreme to cause extreme impacts [58], but researchers tend to investigate the cases of joint extremes in which all drivers exceed the 95th or a higher percentile. The well-studied cases include concurrent drought and heat [59,6], fire weather [60–62], concurrent wind and precipitation extremes [63–65], and compound flooding [66–68].

Attribution of compound events is more challenging than attribution of single events because (1) the dependence structure between contributing drivers affects the exceedance probability of compound events; (2) multivariate hazard indictors (for risk assessment) and multivariate evaluation indices (for model validation) are not available for some types of hazard combination; (3) large observational datasets are required for compound event attribution to achieve the same level of confidence as single event attribution [69,6]. In the case that observational data are scarce, process-based model simulations and reanalysis data are used to extend or replace observational datasets.

3. Attribution methods

3.1. Single event attribution

The two well-accepted methods for EEA are the probabilistic approach (or risk-based approach) and the storyline approach (or process-based approach).

3.1.1. Probabilistic approach

The probabilistic approach uses a statistical model to estimate the likelihood of the observed event occurring in the current climate and in a counterfactual climate, and thus to estimate the influence of climate change [70,71]. This can be based on a statistical model of the trend or on the output of a forced climate model, as in the storyline approach. The probabilistic approach often uses the fraction of attributable risk (*FAR*) to quantify the influence of climate change:

$$FAR = 1 - \frac{p_0}{p_1} = 1 - \frac{1}{PR} \tag{1}$$

where p_0 is the probability that the event occurs in a counterfactual world without climate change. The counterfactual world can be approximated by the pre-industrial climate conditions. p_1 is the probability that the event occurs in the actual world. PR is the probability ratio, indicating that the event is PR times more likely to occur in the current climate than in a pre-industrial climate. FAR describes the contribution of human-induced climate change to the changed likelihood of an event, that is, the proportion of occurrences in the actual world that would not have occurred in the counterfactual world.

3.1.2. Storyline approach

The storyline approach identifies the causal chain of factors leading to the extreme event and assesses the role of each factor [16,72]. The approach relies on climate model sensitivity experiments to disentangle the role of each causal factor. Two forms of sensitivity modeling experiments are commonly used: “all-but-one experiments” in which the influence of one specific factor is removed from the model, and “only-one experiments” in which only a specific causal factor is considered while the influences of other factors are removed from the model [73].

The storyline approach focuses on components that are well understood by scientists and well captured by climate models, allowing for high confidence statements about a portion of the event [16,9]. The framework of this approach is given as follows [7]:

$$PR = \frac{p_1(H)}{p_0(H)} = \frac{p_1(H|D)}{p_0(H|D)} \times \frac{p_1(D)}{p_0(D)} \tag{2}$$

where $p_1(H)$ and $p_0(H)$ are the probabilities of the hazard in the actual and counterfactual worlds, respectively. $p_1(H|D)$ and $p_0(H|D)$ are the probabilities of the hazard for the given dynamical conditions D in the actual and counterfactual worlds, respectively. $p_1(D)$ and $p_0(D)$ are the probabilities of dynamical conditions in the actual and counterfactual worlds, respectively. Extreme events are often associated with atmospheric and oceanic dynamics [2], such as through patterns of climate variability including the North Atlantic Oscillation, El Niño–Southern Oscillation, Madden-Julian Oscillation, Indian Ocean Dipole, Atlantic Multi-decadal Variability, and Pacific Decadal Variability.

The ratio of $p_1(H|D)$ to $p_0(H|D)$ describes the change in the probability of the hazard for the given dynamical conditions. The ratio of $p_1(D)$ to $p_0(D)$ depicts the change in the probability of the dynamical conditions due to climate change. The literature indicated that temperature extremes at the regional scale are dominated by mean global warming trends (e.g., thermodynamics) [2,74], but extreme precipitation and storms are largely controlled by atmospheric dynamics, such as associated with jet stream variability or mesoscale convective processes [2].

