Hype versu Historical Continuity: Situating the Rise of AI in Climate and Disaster Risk Modeling

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ABSTRACT

As governments increasingly adopt Artificial Intelligence (AI) across different application sectors, advocates argue that it will create new disruptions by democratizing access, improving accuracy, and lowering costs. In practice, uncritical adoption of AI tools has been shown to cause significant harms. Our study uses a historical lens to examine the uptake of AI in climate risk management through a study of climate and disaster risk modeling. These techniques originated in the insurance industry, but are now incorporated into many climate and disaster governance processes. Using the concept of 'insurance logics', we demonstrate that many of the original aspects of disaster risk modeling remain despite the transfer of risk assessment tools from the insurance industry to the public sector and new techniques made possible by AI. This highlights technological continuity, rather than disruption, as a key driver of contemporary risk modeling practice. Doing so helps to unsettle problematic, though challenging to identify, aspects of supposedly disruptive technologies and create possibilities for alternatives.

CCS CONCEPTS

• **Human-centered computing → HCI theory, concepts and models**.

KEYWORDS

History, Technological Evolution, Climate Risk, Disaster Risk Models, AI Hype, Responsible AI

ACM Reference Format:
Shreyasha Paudel, Sabine Loos, and Robert Soden. 2025. Hype versu Historical Continuity: Situating the Rise of AI in Climate and Disaster Risk Modeling. In *CHI Conference on Human Factors in Computing Systems (CHI '25), April 26-May 1, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 17 pages. https://doi.org/10.1145/3706598.3713985

1 INTRODUCTION

In 2021, the real estate site RedFin introduced a Flood Factor score for nearly every home on its website, providing potential buyers and sellers with that home's cumulative risk of flooding over the next thirty years, which is the typical duration of a mortgage in the United States [115]. Since then, Redfin has added risk scores for four other climate hazards: wildfires, hurricane winds, air pollution, and extreme heat. RedFin sources these scores from a non-profit climate technology startup, First Street Foundation. RedFin's partnership with the First Street Foundation is one example amongst many of the growing climate-services industry, an industry composed primarily of startup or startup-like organizations that provide climate data and tools to users across the public and private sectors. Much of this data includes information about risk due to extreme hazard and disaster events.

The growth of the climate-services industry is fueled by the promises surrounding Artificial Intelligence (AI), whose advocates claim it can make complex modeling problems more tractable by reducing cost and improving accuracy [119]. Many climate-service startups claim to leverage the power of AI in their analytics [6, 46], while others have partnered with big tech companies and non-profits to provide climate risk information as part of AI for social good and sustainable development programs [6]. However, the use of AI in other public decision-making domains, such as criminal justice, banking, and healthcare, has shown that uncritical adoption of AI may lead to significant harm and inequitable outcomes [13, 99]. These concerns remain when AI is applied to climate and disaster modeling, where risk assessment metrics from the climate service industry are purchased by a wide variety of private and public institutions and used to make decisions about financial markets, insurance rates, and infrastructure maintenance [63]. Further, products from climate-service industry are mostly proprietary and largely unregulated, leading to concerns about the veracity of their outputs and proprietary methodologies [33, 63].

Outside of climate services, concerns have been raised about the use of similar disaster risk models for public decision-making. For example, disaster impacts depend on social and political factors that are not captured by the physical determinants included in risk models [142]. Additionally, disasters often disproportionately affect marginalized groups [105]. With climate change, the uncertainty of disasters and their disproportionate impacts are expected to increase [116]. Risk models, with or without AI, ignore these complex factors and homogenize the potential impacts from disasters into quantifiable metrics of deaths, damage, and financial loss [91, 138]. Moreover, the increasing use of AI has raised concerns related to increased bias, lack of transparency, increased inequity, and surveillance [104, 106]. We argue that these concerns are interconnected, and echo prior research in crisis informatics and responsible AI that has called for a more thorough study of the practices, contexts, and sociopolitical structures that shape the design and use of these tools, along with the information infrastructures they are a part of [10, 100, 139].

CHI '25, April 26-May 1, 2025, Yokohama, Japan

ACM ISBN 979-8-4007-1394-1/25/04...$15.00
https://doi.org/10.1145/3706598.3713985

In response to calls to situate critical studies of AI within historical contexts [95, 104, 147], our study takes a historical and infrastructural lens to the practice of climate and disaster risk modeling. Of particular relevance here is that many of the techniques for modeling risk now being used by the climate services industry derive from methods for quantifying risks of natural hazards and disasters developed by and for the insurance sector. These risk models typically produce probabilistic estimates of potential losses due to future natural hazards by integrating information about physical infrastructure with their hazard exposure and economic value [101]. Originally developed by insurers in the United States to identify the potential impacts of natural hazards to their portfolios and design optimal, or profitable, insurance schemes, risk models have now also been adopted by public-sector and international development organizations [102]. Today these models are widely used to support critical policy-level decisions about the distribution of potential harm and safety, including land-use planning, infrastructure design, and disaster preparation and response processes. This shift from insurance to public decision-making was enabled by two interconnected factors: (1) technological advancements in remote sensing, cloud computing, open-source, and open data in the nineties created a global information infrastructure for computing risk, and (2) a global consensus on risk governance through disaster risk financing advocated by multinational organizations such as the World Bank and the United Nations created a use-case. Today, risk models continue to be widely and globally adopted for an expanding set of use cases, as illustrated by the opening example of RedFin.

Our study traces the influences of the insurance industry on the contemporary use of risk models for public decision-making and what that might mean for new developments in this field, including the recent turn to AI to scale and automate existing practices, new partnerships between traditional risk modelers and tech companies, and new applications in response to climate change. We conducted a document analysis of risk-modeling textbooks, technical specifications of models, risk assessment reports, and policy guidelines for disaster risk management. We find enduring continuities in the infrastructures and practices of disaster risk modeling that persist even when the technology evolved over time, and its application expanded beyond designing insurance portfolios in the U.S. to public decision-making in different geographic contexts. We present these continuities as four 'insurance logics' — calculable, financial, aggregate, and managerial — that render risk neutral, link it to financing applications, and encourage surveillance, auditing, and the removal of local context. For each logic, we describe how they have shaped the evolution of risk modeling, including its incorporation into public decision-making and the ongoing integration of AI in climate and disaster risk modeling applications.

We draw on these findings to consider how continuities, such as those conveyed through the insurance logics, as opposed to rupture, influence the uptake of technology across time, space, and application domains. These insights challenge the current hype that positions AI as a disruptive or novel technology, and draw attention instead to the ways historical and infrastructural factors have influenced the contemporary experimentation with AI in climate and disaster risk modeling. The lasting influence of insurance logics on risk models provides a demonstration of how a focus on continuity, rather than rupture, can offer insights into the possibilities and limits of technological change, including but not limited to the current enthusiasm for AI. In conversation with prior historicist work in HCI and CSCW [18, 140], we conclude with a discussion on how researchers and designers can use insights from historical continuities to not only build critical perspectives on the technologies they develop but also intervene against existing infrastructures and practices that can further create harm.

2 LITERATURE REVIEW

2.1 Historical and Infrastructural Study of Technology

While historical studies of technology have long been used within Science and Technology Studies (STS) as a method to understand trajectories of scientific change, there now is also an increasing interest within the HCI community to use such studies as inspiration for design [121, 140, 141]. Soden et al. argue that a 'historicist sensibility' [141] can help computing researchers to better understand trajectories of technological development, contingencies in contemporary sociotechnical configurations, and get inspirations for design alternatives [18, 121, 141]. A turn to history has been especially relevant in critical studies of AI and data science, where scholars have used historical case studies to highlight the politics of measurement [113], situate dominant practices of AI within longer histories of capitalist and colonial oppression [5, 125], and push back against the narrative of disruption and inevitability of AI [95, 154]. These histories of AI and big data are in conversation with much larger literature within the history of science that have interrogated practices of datafication, modeling, and measurement and repeatedly challenged linear narratives of technological progress [21, 39, 41].

