PIISA

Piloting Innovative Insurance Solutions for Adaptation

D1.2 Advancements in actuarial risk modeling

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Table of contents

1 Introduction 7
2 Methods of literature review 9
2.1 Paper selection 9
2.1.1 Keywords 9
2.1.2 Query 9
2.1.3 Screening 9
3 Methods of stakeholder analysis 10
3.1 Conceptual framework 10
3.2 Sampling 12
3.3 Data collection 12
3.4 Data analysis 13
4 Results of literature review 15
4.1 Model type 15
4.1.1 Risk model 16
4.1.2 Insurance model 17
4.2 Risk 20
4.2.1 Hazard 20
4.2.2 Exposure 21
4.2.3 Vulnerability 22
4.2.4 Location 22
4.2.5 Scenarios 23
4.2.6 Disaster risk reduction (DRR) 23
4.3 Insurance 24
4.3.1 Recipient and the decision to insure 24
4.3.2 Insurance sector modeling 25
4.3.3 Premium calculation 26
5 Results of stakeholder analysis 27
5.1 Context setting 27
5.1.1 Insurance products 27
5.1.2 Climate-related risk information 27

5.1.3 Other model data inputs ... 29
5.1.4 Climate risk models ... 31
5.1.5 Insurance decision-making ... 32
5.2 Uncertainties and challenges ... 33
5.3 Innovation potential ... 35
6 Discussion of literature review ... 38
6.1 State of the art and directions for future research ... 38
6.2 Policy recommendations ... 40
7 Discussion of stakeholder analysis ... 41
7.1 Bridging the gap to innovation ... 41
7.2 Policy implications ... 43
7.3 Limitations and future research ... 43
8 Conclusion ... 44
9 Bibliography ... 46
10 Appendix ... 55

List of figures

Figure 1: Selection process ... 10
Figure 2: Conceptual framework ... 11
Figure 3: Coding scheme ... 14
Figure 4: Inductively derived sub-codes ... 15
Figure 5: Number of papers per model type ... 16
Figure 6: Frequency of hazards mentioned ... 28
Figure 7: Uncertainties and challenges overview ... 35
Figure 8: Innovation potential overview ... 38

List of tables

Supplementary table 1: keywords used in query ... 57
Supplementary table 2: risk and insurance model types ... 58
Supplementary table 3: risk characteristics of the models ... 60
Supplementary table 4: insurance characteristics of the models ... 63
Supplementary table 5: participant roles ... 70

Summary

Climate risk insurance models are increasingly relevant due to the rising losses attributable to climate change. This study provides a comprehensive review of the literature on climate risk insurance modeling to identify lessons learned and knowledge gaps to be addressed by future research. Furthermore, this research conducts a stakeholder analysis of the European Union insurance sector with risk assessment experts from insurance companies. The review finds that insurance models estimate risk for different perils and simulate risk-related parameters for insurance schemes, such as premiums and deductibles. Most forward-looking models indicate that climate change and socioeconomic developments highly exacerbate future risk and increase insurance premiums. Various studies recommend charging risk-based premiums to incentivize disaster risk reduction (DRR) efforts that limit this increase in climate risks. Other findings point toward introducing public-private insurance to cope with climate change and enhance risk spreading by introducing insurance purchase requirements or insurance products that cover multiple climate risks. Gaps that we identify in this literature review include an underrepresentation of insurance assessments for developing countries and for hazards other than flooding. Additionally, we note a lack of research into insurance for non-agricultural commercial sectors. Furthermore, less than half of the studies take a forward-looking approach by incorporating climate change scenarios, and an even smaller percentage consider socioeconomic development scenarios. This limitation shows that current methods require additional development for assessing the effects of future climate risk on insurance. We recommend that future research develops such forward-looking models, considers using a more refined spatial scale, broadens geographical and hazard coverage, and includes the commercial sector. Outcomes of the stakeholder analysis identify current challenges in state-of-the-art climate risk assessment approaches and explore innovative solutions to these challenges. Results reveal significant opportunities for incorporating long-term and adaptive views of climate risk into insurance modeling and pricing. This involves a deeper understanding of nonlinear environmental changes, fostering the development of replicable catastrophe risk models, increased use of emerging technologies, and leveraging open-source initiatives through increased intersectoral collaboration. By identifying these areas, the research supports the design of new insurance products that can better address climate change-enhanced risks. Future research directions based on the stakeholder analysis should focus on evaluating implementation of proposed solutions in practice. Ultimately, this study aims to contribute to more robust and adaptable insurance models, enhancing the resilience of the European Union in the face of climate change.