While it is theoretically possible to compute a *PR* using the storyline approach, in practice it may be impossible to accurately estimate all of the possibilities required to calculate it, and thus the method is more often used to estimate changes in the intensity of events than in the frequency [75,76]. However, when the results from storylines corroborate those from probabilistic methods, we can have increased confidence in the findings from the probabilistic study. The key advantage of the storyline approach lies in its capability to isolate the influence of specific physical aspects of climate change [75–77]. This capability is pivotal for establishing the casual chain between climate change and damage and loss [20–23], which will be discussed in the later section.

3.2. Compound event attribution

Compound events can be classified into five categories: preconditioned, where a weather-driven or climate-driven precondition amplifies the impact of a hazard; multivariate, where multiple drivers lead to an impact; temporally compounding, where a succession of hazards lead to an impact; spatially compounding, where hazards in multiple connected regions cause an aggregate impact; and complex events, where non-climatic stressors exacerbate climate hazard impacts, such as COVID-19 [78,58]. Infrastructure systems are prone to experiencing compound events due to the extensive geographical coverage of their physical structures. Moreover, the interdependency among multiple systems increases the likelihood that a single infrastructure system will be impacted by compound events if other connected systems it relies on are affected [28,34–36]. The literature has shown that concurrent heat and drought can affect hydropower generation, resulting in power shortage [79,80]. Compound heat, drought, and fire can damage infrastructure and property, reduce access to energy and water supplies, and strain firefighting resources [78]. Concurrent wind and precipitation extremes, often associated with hurricanes or cyclones, can lead to road erosion, landslides, mudslides, fallen trees and other large objects, damaging roads, bridges, signs, and traffic lights [35]. This in turn can result in costly congestion and difficult access for emergency response vehicles.

For bivariate events, the fraction of attributable risk (FAR_{xy}) can be estimated as follows [6]:

$$FAR_{xy} = 1 - \frac{p_{0,xy}}{p_{1,xy}} = 1 - \frac{P(x_0 > x^* \cap y_0 > y^*)}{P(x_1 > x^* \cap y_1 > y^*)} \tag{3}$$

where $p_{0,xy}$ is the probability that two variables in the counterfactual simulation (denoted as x_0 and y_0) exceed extreme thresholds $x^*$and y^*, respectively. $p_{1,xy}$ is the probability that the two variables in the factual simulation (denoted as x_1 and y_1) exceed extreme thresholds $x^*$and y^*, respectively. $p_{0,xy}$ and $p_{1,xy}$ are computed using the copula function, assuming that the dependence between x_0 and y_0 is the same as the dependence between x_1 and y_1. The bivariate FAR_{xy} is greater than univariate FAR_x or FAR_y when the dependency between the two variables is weak or when the two variables substantially exceed respective extreme thresholds [6].

4. Incorporating attribution analyses into climate adaptation

4.1. Climate adaptation

Adapting infrastructure to a changing climate requires that engineering practice, including building codes and standards, incorporates the latest research and data from both building science and climate science perspectives [81,82]. Governments typically enforce building codes as minimum requirements for the planning, design, materials, construction, operation and maintenance, repair, and renovation of buildings and non-building structures [35,81–83]. Current building codes largely rely on the climate conditions of the twentieth century to establish criteria for climate loads [84,81,82]. These loads reflect the hazard levels a structure could encounter throughout its life cycle, and in turn, structures are engineered to withstand these loads, ensuring safety and resilience. However, as climate patterns change, the loads likely to be encountered in the lifetime of a structure may exceed those required by building codes based on historically observed events. Reassessing and updating building codes to align with the changed climate conditions is necessary to ensure that structures can provide the desired level of safety and resilience [35,81–83]. The indices presented in Table 1 can serve as a link connecting climate-related hazards to the design of buildings and structures. For example, 15-minute and 60-minute rainfalls with 1 %, 0.5 % and 0.2 % annual exceedance probabilities (100, 200 and 500-year mean recurrence intervals) have been used to design drainage systems for roofs [85]. Flood depths for 100, 500, 750 and 1,000-year mean recurrence intervals have been used to design flood-resistant foundations for buildings and structures [85].