Our study looks at history to ask questions about the dynamics of technology evolution, adoption, and travel. In particular, we are interested in questions of historical continuity as one technology, disaster risk modeling, travels from a very specific context — a predominantly United States-based segment of the insurance industry, to a much wider one — public decision-making in North America and around the world. One lens to do so is through the lens of infrastructure. Star and Ruhleder introduced infrastructure as a fundamentally relational concept that has a temporal and spatial reach, often emerges out of 'installed bases', and over time becomes linked with conventions of practice and taken for granted [144]. Studies of large-scale knowledge infrastructures have drawn attention to the ways these infrastructures evolve over time [72], need to be adapted to fit local needs [144], and introduce path-dependence and infrastructural biases that influence future trajectories of technology [65, 117, 136]. Another crucial aspect of this infrastructural lens is that it expands the traditional definitions of infrastructure beyond the physical and technical artifacts to include the institutions, social conditions, and human actions [83, 123].

In STS, actor-network theory has provided a set of tools to study technology travel and evolution by following the role of heterogeneous actors and their networks in the adoption and evolution of technology [80]. Relations within these heterogeneous networks are emergent and create social phenomena such as agency, knowledge, institutions, and power. These tools have been useful for examining the sociotechnical and temporal aspects of large-scale information infrastructures, including how technology travels across geographies and different use-contexts. Latour used the concept of immutable mobile to refer to technological entities that can travel from one point to the other without suffering from distortion, loss, or corruption [80]. Extending this concept, Law and Mol argue that for science (as well as technology) to successfully travel from one context to another, "they also have to be fitted into the local context — the next laboratory — in the right way." Science and technology can be mobile not only when it is immutable but "when the configuration of facts-and-context can be held stable" [82]. Sometimes, this happens through 'fluid' technology that is adaptable, flexible and responsive [38]. We draw on the concept of immutable mobiles and technological fluidity as a way to consider what remained constant and what was adapted when the use of risk modeling techniques expanded from the insurance industry in the United States to public decision-making across the world.

STS has also examined the role of bilateral development agencies and non-government organizations in imposing hegemonic technologies and imaginaries of innovation in the Global South [62, 146]. Within computing, scholars have used the lens of post-colonial theory to pay attention to the "global processes, frictions, and boundary crossings" that occur when technology travels across sociocultural contexts [112]. These questions become particularly important to understand the history of disaster risk modeling when we consider the role of international development agencies in institutionalizing contemporary risk assessment and risk governance practices in the Global South. As we will discuss, these institutions are playing an important role in the current turn to AI. While critical AI researchers have used post-colonial and historical lens to examine how (mostly) US-based private corporations are increasingly shaping agendas for AI research and adoption [14, 24, 77], this focus misses the role of pre-existing institutions and powerful actors in enabling these agendas. Our study, by situating the adoption of AI within a much longer history of the evolution and travel of disaster risk modeling, demonstrates the importance of contextualizing contemporary discourse around the emergence of AI in relation to pre-existing structures and historical continuities.

2.2 AI in Climate and Disaster Risk

There is a growing body of literature interested in the role of AI as a tool to combat or mitigate the impacts of climate change. This work suggests a range of potential applications, such as improving scientific understanding, better prediction of environmental hazards, and designing more efficient electricity grids and supply chains to reduce dependence on fossil fuels [36, 61, 119]. At the same time, critical scholars working in this area have raised concerns about the potential harms of AI, including associated carbon emissions and resource needs, and the use of AI to accelerate environmental exploitation [37, 93, 106, 156]. Others have begun to examine how AI is shaping environmental governance and decision-making, with particular attention to the potential exacerbation of structural inequalities and climate injustice due to increased reliance on algorithmic decision-making [29, 52, 104, 139]. Our study draws on these concerns to focus on a rapidly expanding area of application: the use of AI in service of efforts to develop computational models of climate and disaster risk.

The Intergovernmental Panel on Climate Change (IPCC) defines climate risk as "the potential for adverse consequences for human or ecological systems" that arises from the potential impacts of climate change, as well as human responses to it [116]. These risks are multifaceted and difficult to measure comprehensively. Most often, climate risks are measured by quantifying the impacts of climate-related hazards on affected populations and/or infrastructures [84]. The techniques for measuring climate risks in this way are closely related to the techniques for quantifying the risks of natural hazards and disasters, i.e., disaster risk modeling [81]. Generally speaking, disaster risk models use computational techniques to estimate risk in terms of the likelihood of an event and associated impact. Risk models are critical tools within a broader ideology of governance, which treats risk as an objectively knowable fact that can be quantified and managed through scientific calculations and rational decision-making [94]. This approach to risk management has been prevalent not just in the realm of climate change and disaster risk but in many areas of environmental and economic governance in modern society [11, 17, 43, 94]. Historians have noted that this form of risk governance became prevalent with the expansion of contemporary capitalism through neoliberalism, where risk models and other tools promised to enable the disciplining of uncertainties [85, 92].

A notable feature of contemporary risk governance is the role of expertise regarding the development and use of technology to characterize different risks and the crafting of solutions to manage them [17]. Historically, information technology and data practices have been an integral part of this process, especially in environmental decision-making, where maps and models determine how environmental issues are understood, as well as what becomes an environmental issue in the first place [17, 56]. Through participation in a global community of practice that includes scientists, the private sector, government, international development agencies, and many individuals who move between these sectors over their careers, experts in risk modeling wield significant influence over our relationships with nature [29, 41, 136]. In particular, historians have noted that some of the earliest motivations for risk calculation came from the desire to manage uncertainties of natural hazards in navigation and trade, ultimately leading to the development of early forms of insurance [92]. The insurance sector continues to be a major influence in shaping both the production of knowledge about climate and disaster risk [66, 74] as well as participating in the financial markets that can profit from that knowledge [32]. As we will argue, this influence serves to narrow societal understanding of climate impacts through the expert lens provided by the actuarial logics of the insurance industry [88] and is setting the conditions for the specific ways in which AI is being brought to bear on the question of climate risk.

3 BACKGROUND: CLIMATE AND DISASTER RISK MODELING

Probabilistic climate and disaster risk models, also referred to as catastrophe or hazard-impact models, are computational and mechanistic models designed to estimate the potential impacts of natural

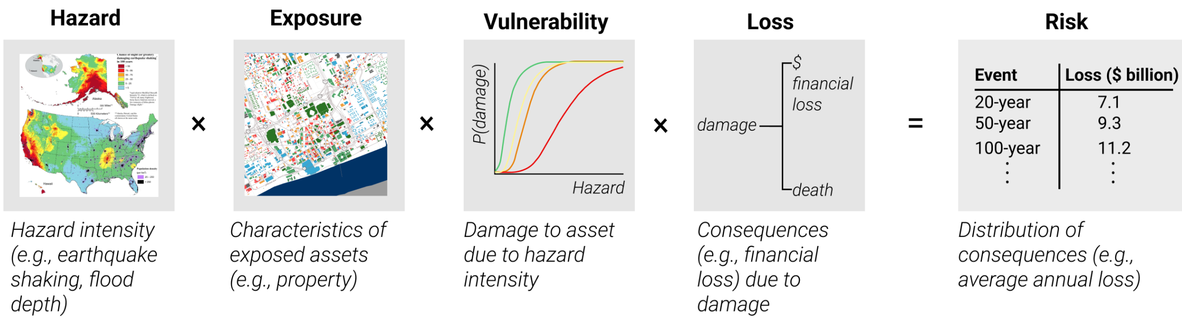

Figure 1: The components of a traditional disaster risk modeling framework

hazards such as earthquakes, droughts, hurricanes, floods, and landslides. These models combine approaches in the physical sciences to capture natural hazard frequency and severity with engineering and economics to obtain a probabilistic estimate of potential losses from future events. These computational models were originally developed to capture the risk associated with property damage for insurers and re-insurers and are still commonly used to transfer and distribute risk [58]. Today, with strong industry demand for data, and encouragement from rating agencies and regulators, nearly all financing policies covering natural disasters or man-made risk are subject to numerical modeling. Increasingly, they are also being used by governments and developmental organizations for public decision-making, such as evaluating the safety of public infrastructure (like dams or bridges), calibrating design standards (like building codes), designing land use policies, and developing early warning systems [101, 137].

A typical risk model consists of four main components, namely hazard, exposure, vulnerability, and loss (Figure 1). The hazard module simulates the probability of severity and extent of future natural hazards like earthquakes, floods, or hurricanes using scientific models and historical data from prior events [58, 129]. The second module is called exposure, which maps the distribution of assets and their characteristics that are exposed to the hazard. Examples of such assets traditionally include physical infrastructure like buildings, roads, or bridges though sometimes direct population exposure is also used. Exposure models usually comprise of large databases where physical assets are characterized by geographic location, age, structural properties, and economic value [19, 58]. The third component, vulnerability, typically consists of a model that calculates the expected damage to an exposed asset at each hazard intensity [19]. Typically, the vulnerability component is expressed through vulnerability and fragility curves for physical infrastructure. The outputs of the hazard, exposure, and vulnerability modules are modified by the loss component to provide a quantifiable consequence for the damage [102]. In insurance applications, loss includes estimates of fatalities (or deaths), infrastructural damage, business disruption, and financial losses due to damage or disruption [42, 58, 129]. In public applications, losses also include societal losses, cost of emergency response, relief administration, and long-term effects to market due to changes in property values or business climate [42]. In the end, these four components provide an estimate of probabilistic disaster risk, characterized as the probability distribution of potential future losses over a variety of hazard scenarios.

4 METHODS AND ANALYTIC APPROACH

In our study, we were particularly concerned with the following questions:

- RQ1: How does the origin of disaster risk modeling in the insurance industry influence their design and use today, especially in public decision-making applications?
- RQ2: What can we learn from this history about how this practice will evolve with new technological advancements? In particular, how has this history shaped the ways AI is being integrated within the practice of climate and disaster risk modeling?
- RQ3: Beyond disaster risk, what can such historical continuities tell us about technological evolution? How does a more realistic assessment of technological continuities help HCI and AI researchers prioritize design interventions toward more lasting social change?

To answer these questions, we started our investigation by reading scientific texts that provide an overview of the evolution of technical practices in disaster risk modeling. This included risk-modeling textbooks [9, 19, 58, 101, 102, 124] and academic papers that discuss recurrent challenges and future directions of the field [61, 76, 81, 84, 114, 126, 130, 148]. Since most of these overviews produced a singular narrative of linear progress, we sought more details about technical practices, material resources, and institutional incentives through a reading and analysis of institutional reports, which included technical specifications of risk models, risk assessment reports, and policy guidelines for disaster risk management. We primarily sourced these documents from the web archive of the World Bank Global Facility for Disaster Risk Reduction (GFDRR). As we describe in section 5, GFDRR has played an important role in enabling the use of disaster risk models throughout the world, especially in the Global South. They have also made their technical reports and model specifications publicly available as part of the commitment to open-data practices. In addition, the authors have prior experience working with and on risk assessment, open data, and machine learning projects with the World Bank and the GFDRR [49, 78, 89, 135, 138], which they draw upon as additional context to inform the analysis. The World Bank has also made its data, models, and reports publicly available as part of its commitment to open-data and open-science. In addition, we supplemented these sources with academic and activist critiques that have problematized the use of these models in climate and disaster risk financing. This helped us identify the assumptions and normative biases in the expert practices of disaster risk modeling.

Through our reading and analysis of these documents, we undertook a form of 'infrastructural inversion' [20] to identify the people, organizations, data, equations, computing platforms, and disciplinary practices that together constitute the infrastructures of disaster risk modeling. We paid particular attention to how these infrastructures have changed over time, and the resources and incentives that have enabled the use of risk modeling in the real world. We then drew on a rich body of literature from risk and insurance studies to build an analytical framework that helped us identify the influences and historical continuities on these infrastructures from the insurance industry. In subsection 4.1, we describe this framework. Then as findings, we present a general overview of the evolution of disaster risk models in section 5 and a more in-depth explanation of the insurance influences in the form of 'insurance logics' in section 6.

4.1 Analytical Framework: Insurance Logics

We build our analytical framework from studies that describe insurance as a technology for governing risk in modern society [43, 45, 122], particularly drawing on this characterization in the context of disaster and climate risk [32, 59, 145]. They define insurance as an important institution of governance that shares goals and methods with the state and is also subject to similar social forces [43, 122, 145]. This literature has examined how insurance produces knowledge of risk that is distinct from how we understand risk in everyday life. Ewold argues that insurance risk is defined by three distinct characteristics: it is made calculable, it is collective, and it is a capital [45]. In insurance, risk is calculated by objectifying everything into degrees of chance and harm, which is independent of the action of the will. This objectified number is then turned into a commodity and offered as an economic guarantee against a loss of capital [43, 45]. "What is insured is not the injury, that is actually lived, suffered, and resented but a capital against whose loss the insurer offers a guarantee" [45, p.204]. Insurance is fundamentally an economic and financial technique, used to turn future uncertainty into probabilistic estimates and a product that can be capitalized with market forces [88]. Furthermore, insurance is a fluid technology that is applied in practice in multiple ways depending on the social context and occurs through an assemblage of insurance institutions, actuarial experts, forms of insurance, and insurance imaginaries [45].

Through a collective and iterative process, we draw on this literature to identify four 'insurance logics' (shown in Table 1) that disaster risk models have inherited from their original development in the insurance industry. Our findings describe how these logics have shaped the evolution of risk modeling, including its incorporation into public decision-making and the integration of AI in climate and disaster risk modeling applications today. We argue that 'insurance logics' have shaped a particular understanding and application of disaster risk that has remained constant even as the infrastructure, practices, and context of use have evolved. Some of these understandings may pose challenges against the goals of equity and justice in disaster response and climate adaptation.

4.2 Challenges and Limitations

We note that all reading of history is partial, including the history of risk modeling that we trace below. Public decision-making about disasters across the world is varied, and our analysis has only captured a few. No doubt, there are disagreements and debates within the practitioner community that are unavailable to us through a desk study. While our analysis captures the general trend, we might have missed many specific contexts and actors as it was not possible to evaluate all risk assessment projects. For example, we focused on the World Bank, but there are other donor agencies and development and humanitarian organizations that likely conduct disaster risk assessment slightly differently. Lastly, as we note in our findings, much of the information about the models and their data is proprietary. We have tried to extrapolate based on our previous experiences with disaster risk modeling and publicly available information but we note that this is incomplete. Nonetheless, the historical account we provide aligns with how practitioners understand the evolution of their techniques [114, 124] and expands upon it with a focus on topics of interest to HCI, such as the material practices, networks of people, and sociopolitical contexts that have shaped this evolution.