Several countries have begun to incorporate climate change modeling into their national building codes. For example, New Zealand's Building for Climate Change Program is investigating the robustness of modelled future climate data, the degree of conservation inherent in current building codes, and the changes needed for building codes to enable a resilient future [81]. The Standards Council of Canada is developing guidance for weather data and climate information, updating existing infrastructure standards, and investing in new technical standards concerning infrastructure adaptation and climate resilience [86,82]. In the United States, the American Society of Civil Engineers (ASCE) is working with NOAA to update design parameters and hazard mapping used in ASCE provisions and to interpret the implications of climate model uncertainties (particularly climate scenarios) in engineering contexts [84]. At the municipal level, New York City developed guidelines for using forward-looking climate data in the design of city facilities [87]. The guidelines provide a consistent methodology for engineers, architects, landscape architects, and planners to tackle three climate stressors: heat, precipitation, and sea level rise.

Most building codes address extreme events based on the probability of the occurrence of the specific event, with the design requirements varying in accordance with the potential severity of the event and the criticality of the building [81,85,87]. For example, the ASCE 7 code defines four risk categories of buildings based on the potential risk to human life in the event of failure. Each risk category is linked to specific requirements for flood, wind, snow, ice, and earthquake loads [85]. Yet some extreme events have not been considered in building codes. For example, U.S. building codes do not account for heatwaves and droughts [35]. Canada's national model codes do not consider extreme flood, wildfire, and extreme heat [81]. New Zealand's national codes do not address extreme flood, drought, bushfire, and extreme heat [81]. Japan's building codes do not take extreme weather and climate events into account at all [81]. These extremes did not have significant impacts on the built infrastructure in the past. However, given the projected changes in their frequency and severity, integrating the changing likelihood and intensity into engineering risk assessment and design concepts is important to ensure the integrity, functionality, and durability of structures and systems in the future [81,35].

4.2. Quantifying climate risk

Climate risk reflects a combination of climate-related hazards, exposure, vulnerability, and human responses to climate change [2,3]. In system engineering, climate risk is computed as a summation of possible losses due to different climate scenarios, climate stressors, and system failures [83,88,89]. Annual climate risk (R) is given as follows:

$$R = \sum_{C_c} \sum_{C_s} \sum_{F} \sum_{L} P\left(C_c\right) P\left(C_s|C_c\right) P\left(F|C_s\right) P(L|F) L \tag{4}$$

where C_c denotes climate scenarios. C_s denotes climate stressors (e.g., more frequent and intense precipitation events, heat waves, coastal flooding, and wildfires). F denotes system failure. It can refer to a single or a complex infrastructure system. L comprises direct and indirect economic losses due to physical damage of components and loss of services [39,90]. L is a function of hazard levels. $P(C_c)$ is the probability that a climate change scenario occurs. $P(C_s|C_c)$ is the probability that a stressor intensifies when climate changes, indicating the hazard. $P(F|C_s)$ is the probability of system failure when the stressor intensifies, indicating the exposure. $P(L|F)$ is the probability of loss when the system fails, indicating the vulnerability. In this paper, R denotes the absolute climate risk (the expected value at risk due to the various climate-related factors considered), and ΔR denotes the added risk due to climate change.

In the case that loss L is directly proportional to the magnitude of an extreme event (or, by extension, inversely proportional to the exceedance probability of an extreme event), ΔR can be estimated as follows [91,92]:

$$\Delta R = FAR \times R \tag{5}$$

However, the loss L is often not linearly proportional to the magnitude of extreme events [93], as shown in Fig. 2. For an extreme type under a given climate scenario (e.g., a global warming level of 1, 1.5, 2, or 4°C), where C_c is fixed and thus $P(C_c)$ equals one, Eq. 4 can be rewritten as follows:

$$R = \sum_{E} \sum_{F} \sum_{L} PR_E \cdot P(x \geq E) P(F|x \geq E) P(L|F) L \tag{6}$$

where E denotes the hazard level. PR_E is the probability ratio that adjusts the probability of experiencing an event more extreme than E from the baseline to the given climate scenario. PR_E is estimated through the attribution analysis via Eq. 1 or 2. $P(x \geq E)$ is the probability that the extreme exceeded the level E in the historical climate condition. $P(F|x \geq E)$ is the probability of system failure when the extreme exceeds the level E, which can be estimated through numerical or statistical modeling, including but not limited to simple extrapolation [39,94]. In practice, the hazard level E may consist of binned or grouped data due to the rarity of extreme events and thus limited cases available for attribution assessment. For example, wind extremes can be categorized into five levels according to wind speed: level 1 (119-153 km/h), level 2 (154-177 km/h), level 3 (178-208 km/h), level 4 (209-251 km/h), and level 5 (252 km/h and higher) [95]. Climate risk associated with a particular hazard level can be approximated from the events that fall into this range.

Fig. 2 shows a schematic of loss curves with and without climate change, highlighting the additional risk due to human-induced climate change. The shaded area represents the annual risk incurred by extreme events in a changing climate. The shaded area with a white background depicts the annual risk without climate change. The shaded area with a blue background describes the increased annual risk due to anthropogenic climate change. It should be noted that modern infrastructure systems are designed to endure frequent, low-intensity hazard events without incurring losses [34]. Losses typically occur when an event surpasses a specific hazard level, referred to as the trigger point. As the hazard level escalates, losses intensify until reaching their maximum. The hazard level that leads to the collapse of the service is called the tipping point [96,97]. Fig. 2 presents the loss curves between the trigger point and the tipping point.

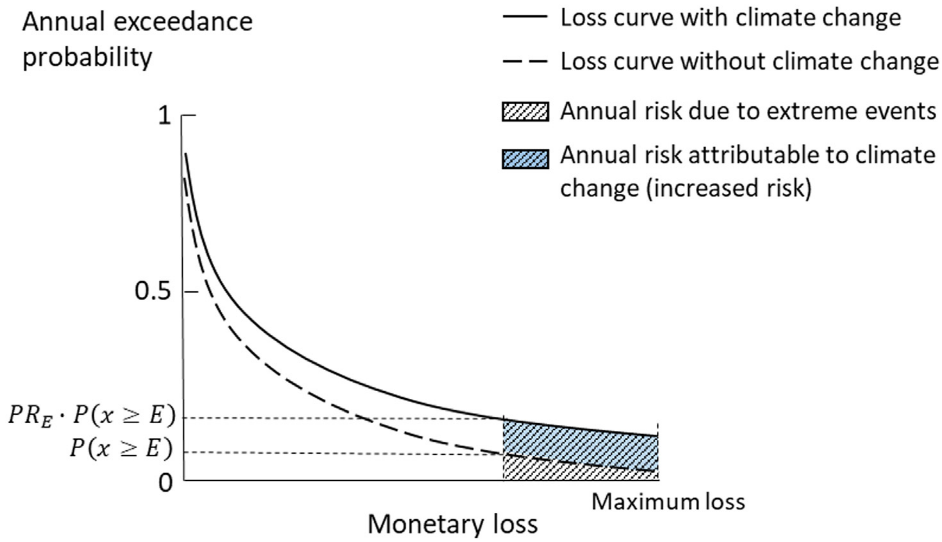

Fig. 2. Loss curve. $P(x \geq E)$ is the probability that the extreme exceeded the level E in the historical climate condition. PR_E is the probability ratio that adjusts the exceedance probability to the given climate condition. The maximum loss refers to the total property loss.