5 A BRIEF HISTORY OF DISASTER RISK MODELS

Modern techniques for disaster risk modeling can be traced back to the late 1950s, when modelers in the insurance industry in the United States started combining empirical loss data, such as building damage, with physical models of natural hazards to produce a damage function that estimates the probability of property damage for a given hazard intensity [114]. In the two decades that followed, these modeling techniques developed rapidly and became standardized by the mid-1980s to Geographic Information Systems (GIS) based mechanistic and computational models. These models linked four different components together — physical models of natural hazards, exposure models of properties at risk, vulnerability curves that represented engineering-based damage functions, and economic models that estimated loss (Figure 1) [58]. The use of these models by insurance firms accelerated after large-scale disasters such as Hurricane Hugo in 1989, the Loma Prieta Earthquake in 1989, Hurricane Andrews in 1992, and the Northridge Earthquake in 1995. These disasters caused billions of dollars in damages and caused many insurance firms, especially those who did not yet use computational models, to be insolvent. Leading vendors for disaster risk models also emerged at this time [58]. By 2001, the use of risk models was standard practice in the insurance and (re)insurance industry. In addition, the availability of quantitative models for disaster risk led to the rise of new financial products like catastrophe bonds, which helped distribute risk and increase profits for the insurance providers [102].

Table 1: Insurance Logics in Disaster Risk Modeling

Insurance Logic	Definition
Calculable	Risk is made objective and calculated as a probabilistic estimate that is independent of an individual's actions
Financial	Insurance does not prevent future harms but offers an economic guarantee against loss of capital
Aggregate	Risk estimate is calculated collectively over an aggregate risk pool
Managerial	Risk governance is expert-driven and conducted at a distance using tools of surveillance and audit

Along with the widespread use of risk models in the insurance industry, these proprietary models were also made open and integrated into public decision-making by national and local governments in the 2000s. A key milestone in this was the release of the open-source platform Hazus by the United States Federal Emergency Management Agency (FEMA) in 1997 [42, 126]. Hazus is a loss estimation program for multiple hazards (earthquake, flood, hurricane), based on the same framework as one used in the insurance industry. In fact, many insurance-based risk modeling agencies were hired to develop the program [126]. Today, this program provides standardized tools and open source data for estimating risk from multiple hazards and is used by emergency managers, GIS specialists, geologists, state and local planners, consultants, academic researchers, and other stakeholders within the US [73, 126]. The open-source modules and datasets released by the Hazus program are also foundational to other risk assessment tools used for public decision-making, and have been adopted and adapted by software platforms and assessment projects used throughout the world [135].

In addition to open platforms such as Hazus, the global adoption of disaster risk models in policy and decision-making was also facilitated by the United Nations' International Decade of Natural Risk Reduction, which linked risk modeling with development goals [97], and the Intergovernmental Panel on Climate Change (IPCC) Assessment reports in 2001 and 2007, which led to heightened concerns about disaster risk as a consequence of climate change [102]. Importantly, the World Bank played the role of a key catalyst and advocate for expanding the use of these models with the establishment of the GFDRR in 2006 [135]. The World Bank established GFDRR together with a consortium of governments and other international agencies to "institutionalize sustainable and cost-effective disaster risk financing strategies" as part of the global effort towards integrating disaster risk reduction and climate change adaptation with sustainable development [35, 67]. As part of these efforts, GFDRR has provided grants and technical support for developing risk assessment platforms, regional and national risk assessment projects, and training for policymakers and disaster risk management experts [67, 135]. Following GFDRR's lead, similar projects have also been funded by other developmental donor organizations such as the Asian Development Bank, the United States Agency for International Development, the International Federation of the Red Cross, and others throughout different parts of the world [53].

In the last two decades, these models have become an important tool to shape our understanding of the risks and impacts of climate change. There is a growing recognition of the increased frequency of extreme hazard events due to climate change impact and the need to merge disaster risk management with climate change adaptation policies [116, 135]. Increasingly, this takes the form of using probabilistic models to strike the balance between reducing climate and disaster risk and transferring risk through financing mechanisms [87]. The insurance industry and risk modeling firms have continued to innovate their modeling techniques to account for increased uncertainty and long-tailed impacts due to climate change [32]. In addition, there is an emerging climate-tech industry that includes startups and non-profits that provide climate risk analytics to government agencies, developmental organizations, insurance firms, and private corporations [33, 63].

The recent advances in AI have also led experts in both public and private sectors to turn to large datasets and AI algorithms to improve the usability, efficiency, and accuracy of risk models. We found examples of AI experiments for each component of the disaster risk modeling framework (Figure 1). For example, multiple academic papers and prototype projects have used machine learning and AI to augment climate models and historical disaster data, map hazards, detect building and infrastructure exposure, and estimate socioeconomic disaster impacts [49, 71, 148]. Many consultancies and climate-tech startups that provide risk analytics claim to harness the power of AI in their websites, though it is not always clear how they do so [46]. Furthermore, big tech companies such as Microsoft, Google, and NVIDIA now offer AI-powered platforms and tools to analyze geospatial data, which they claim are being used by public agencies, non-profit organizations, and academic researchers for disaster risk management and climate mitigation [106]. Lastly, with recent breakthroughs in Generative AI, its use has been recommended for developing disaster scenarios for preparedness and developing synthetic datasets [55]. In practice, generative models are also being applied to synthesize complex geospatial data [30], understand built environment at scale [25], fill disaster loss data gaps [68], and communicate risk information to the public [108].

6 INSURANCE LOGICS IN PROBABILISTIC DISASTER RISK MODELING

Following the broad overview of the evolution of disaster risk models in the previous section, below we present a more targeted engagement with the insurance influence on disaster risk modeling practices, both in the present, and how it might evolve in the future. We present these influences in the form of four 'insurance logics' (shown in Table 1) that have shaped a particular understanding and application of disaster risk. For each logic, we describe how these logics show up in the initial design of risk models in the insurance industry, the mechanisms that allowed them to persist across geographies and new use contexts in public decision-making, and how those same mechanisms play a role in the way AI is being integrated into risk modeling today.

6.1 Calculable

In insurance, a disaster event becomes a risk when its likelihood and consequence can be calculated as a probabilistic estimate [45]. Ewold states that such risks are estimated from a dual basis: "the statistical table which establishes the regularity of certain events, and calculus of probabilities applied to that statistic, which yields an evaluation of chances of that class of event actually occurring." [45, p.202]. This logic of probabilities and statistical tables helped make the intangible problem of predicting the impact of future disasters into a tangible problem of calculating the probability of occurrence of a hazard with an estimate of measurable damage. This led to the first formulations of disaster risk, as early as the 19th century, where insurers averaged annual loss data to calculate premium rates [114]. In the 1950s, advances in hazard modeling and computational technology made it possible to create a modular framework that would first calculate the probability of the hazard process and the probable loss, and then combine it into a probabilistic model of risk [114]. These early models simulated damage using physical hazard models and then validated the estimate with historical data. Over time, this modular framework evolved into the standard equation represented in Figure 1 as researchers developed better characterizations of hazards, vulnerability, and exposure. This framework further became institutionalized through collaborations between the US FEMA and the insurance industry during the introduction of the Federal Flood Insurance Act, the National Flood and Earthquake Insurance Studies, and the introduction of national standards for damage and loss estimation such as the ATC-13 [31, 114]. Today, disaster risk is universally understood as a function of hazard, exposure, vulnerability, and loss modules (Figure 1) that encode estimates of the likelihood of different types of hazard events and their measurable consequences using a database of historical disasters, engineering information about the built environment, and a financial loss model that translates physical vulnerabilities into economic estimates [66, 129].

Calculating risk probabilistically also legitimized it as a neutral, objective, and apolitical metric. As the mathematical framework for risk modeling formalized in the 1990s, probabilistic risk models became the scientific and objective way of dealing with the inherent uncertainty of disaster risk [7]. For example, in the United States, where insurance was already an integral part of disaster risk management policy through national insurance and reinsurance programs, risk models became a useful tool to assess the costs and benefits of different plans and land-use management strategies [58]. Similarly, development organizations and disaster risk management experts in the 1990s were emphasizing a shift from post-disaster response to evidence-based disaster preparedness and risk reduction strategies [35]. Disaster risk models, which were already widely used in the private insurance industry, became a tool to identify preparedness needs and conduct cost-benefit analyses for risk reduction measures by comparing estimated average annual losses for different scenarios. A significant milestone in this transition was in 2007 when the World Bank published policy that laid a framework for developing nations to calculate disaster risk in the short, medium, and long term [50]. This document became the basis for future risk assessment projects led by the World Bank's GFDRR, which encouraged the adoption of risk assessments and their applications in disaster risk financing in many developing countries.

Key to this shift was the adaptability that came from the calculative logic and the modular structure of risk models. When risk models were used in a new location or for a new use-case, they could be easily generalized by making small changes within individual modules while reusing the standard equation in Figure 1. Risk output would be expressed in a universal format regardless of context, usually, as damage-based financial losses in a dollar amount. For example, the Hazus program included new forms of financial losses that measured public impact such as infrastructure impact and economic disruption losses [42]. Exposure databases and vulnerability modules were modified to include public infrastructures of interest instead of insurable properties [135]. Similarly, outside of US contexts, the World Bank recommended new economic metrics that were more relevant for policy-making, such as the cost of relief distribution and the loss of tax revenue at the national scale [50].

The calculative logic also allows disaster risk modelers in government and international development agencies to address critiques regarding bias and inequities by incorporating more data and designing more sophisticated models. This is one of the factors incentivizing the adoption of AI and big data techniques. We find two main ways that AI and machine learning are being integrated within today's disaster risk modeling practices to aid with the calculative logic. First, AI is frequently used to make the built environment more legible to the existing logic. For example, new machine learning models estimate building exposure at scale and across regions using openly available earth observation data from satellites and other forms of remote sensing [25]. Second, AI is also used to develop more complex models with large amounts of historical data—and in some cases historical data built using AI techniques—to better characterize impacts. For example, several data-driven models have been proposed to estimate post-disaster impacts that are not traditionally included in the loss component of disaster risk models, such as population displacement, recovery, or post-traumatic stress disorder [61, 90, 109, 120]. Similar methods have been applied to augment the loss module for pre-disaster risk assessment as well [111]. These approaches acknowledge and have the potential to circumvent limitations in existing risk modeling frameworks; however, both input and output variables continue to be limited by what impacts count as measurable and calculable. The use of AI to extend exposure and loss modules draws on the calculative logic to either scale existing calculations or turn previously unmeasured social impacts from disaster into something that can be calculated as loss.

6.2 Financial

Insurance is fundamentally an economic and financial technique that does not prevent harm, but rather offers a financial guarantee that can be enacted if harm occurs [45]. With this logic, insurance translates a technology to predict the future to a technology that profits from the inherent uncertainty of predicting the future. We find that this financial logic continues to provide the metrics to evaluate the success of a risk model. Early risk models, designed by the insurance industry, were successful if the estimated premiums for the insurance firms generated profit. With the rise of reinsurance companies and climate finance, today's models are successful if their estimates can be leveraged in public markets. This has led to a rise in disaster risk financing products such as parametric insurances, sovereign risk funds, and catastrophe and climate bonds.

Our research finds that risk financing applications were one of the first use cases for these models in public decision-making. Donor organizations like the World Bank viewed sovereign risk funds and catastrophe bonds as innovative technology for developing countries to access financial markets so that they can manage their budget volatility and liquidity crunch during large-scale disasters [51]. For example, in 2006, under the GFDRR's Multicat program, Mexico issued the first-ever parametric catastrophe bond by a sovereign nation, CatMex, to transfer earthquake risk to the international capital markets. This decision was justified using the analysis from disaster risk modeling and an economic loss simulation [26]. Similarly, in 2007, with the assistance of World Bank, the Caribbean Catastrophe Risk Insurance Facility (CCRIF) was founded. CCRIF acted as a regional risk pool with parametric insurance and access to the international market [50] and developed the open-source CAPRA (Caribbean Probabilistic Risk Assessment) platform to conduct required risk analysis. CAPRA has evolved into a comprehensive risk assessment platform for the Caribbean region and an important tool for disaster governance [50]. In the fifteen years since, the World Bank and other donors have cited CCRIF and CAPRA as innovative programs that should be adopted throughout the world and funded similar projects and platforms in many developing and low-income countries, that have resulted in other regional risk pools, catastrophe bonds, and parametric disaster insurance reinsurance programs [50, 135].

This ongoing use of risk assessment for parameterizing financial instruments has shaped the outputs of these models to primarily be estimates of potential macroeconomic effects. This has also constrained the kinds of interventions that are possible. Financialization allows one to benefit from the inherent uncertainty of predicting the future. As a result, we find that decision-makers tend to assume that insurance and disaster financing are the best approaches to cope with uncertain environmental and climate hazards [59, 145]. Such a process has reorganized measures of disaster and climate risk into speculative assets, increasingly tied to international markets, that can be leveraged for growth while conflating economic security with human security [59, 74]. The estimates of disaster risk and policies that govern them are decoupled from disaster vulnerabilities and material actions required to physically address these risks. For example, parametric insurances do not cover actual losses but instead, provide a predetermined remuneration based on specific parameters [60]. Similarly, sovereign risk funds and catastrophe bonds help create new financial resources but do not necessarily incentivize the political will to invest in mitigating long-term structural inequalities that cause the biggest disaster impacts.

On the other hand, it is difficult to find successful applications of disaster risk models outside of disaster risk financing. For example, loss estimates from Hazus have neither been found useful to change household-level behavior nor adequately estimated economic impacts to be useful to local emergency planners [27]. While we found multiple national and regional risk assessment reports, it was unclear how the results of these reports materially impacted disaster risk management and mitigation efforts outside of financing applications [110]. In their study of rebuilding and rezoning processes in Indonesia, Iuchi et al. found that regional governments encountered challenges when integrating hazard maps into risk reduction and rebuilding projects because it overlooks affected populations' priorities and livelihoods [69]. Similarly, the Oregon Department of Forestry recently withdrew a risk-based wildfire map and replaced it with a hazard map after a large public outcry over overstated risk [98]. Disaster risk practitioners have also discussed the difficulty of building and using these models in places with limited data and resources, as well as the possibility of policymakers and decision-makers, who are often non-experts, misinterpreting them [40, 61]. These challenges have also shaped the landscape of the emerging climate tech industry. We could not find examples of risk analytics startups using their products in material efforts toward disaster risk reduction or climate adaptation. Instead, most of the startups, including non-profits such as First Street Foundation, generated revenue by selling risk estimates to the real estate industry and investment firms [47, 48].

6.3 Aggregate

The aggregate logic allows the inherent uncertainty and errors in the estimate of risk to be averaged out by spreading it over a population [45]. As a result, risk estimates are only accurate when calculated over an aggregate risk pool. We find this to be the case in disaster risk models as well. For example, the standard outputs that are used as measures of risk, such as annual average loss, average number of fatalities, and loss exceedance curves, are often calculated at global, regional, and national scales and over long time horizons [42].