The annual risk after the implementation of an adaptation measure can be estimated as follows:

$$R_{adapt} = \sum_{E}\sum_{F}\sum_{L} PR_E \cdot P(x \geq E)P_\alpha(F|x \geq E)P_\alpha(L|F)L_\alpha \tag{7}$$

where $P_\alpha(F|x \geq E)$ is the probability of system failure after adaptation. $P_\alpha(L|F)$ is the probability of loss after adaptation. L_α is the loss function after adaptation. α is the coefficient of risk reduction due to climate adaptation, ranging from 0 to 1. In most cases, α is set by strategy designers as the target for an adaptation. For example, in order to reduce the annual climate risk for electricity systems by 50 %, strategy designers may explore options such as retrofitting existing buildings to improve their energy efficiency, increasing electricity generation and optimizing energy distribution system, and increasing the share of renewable energy in energy supply, until

$1 - R_{adapt}/R \geq \alpha$. The risk reduction coefficient α can be validated and refined through numerical and statistical modeling [88,89].

The benefit of adaptation (B_{adapt}) can be estimated as follows:

$$B_{adapt} = \sum_{t=t_0}^{T} R_{adapt}(1+r)^{-(t-t_0)} + B_c \tag{8}$$

where T is the planning horizon in the future time period, over which benefit and cost are counted [39,90]. Planning horizon is typically aligned with the expected lifespan of a building or structure. r is the annual discount rate, used to adjust future cash flows back to the present value. t_0 is the year when adaptation strategy is implemented. B_c is the co-benefit of adaptation, such as reduced losses to moderate events and other hazard types. It should be noted that Eq. 7 typically uses a static estimate for PR_E based on historical data. If PR_E is expected to increase over time, Eq. 8 will be a conservative estimate of the benefit. For example, the likelihood of exceeding a particular temperature threshold is likely to increase over time, in which case PR_E will also increase over the lifetime of the structure being designed. On the other hand, if PR_E is expected to decrease over time, which is the case for cold extremes, Eq. 8 will lead to an inflated estimate of future benefits. However, it is straightforward to allow PR_E to vary with t in Eq.s 6 and 7 so as to avoid this problem.

When the total benefit outweighs the total adaptation cost over the planning horizon, the adaptation measure is considered cost effective. It should be noted that cost-effectiveness is only one of the criteria for decision making. Other factors such as justice and equity also should be considered in adaptation planning. Justice and equity are challenging to quantify and monetize, but subjective or qualitative analysis can be employed to evaluate them.

4.3. *Advantages of attribution analyses and future research needs*

Attribution assessment offers three advantages for adaptation planning. First, EEA can support both vulnerability-based adaptation planning and hazard-based adaptation planning. The vulnerability-based approach assesses current vulnerability based on existing biophysical and socioeconomic conditions, and determines the likelihood that the community will be vulnerable in the future [98,99]. This approach is advantageous in situations with limited resources (such as time or data) or significant uncertainty in climate and impact projections. A recent report from NASEM also stated that given large climate uncertainties, it is impossible to design infrastructure to resist all future extreme events; instead, the goal should be to pick a design event (e.g., historical high-impact event) and then design systems, programs, cultures, and mechanisms to reduce suffering and accelerate recovery when the design event is exceeded [100]. Therefore, EEA can be utilized to evaluate the changing likelihood and intensity of a design event and to improve the understanding of changing vulnerability of population and infrastructure when vulnerability assessment is integrated.

The vulnerability-based approach has long been used in the development of building codes. For example, in the aftermath of catastrophic events, thorough investigations are carried out to examine the causes of building failures. The findings are then utilized to inform and recommend revisions to existing building codes with the goal to prevent similar failures in the future [101]. By integrating the knowledge of stakeholders, experts and local communities, the vulnerability-based approach enables comprehensive assessment and adaptation planning. However, it is important to note that, the vulnerability-based approach is local-focused and location-specific. Its capacity for broader-scale applications arises when a substantial number of cases are compiled, fostering a more comprehensive understanding of patterns, implications, and generalizations across various geographic contexts [98,99].