We find that this logic helped in the standardization of risk modeling by making it scientifically defensible to calculate exposure, vulnerability, and loss more generally without accounting for localized differences. For example, building damage is most commonly calculated using generalized fragility curves based on broad structural classes of building types [133]. While this is sufficient to calculate aggregate damage over a broad geographic area, such a model is incapable of calculating the precise risk of any individual building.

On one hand, this has created recurring challenges that make the risk estimates inadequate to meet decision-making needs. In the case of hurricane risk models for Florida, Weinkle and Pielke found substantial disagreements among different model vendors in their estimates of risk [152]. They argue that this is an inherent limitation of current scientific practice and requires political choices to choose one estimate versus another. In practice, the details of these choices are often hidden in proprietary algorithms and datasets of modeling firms, and unstated assumptions of the risk modeler. Another challenge is the lack of precise risk estimates that account for specific contexts. For example, Cooper et al. find that many national-scale flood-risk estimates fail to account for regional flood-risk dynamics, especially information that integrates projected future changes [34]. By inheriting the aggregate logic of insurance that puts all individuals who compose a population on an equal footing, risk estimates from these models also tend to obscure the disparate impact of disasters and how such impacts are shaped by social and economic inequities. For example, the payouts from CCRIF have been repeatedly found to be inadequate to meet the needs of vulnerable communities at the local scale [57].

On the other hand, the aggregate logic has also made it easier for disaster risk models to travel across geographic regions and different hazards, and especially for the models to be implemented in developing countries where data availability is limited. For example, in a national risk assessment project in Nepal, the assessment team filled data gaps in exposure and vulnerability modules by adapting literature from housing classification models developed for South and Southeast Asia, or sometimes even international standards such as ATC-13 [110]. Practitioners see this as one potential application of AI. We found examples of AI being used to develop synthetic datasets or improve geographic resolution of existing datasets as a way to fill data gaps [25]. However, the inherent uncertainty and lack of data means that these synthetic outputs will be hard to validate and identify missing context.

Furthermore, Ewold argues that the collective logic of insurance goes hand in hand with individualization [45]. While risk estimates are aggregated collectively, insurance logic simultaneously shifts the responsibility to act to an individual by calculating an individualized estimate. We find that this logic was well-aligned with the neoliberal shift in disaster governance that led US state agencies and later donor organizations to view insurance mechanisms and disaster financing as an appropriate technology for disaster response [8, 145]. Insurance mechanisms also became a policy solution to incentivize public preferences and private investments to reduce long-term risk in the absence of a precise risk estimate that could account for the disparate impacts of disasters.

6.4 Managerial

Lastly, the managerial logic refers to the way risk governance is led by actuarial experts and occurs from a distance through surveillance and auditing. Historically, the insurance industry was at the forefront of investing, developing, and using large-scale information systems long before the contemporary age of big-data [122]. This is true for disaster risk models as well—the initial versions of these models were developed through collaborations between engineers and insurance experts [130]. They were made feasible using the large-scale computing power and historical databases available from the insurance industry [102]. These models then became more accessible to use with the availability of GIS technology and open datasets about hazards, exposure, and vulnerability. Even today, most of the models are developed by a few specialized firms [74]. They are applied and interpreted by a network of technical experts—usually from a distance—through maps, models, and databases [66].

This expert community has played a significant role in expanding the use of risk models beyond insurance firms. Engineering and economic experts from the insurance industry promoted the use of these models for a broad range of applications, such as emergency response planning and land-use policy [58, 76]. In many cases, they also provided technical expertise to develop and use these models. For example, the modeling firm Risk Management Solutions (RMS) and a consortium of 30 experts acted as expert consultants to FEMA during the development of Hazus [73]. Similarly, donor organizations like the World Bank hire risk modeling firms as technical partners in many of their risk assessment projects throughout the world.

Outside of technical expertise, these experts also form a community of practice that simultaneously legitimizes the production of risk information while also creating financial incentives for its use [74]. Insurance companies and modeling firms feature academic experts on their boards and advisory committees. Top university research programs on risk modeling often get funding from the same firms [151]. Similarly, insurance representatives are included in global consortiums that publish standardized datasets, policy guidelines, and international frameworks for climate and disaster risk reduction [135]. This has shaped how disaster risk models evolve and how they are used. For example, in the last several years, donor-supported disaster financing programs have led to a surge of initiatives related to insurance and climate change, often through collaborations between private insurance and reinsurance firms, national governments, developmental organizations, and non-profits [32, 87]. Often, the donor organizations receive funds from insurance companies to fund these projects [32].

The managerial logic also continues to shape the evolution of disaster risk modeling through its technocratic focus on better science and better data. We find that governmental and development projects related to climate and disaster risk management prioritize investing in better sensors, more data, better models, and software platforms that enable better estimates of risk while ignoring policies and projects that can use these estimates for mitigation. For example, the GFDRR considers one of its main focuses to be the promotion of open data and information sharing between government agencies, the scientific community, and international experts and decision-makers, launching multiple grants for developing such platforms [75]. Most of the assessment reports published by GFDRR since its founding in 2007 recommend investing in more data and sensors to improve understanding of risk [135]. This logic is fueling today's turn to big data and AI. Risk modelers and users are trying to use remote sensing, computer vision, and machine learning to improve data resolution, reduce cost, increase precision, and get more accurate estimates of individualized risk. Most frequently this is done by augmenting AI to existing practices without fundamentally changing the process. For example, AI has been successfully applied to extract building footprint data from satellite images [25, 86]. While this has resulted in exposure datasets that have better resolution and are more frequently updated, automated labeling also removes opportunities to collect place-specific context and local understanding of disaster risks, exacerbating existing biases and inequities in the production of disaster and climate information.

7 DISCUSSION

The four 'insurance logics' that we present in the previous section illustrate the enduring continuities that continue to influence the contemporary practice of disaster risk modeling and its future evolution, despite significant shifts in users and use contexts for their outputs. We find that these insurance logics are shaping how AI is being adopted in significant, and sometimes, concerning ways. Below, we draw on these findings to discuss three observations about AI and the uptake of new technology. First, we use our insights from disaster risk modeling to challenge the perception of AI as a disruptive or novel technology and consider instead how contemporary AI hype is institutionalized and incentivized by historical continuities. Then, we use the example of insurance logics to show how historical continuities are sustained, often unintentionally and invisibly, through sociotechnical practices that are incentivized by existing infrastructures and institutional structures. We argue that rendering these specific mechanisms visible provides insights into the dynamics and power structures that shape technological evolution, including the current enthusiasm for AI. Finally, we build on these insights to further ongoing conversations about the role of HCI and design in designing against problematic practices in AI [28, 103]. HCI research and design practices can have a more lasting impact not just through the design of new technological tools, but also by interventions that unsettle prevailing infrastructures and incentives. In subsection 7.3, we offer critical reflection, design of new infrastructures, and refusal as three tactics to do so.

7.1 There is no such thing as a disruptive technology

Our study uses a historicist lens to situate the increasing adoption of AI and the resulting social concerns related to bias, hype, and privacy within the longer history of climate and disaster risk modeling [104]. Like many other areas of applications, we find significant interest and enthusiasm among disaster risk practitioners regarding the potential of AI for creating breakthroughs to solve longstanding challenges in disaster risk modeling. However, as we show, from their initial inception in the insurance industry, disaster risk models have relied on statistical methods to calculate risk. The latest iteration of risk modeling with AI is therefore a continuation of similar techniques rather than a disjuncture or paradigm shift and therefore unlikely to result in estimates of risk that account for intangible impacts, diverse sociocultural contexts, and structural vulnerabilities that are the root causes of disaster inequities and climate injustice [105].

In doing so, this study adds to the increasing body of work in HCI and critical data studies that deploy historical approaches to push back against the 'rupture-talk' [64] of AI — the narratives that position AI as a new and disruptive technology that will fundamentally change the world. It is now well-established that outputs from AI tend to be biased towards status quo due to the way they are trained and optimized [13, 14]. This body of work has also shown how current AI techniques inherit from older technologies of surveillance, control, and discrimination and replicate existing racial, gender, and class hierarchies. For example, Scheurman et al. describe automated facial analysis technologies as a new iteration of previous colonial projects and physiognomic practices [125]. These historical legacies point to the risk of enduring harm and injustices when AI is used to solve complex social problems [13, 14, 99, 107].

While there is an increasing chorus of academic and other voices that are pushing back against the hype and uncritical adoption of AI, the dominant narrative remains that AI is a transformative technology [96]. In the case of climate and disaster risk modeling, we find that AI continues to be taken up despite concerns about hype because of institutional incentives that prioritize innovation at the expense of careful consideration of impacts. For example, Moitra et al. find that disaster risk practitioners consider the pressure they face to adopt AI and position their methods as innovative as an important ethical concern [104]. Similarly, in our research, we found many examples of experimental projects, grant calls, and marketing materials that claim AI's potential to drastically transform disaster risk modeling but struggled to find real examples of such a transformation. In practice, AI was generally used as an incremental change to existing practice, usually to reduce data-processing costs or increase accuracy of existing metrics.

Narratives of disruption and the tendency to adopt technology hype, such as with AI, do not happen in a vacuum but are shaped by the normative practices, infrastructures, and institutions of the domain area. The discourse of AI disruption interacts with the existing incentives, disciplinary norms, and practices to shape expectations and concerns about AI. In the case of disaster risk, we show how the adoption of AI is being shaped by the insurance logics that have guided the design of risk models since their original inception in the insurance industry. For example, we find that AI is well-suited to solve data availability or data scalability problems within the existing hazard, exposure, and vulnerability modules but is not very useful for modeling social and political factors that are the root causes of disaster and climate injustices [105]. Thus, the use of AI is likely to entrench existing dominant practices in the application domain, instead of creating opportunities for new approaches to modeling and measurement. Such concerns are not specific to disaster risk modeling but would apply to applications of AI in many other areas of public decision-making such as criminal justice, public health, education, and social welfare. In each of these areas, critical researchers have raised concerns about the way the computational logic of AI has created feedback loops that exacerbate structural problems within the application domain [4, 15, 44, 107].

In addition, a historical lens also shows that the adoption of new technology in an application domain creates new potential for financial and regulatory capture. The implementation of AI in practice will always be embroiled in local context, history, and politics that will shape its effects. Prior research in critical AI has raised concerns about capture by big tech corporations who fund knowledge production [23, 157], concentrate data and compute [154], and shape media and regulatory discourse [24]. We find that the conditions of capture are also shaped by powerful actors and interests that already hold sway over the existing application domain. For example, insurance companies fund academic research that could lead to new scientific breakthroughs, are part of international collaborative groups developing data standards, and provide financial and technical support for risk assessment projects and platforms. Such capture is an example of the long-term effects of AI hype, which will constrain future possibilities even if the AI hype deflates [155]. We argue that it is essential to understand the specific practices and infrastructures of the different application domains to better understand the forces shaping adoption of new technologies, such as AI, and the long-term consequences of it. Taking a historical lens and tracing continuities can be one way to do so.

7.2 Historical continuities provide insights into the power dynamics that shape narratives of technological innovation

The insurance logics that we identify are sociotechnical constructs that accomplish continuities across space, time, and different use contexts. These continuities are sustained materially and discursively and often tend to represent dominant narratives and powerful interests. We find that sociotechnical continuities both persist alongside, and may even help propagate narratives of disruption. In this section, we examine the specific mechanisms and practices that allowed insurance logics to persist as disaster risk modeling was taken up in public decision-making to reflect more broadly on the relationship between historical continuities, technological evolution, and existing political context. Where do these continuities reside? How do they persist even as technological objects, practices, and use-cases change? And what do these historical continuities tell us about the forces that are shaping current technological evolution, including the turn to AI?

An obvious starting place for tracing continuities is within formalized standards. Standards are ubiquitous, yet invisible, and impose a common framework that allow information practices to be combined across geographies and application domains [143]. In our study of disaster risk models, we were able to identify insurance logics by examining the ways risk equations, loss metrics, and global datasets in the models used for public-decision making were derived from the ones used in the insurance industry. We find that the travel of these standards across use-contexts was facilitated by discourses of innovation. The development of Hazus and the GFDRR-funded risk assessment projects was based on the consensus that risk modeling was a necessary and innovative technology for dealing with natural hazards. As a result, they inherited risk modeling techniques that had stabilized in the insurance industry without critically appraising their suitability in public decision-making applications.

Once formalized, technical standards play a dual role in perpetuating continuities. On one hand, they facilitate the travel of technological objects by acting as an 'immutable mobile' [80] that remains stable and combinable. For example, the risk equation (Figure 1) that defines it as a function of hazard, exposure, vulnerability, and loss remains immutable, allowing individual variables within that equation to be adapted based on hazards, geographical scales, data availability, and decision-making contexts. On the other hand, they create path-dependence and technological lock-in. As Bowker and Star remind us, standards are also political. There are epistemological, political, and ethical stakes in the day-to-day work of building and maintaining standards [22]. In our study, the modular risk equation has made it difficult to integrate dynamic social factors and differential impacts into estimates of risk [27]. Yet, standards persist because they are invisible and difficult to dislodge. Changing standardized practices is expensive, requiring innumerable material changes and coordination work [80].

In addition to rigid standards, continuities also travel with the networks of people and communities of practice in less formalized and more contingent forms. Such networks play an important role in sustaining continuity within technological change, as illustrated by Hecht in her study of colonial continuities and nuclear rupture in the sociotechnical practice of uranium-mining in post-colonial Africa [64]. Insurance logics in disaster risk models traveled through the core network of actuarial experts and engineers who positioned risk models as innovative technology for public-decision making, recruited disaster risk managers and development experts into their epistemic communities, and shared their expertise to facilitate the transition. Such networks and their social practices, referred to as human infrastructure, help information infrastructures to emerge [83] and have been found to play a significant role in overcoming resource constraints during technology transfer in transnational contexts [70, 123]. We find that to be the case for disaster risk modeling as well. Technical consultants hired by developmental organizations such as the World Bank were essential in the travel of disaster risk models from western industrialized nations where insurance was already a primary means of disaster response to low-income countries without such practices. They drew on their experience with insurance applications to enforce data standards and develop workarounds when such standards did not exist. More importantly, they legitimized insurance and financing as the most effective approach for mitigating climate and disaster risk, including in communities, where insurance was not previously commonplace. Thus, following networks of people allowed us to discover how insurance logics traveled alongside the practice of risk modeling, and helped it to be more fluid and adaptable to context. These continuities are not always formal and rigid, but that also makes them more invisible and enduring.