In contrast, the hazard-based approach aligns with ongoing adaptation practices that advocate for progressive enhancement of infrastructure based on the most reliable future climate projections [83]. This approach applies climate projections to impact models to assess the future failure probability of the components and systems [98,99]. The results are then used to determine the timing and level of adaptation, depending on acceptable risk levels and adaptive capacity. The results can also inform decision makers about the urgency of mitigating climate change, reducing climate risks at their source. The selection of climate scenarios represents the major uncertainty in the hazard-based adaptation planning [84]. Given the ability of EEA to project the changing probability of a type of event, the changing probability of component and system failure can be estimated. While the hazard-based approach leans more towards scientific analysis, its comprehensiveness can be enhanced by integrating non-climate factors, such as policies and socioeconomic conditions, in a later stage.

Second, the storyline approach seeks to develop a qualitative understanding of the driving factors for extreme events and the plausibility of these factors [72,75]. Recent studies suggest that the storyline approach can be applied to establish the casual chain between climate change and individual injury and property loss through a deductive process [9,22]. This could provide the evidence needed to initiate and plan for mitigating climate risks [77]. Moreover, by improving the understanding of the changes in the likelihood and intensity of extreme events already observed, EEA can motivate decision makers to account for climate change in future plans [26], and help stakeholders to develop adaptation strategies within a context of deep uncertainty caused by the varied local or regional atmospheric circulation, greenhouse gases and aerosol emission, and land cover conditions [102]. Future attribution work should address the challenge of disentangling the confounding roles of external factors [49,102], such as land use and land change, trends in anthropogenic aerosols, or multi-decadal natural climate variability, which may influence the attribution statements used for adaptation planning.

Third, EEA can promote justice and equity in climate adaptation [32,103–105,92]. Huggel et al. (2016) articulated three justice principles for climate policies: (1) Those who have contributed more to anthropogenic climate change have the responsibility of minimizing and preventing climate change impacts in proportion to the magnitude of their contribution to the problem; (2) Those who have benefited from past emissions but have not directly contributed to climate change have the responsibility of assisting those impacted by climate change; (3) The above two principles do not apply to those incapable of taking climate change measures or reducing carbon emissions [103]. Moreover, Burger et al. (2020) stated that it is reasonable to impose responsibility on upstream producers or midstream electric generators because it is easier to regulate a small group of well-informed companies than a large group of poorly informed consumers, and some of the costs imposed on upstream and midstream entities will eventually flow down to consumers [9]. In addition, fossil fuel producers and energy companies have long known about the climate risks posed by use of their products but chose to challenge the legislation aimed at curtailing production [9].

By establishing the causality between greenhouse gases and extreme events, EEA can facilitate strategic interactions across stakeholders for mitigating experienced and expected climate impacts [103,104]. Moreover, EEA can be combined with exposure and vulnerability assessments to attribute inequality of extreme event impacts to climate change [92]. Identifying inequality is essential for developing equitable and targeted interventions, policies, and strategies to address the specific challenges faced by vulnerable groups or areas. Nevertheless, some studies suggested that establishing the causality can discourage adaptation action from those who contribute little to climate change. For instance, some governmental officials ascribed the responsibility for increased disasters to major carbon emitters, and deflected their responsibility for inaction or improper action on social vulnerability issues [24,25,27]. Future research may assess the relative contributions of different sectors, activities, and entities to climate change, and focus on disadvantaged communities that suffer a high burden of climate impacts but have low capacity to adapt to climate change, so as to provide a basis for allocating responsibility for minimizing and preventing climate change impacts, and an approach for promoting justice and equity in adaptation finance and resource allocation. Table 2 summarizes the potential applications of event attribution and climate projections in adaptation planning.

Table 2
A comparison for extreme event attribution and climate projection.

Approach	Extreme event attribution	Climate projection
Outcomes	Change in frequency and intensity of a particular event or type of event due to anthropogenic climate change	Future trends and levels of climate-related hazards (e.g., frequency, intensity, duration)
Potential engineering applications	**Building code improvement.** Current building codes evaluate risk based on past weather experience and extreme events. Codes are amended after events to reduce identified vulnerability. **Strategy assessment.** Attribution results can be used to assess the cost-effectiveness of strategies designed to mitigate the impacts of anthropogenic climate change only. **Strategy optimization**. Attribution assessment helps to recognize the responsibility of stakeholders for past climate change and to optimize adaptation strategies for justice.	**Building code improvement.** Future building codes are expected to reduce climate change risk based on model projections. Design parameters and hazard mapping need to be updated regularly. **Strategy assessment.** Projection results can be used to assess the cost-effectiveness of strategies designed to mitigate the impacts of overall climate change. **Strategy optimization**. Hazard projections help to identify the regions or populations that will be most affected by climate change and to optimize adaptation strategies for social equity.

4.4. Limitations of attribution analyses and future research needs

There are three major concerns regarding the use of EEA in adaptation planning. First, EEA primarily characterizes past events because quantifying future changes in the probability of extreme events requires considerable computational resources [33]. Moreover, the shifts in the thresholds of future extremes and potential alterations in the shapes of probability distributions introduce additional complexities and uncertainties to EEA [33]. However, adaptation planning requires a good understanding of prospective risks, enabling the integration of anticipatory measures in the early stages of design and construction. This imperative arises from the limited flexibility or adaptability of many physical objects in response to evolving environmental conditions. Infrastructure, in particular, is typically designed with a lifespan of 75 to 100 years, during which their adaptation capacity is restricted by the initial construction.

Recent research has introduced several frameworks to predict probability changes of extreme events in a 1.5°C or 2°C warmer world or under other climate scenarios [33]. These frameworks offer valuable tools for preparing and planning for unprecedented events in the future, even though the confidence of attribution diminishes as the studied extremes exceed historical ranges [33]. It is worth noting that most WWA studies already include projections for changes in the likelihood and intensity of extreme events [4,106]. Moreover, attribution analyses and climate projections together could be expected to give more useful information than either attribution or projections alone. Specifically, attribution analyses are rooted in historical events with real loss data, allowing robust estimation of the costs and impacts. Climate projections foresee future changes due to both greenhouse gases emissions and natural climate variability, allowing for comprehensive evaluation of climate-related hazards.

Second, EEA can lead to adaptations in sectors and regions with most attributable impacts to climate change rather than sectors and regions that are most vulnerable to weather and climate extremes [17]. The most attributable impacts to climate change are illustrated in Fig. 1, including extreme cold and heat events. Heatwaves have resulted in significant death tolls and social impacts in the last two decades [107]. However, winds and floods pose a greater threat to properties and assets across the world, accounting for two thirds of economic losses from climate-related hazards during 1980-2016 [108]. It is important to recognize the various impacts arising from extreme events, such as mortality rates, population displacement, property loss, and economic losses. Emphasizing one aspect while neglecting others may lead to an incomplete understanding of the overall impact. In less developed regions, while addressing climate change is undoubtedly a critical concern, basic infrastructure needs must not be neglected, because inadequate infrastructure can hinder social and economic progress, limiting access to education, healthcare, and economic opportunities [109,110]. Unreliable infrastructure can impair emergency response, disaster resilience, and sustainable urban development [111]. Therefore, a balanced approach is needed that both meets immediate needs and incorporates long-term climate considerations.

Even without climate change, some communities can be repeatedly disrupted by disasters due to improper urban planning, infrastructure investment gaps, or systematic inequity and marginalization [35,112]. In the United States, the exposure of property and infrastructure to climate-related hazards is increasing due to urban expansion and suburban growth [113]. The vulnerability of critical infrastructure is also increasing due to the aging and deterioration of components [35,114] and increased burdens resulting from population growth without corresponding infrastructure support [115,35]. In order to provide a complete picture of climate risk, future attribution work should include an evaluation of vulnerability and exposure alongside the meteorological hazard, similar to those produced by WWA [41].