These continuities are not inevitable, but enacted and maintained by powerful institutions such as the World Bank, insurance firms, major universities, and nation-states. Latour argues that administration, bureaucracy, and management are the big resources that help expand the network of technoscience as well as produce the stable state necessary for science to be considered universal [80]. In the case of disaster risk modeling, institutions helped create networks and incentive structures that were well prepared to share and enact insurance logics. Some of this work was discursive. However, these discourses and ways of thinking eventually became normalized and ubiquitous through standardization and black-boxing of science [80]. For example, the training manuals, risk assessment reports, and guidelines published by institutions, such as the World Bank helped to create shared practices among disaster risk modelers working in varied geographical contexts. It also helped create resources to train new generations of modelers. Some of these guidelines were then formalized into textbooks where insurance logics were considered the default mode of risk-modeling. Furthermore, these powerful institutions also provided material incentives for these networks and the logics to expand via policy frameworks, funding, technological support, and collaboration opportunities.

As we show above, continuities, such as insurance logics, are sustained through sociotechnical practices that are incentivized by institutional structures and embedded in the data standards, infrastructures, and community of practice. Rendering them visible helps us better understand the discourses, resources, and institutional networks that influence technology adoption and evolution. These historical patterns also provide insight into the dynamics and power structures that are shaping the development and adoption of emerging technologies, such as AI, in various application domains. For example, critical researchers concerned with algorithmic injustice have repeatedly raised concerns about the role of data standards in perpetuating historical biases and harming vulnerable communities [13, 15, 149]. Others have noted the role of powerful institutions and networks in shaping public discourses and material resources in the current turn to AI [147, 154, 155]. By historicizing disaster risk models, it becomes clear that these standards, networks, and institutions, while powerful, are contingent on social and political contexts. Often, they are also in tension with implementation realities. These tensions and contingencies can be a generative site for design interventions that can meaningfully challenge prevalent power disparities and create more justice-oriented alternatives. In the next section, we describe some potential ways to do so.

7.3 Designing against prevailing infrastructures

Research on computing that seeks to re-imagine existing systems may struggle if it does not situate critical alternatives within the contemporary socio-technical context. As we have shown, even supposedly novel technologies like AI for climate risk assessment are shaped and constrained by standards, infrastructures, and communities of practice developed years or even decades in the past. Design, when informed by these histories, can render such continuities visible as well as suggest routes out of the lock-ins and path-dependencies they create [140]. A design practice that can engage with path-dependencies is particularly important in contemporary data-driven AI, which so often invisibilizes and replicates historical biases [149]. In what follows, we draw from critical AI literature and HCI to recommend three approaches to help unsettle infrastructure's problematic continuities and create possibilities for more desirable futures.

7.3.1 Critical Reflection on Existing Practices. Sociotechnical continuities, such as insurance logics, persist because they are made common-sense and invisible through shared practices within an epistemic community. These practices and understandings shape how one perceives critiques of technology and what they do to address it [2]. In the context of disaster risk modeling, we observe that practitioners continue to find risk outputs are inadequate to meet decision-making needs in public policy and are motivated to use larger datasets and new advances in AI in an attempt to address these limitations. However, we did not find examples where these datasets and new algorithms have fundamentally changed disaster risk management practice. Instead, they have raised new concerns such as increased financialization, surveillance of the most vulnerable groups, reduced accountability, and new forms of biases [104]. One way to unsettle this would be via Agre's approach of Critical Technical Practice (CTP) [2]. CTP combines technology development with critical reflection, thereby helping practitioners recognize the unstated dominant beliefs in a technical practice and their limitations. CTP has been adopted by computing researchers to examine hidden biases [103, 128], create new interpretations of technological artifacts [1, 128], and move beyond techno-solutionistic designs in AI [1, 127]. In disaster risk modeling, a historically informed critical practice would help practitioners move beyond the insurance logics and ask different questions about disaster risk that prioritize people's well-being. Instead of simply using AI to make the environment more legible to the model, risk practitioners could use participatory assessments to make risk models and risk governance more legible to the communities [79]. Such practice could also be a tool for sociotechnical foresight that resists the view of AI as the fix-all solution and instead imagines alternative realities more aligned with just and equitable futures [103].

7.3.2 Infrastructural Interventions. A significant challenge for critical practitioners to change disciplinary bias occurs due to 'infrastructural bias' [136] that prevents a significant break from existing practices. Existing infrastructures are hard to unseat, and what is possible is limited by the tools that are available. In disaster risk modeling, existing datasets, standards, and policies have played a significant role in helping sustain a calculative and financial understanding of disaster risk. Therefore, a priority for equity and justice-oriented design work should lie in designing alternative pathways to diverge from existing infrastructures. Such work can take different forms. For example, Ribes and Polk describe the ways the Multicenter AIDS Cohort Study adapted as a research organization to accommodate ontological changes in understanding of AIDS [118]. Their tactics can provide insights into designing information infrastructures that can accommodate ontological changes in understanding of climate change and disasters, including ones informed by critical social science research. Similarly, HCI and responsible AI researchers have been co-designing with civic society and activist groups to create new datasets, tools, and infrastructures that support counterdata practices and civil society mobilizations outside of institutions of power [16, 150, 153]. Infrastructural interventions by researchers and designers should also go beyond technological fixes, and prioritize struggles over interpretation, maintenance, and regulation of sociotechnical practices. Whitney et al. show some example tactics to do so developed during their advocacy for public oversight in the implementation of smart city infrastructure in San Diego [153].

7.3.3 Refusal. Lastly, a more radical approach to diverge from technological continuities that exacerbate inequalities is through refusal to engage with problematic infrastructures and practices. It is not enough to create alternative forms of infrastructure; we need to also resist the ever-expanding role of powerful interests and extractive logics in shaping current technological and knowledge landscapes. Historical studies of technology and sociotechnical practices show multiple examples of such refusals. For example, Sabie et al., use the historical case study of Luddism to illustrate how HCI can use unmaking for emancipation [121]. There have been recent calls to similarly resist, reject, and sabotage AI using Luddism as an example [3, 99]. Tools like Nightshade and Glaze that corrupt training datasets to help protect artists from unauthorized use of their art by Generative AI are present-day examples of such refusal [131, 132]. Beyond AI, there have also been calls for 'informed refusal' [12] by Indigenous, feminist, and decolonial scholars to resist harmful data regimes and knowledge practices that perpetuate historical and systemic patterns of violence and exploitation [54, 134, 158]. They cite numerous examples of encampments, blockades, and non-cooperation movements by climate and environmental justice activists that can serve as inspiration.

8 CONCLUSION

As extreme weather events become more unprecedented and frequent due to global climate change, being able to accurately assess disaster risk becomes increasingly important to mitigate harms and ensure equitable impact. In this study, we took a historicist lens to show how the origins of disaster risk modeling in the insurance industry have had an enduring influence in how disaster risk is understood, measured, and mitigated in public decision-making. These influences, which we describe as 'insurance logics', are sustained both materially and discursively and continue to shape how emerging technologies, such as remote sensing and AI, are integrated into existing modeling practices. If we want to understand how the use of AI in disaster risk modeling contributes to increase social inequalities, we need to pay attention to these historical continuities and intervene not just through new technological solutions, but with design interventions that address sociotechnical practices and infrastructures.

ACKNOWLEDGMENTS

We would like to thank those who have directly contributed to this work, including Charles Huyck, Ron Eguchi, Yue 'Major' Zeng, and several other participants of the *Social Equity and Risk Working Group* who provided valuable information on histories, techniques, and challenges in disaster risk modeling. We would also like to thank the attendees of the *Himalayan Climate Data Field Lab 2024* and *Rethinking the Inevitability of AI* conference who gave valuable feedback on our preliminary findings and helped shape this work. Additionally, thank you to the anonymous reviewers, Simone Curtis, Taneea Agrawaal, Aarjav Chauhan, and colleagues at Toronto Climate Observatory and the AIDD Labs for their constructive and thoughtful feedback that improved this work.

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