Third, EEA involves various sources of uncertainties, including differences in definitions and indices for extreme events, climate models used to reproduce the events, bias correction methods applied to climate model outputs, and unconditional (full) or conditional probability employed to depict *FAR* [116,105]. Unconditional probability or unconditional attribution uses preindustrial conditions as the baseline to evaluate anthropogenic influence on the change of extreme events. In contrast, conditional attribution presumes an initial level of anthropogenic forcing (e.g., sea surface temperature warming), mode(s) of climate variability (e.g., El Niño), or atmospheric circulation pattern, and evaluates anthropogenic influence conditioned on those presumptions, which avoids running models from preindustrial time to the present day [7,117,30].

The various sources of uncertainties can cause divergent results and low confidence of EEA results, and therefore it is a recommended practice to use the multi-method multi-model attribution approach to capture some of the uncertainties associated with event definitions and climate simulations [41,42]. Moreover, as the number of available studies increases, stakeholders will have access to a large body of evidence that may be able to give more confidence to the findings of individual studies. Future research should examine the sensitivity of engineering design to uncertainties in climate modelling, and investigate the level of conservation (e.g., coping range, adaptive capacity) required by building codes to provide adequate protection in an uncertain world.

5. Summary and conclusion

Extreme weather and climate events have become more frequent and more intense in recent decades. Extreme event attribution provides an explanation for these observed changes from the meteorological and long-term climatological perspectives, and answers the question whether and to what extent the increase in greenhouse gas concentrations has affected the probability and magnitude of a particular event. While there is a lack of knowledge on how dynamic atmospheric processes respond to increased greenhouse gases, there is already high confidence in attributing extreme cold and heat and extreme rainfall events to human-induced climate change.

In recent years, rapid event attribution services and compound event attribution have received increased attention. Rapid attribution services can provide timely information about the causes of events and vulnerabilities of communities. Compound event attribution extends the method employed in single event attribution to address more intricate and complex scenarios. Because each event is unique, there is no standard way to perform EEA. Each event definition should be carefully considered to ensure that it best reflects the observed impacts. In addition, it is a recommended practice to consider multiple event definitions, compare a hierarchy of climate models, and evaluate different modeling approaches when studying the same event [41,42]. This practice also facilities the measurement of uncertainties inherent in EEA methods.

This study proposes a method for incorporating EEA into infrastructure adaptation planning. The fraction of attributable risk and probability ratio derived from EEA can be integrated into the risk assessment framework to compute increased risk due to anthropogenic climate change via Eq. 5 or 6. This in turn can be used to evaluate the benefit-cost ratio of adaptation measures via Eq. 8. Notably, this framework can also be applied to assess mitigation measures for climate hazards and improve decision making concerning reduction of greenhouse gases. In comparison to climate projections, EEA presents additional advantages in unveiling the processes affecting the vulnerability of communities to climate change, and establishing the causality between greenhouse gases and extreme events, which may help enhance justice and equity in the allocation of adaptation resources.

Finally, this paper reviews the ongoing adaptation efforts to integrate forward-looking climate data into national building codes. Many challenges emerge throughout this process, including interpreting uncertainties of climate modelling within the context of engineering design, developing methodologies to routinely update design parameters and hazard mapping based on evolving climate projections, and developing guidelines for extremes that are not considered in current building codes but may threaten the integrity or resilience of infrastructure with continued global warming. In this context, EEA can be used together with long-term climate projections to enhance the comprehensiveness of decision making, including planning and preparing for unprecedented extreme events. Moreover, EEA can be more useful to adaptation planning when the exposure and vulnerability of communities to past events are analyzed alongside the meteorological hazard, and future changes in the probability of extreme events are evaluated for a global warming level of 1.5, 2, or 4°C or other plausible scenarios.

Declaration of competing interests

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.

Relevance to resilience

This paper overviews the methods for extreme event attribution and proposes to incorporate attribution assessment into climate adaptation through a probabilistic risk approach. These efforts could contribute to improved decision making on climate and disaster resilient infrastructure, as well as improved adaptation practice in integrating climate change information into national building codes.

Acknowledgement

We extend our sincere gratitude to the diligent reviewers whose insightful comments and constructive feedback significantly enhanced the quality of this work. Their expertise and dedication are sincerely acknowledged and deeply valued.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability

Not applicable.

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