Keywords

actuarial models, catastrophe models, climate change, insurance, natural disaster risk.

1 Introduction

Climate change will increase the frequency and severity of natural disasters (IPCC, 2023). Future risk will increase due to trends in climate extremes and socioeconomic developments like urbanization and population growth. The number of natural disasters with high economic impacts has tripled since the 1980s, and this trend is expected to continue into the future (Hoeppe, 2016). With an increasing number of individuals residing in hazard-prone areas, the potential for losses from climate-related events is anticipated to rise (IPCC, 2023). Natural disasters and future climate risk lead to significant direct and indirect damage for society (Botzen et al., 2019). Insurance can be a tool to soften this burden on society by compensating the losses to households and private businesses (Linnerooth-Bayer & Hochrainer-Stigler, 2015). An efficiently working insurance system accelerates recovery after a natural disaster, minimizes the damage to the economy, and can improve the resilience of communities against natural disasters by incentivizing disaster risk reduction (DRR) (Botzen, 2021). However, as of now, less than half of the global natural disaster losses are covered by insurance (Munich Re, 2023), indicating a large protection gap.

Designing an effective insurance system to cover losses from natural disasters is a complex task (Surminski et al., 2016). A viable insurance system for natural disasters uses a multitude of variables to optimize its operations, including the spatial and temporal pooling of risk (to spread the risk through space and time), the combining the underwritten risk with other risks, and premium-setting rules such as making insurance for certain risks mandatory. In addition, the increase in natural hazards due to climate change (IPCC, 2023) and the increase in the exposure of assets and people (Hoeppe, 2016) necessitate larger (future) capital requirements for insurers. Consequently, this results in higher premiums for consumers, diminishing the appeal of purchasing insurance, increasing the insurance coverage gap (Botzen, 2021). Other challenges for developing a viable insurance system are the (often unexpected) high impacts of catastrophic events (Kousky & Cooke, 2012). Furthermore, climate change is often not addressed in current insurance schemes (Surminski, 2014), and there is much uncertainty in future climate risk projections, which increases uncertainty in future premium settings (Adger et al., 2018; Botzen, 2021).

The modeling of climate-related risk insurance is an emerging research field to prepare the insurance sector for the increasing natural disaster risk. By assessing how climate change may stress the insurance sector, strategies can be developed to enhance the resilience of this sector to increasing climatic risks. For example, insurance could stimulate risk-conscious decision-making by policyholders, which may limit the impact of future climatic hazards. In light of the necessity for policyholders to make decisions considerably in advance of climate change impacts, it is imperative that the design of insurance policies embraces a long-term, future-oriented outlook.

A key foundation of a climate risk insurance model is accurately estimating current and future risk through catastrophe modeling, actuarial approaches, or probability/theoretical methods. Over the last 20 years, numerous climate hazard and risk models for different perils have been developed. As a few examples, models for flooding such as Ward et al. (2013) and De Roo et al. (2000); models for wildfires such as Filippi et al. (2009); models for hurricanes such as Bloemendaal et al. (2020), Vickery et al. (2006), and Emanuel et al. (2006); or models for hail such as Brook et al. (2021).

In addition, a climate risk insurance model can be applied to assess the impacts of climatic risks on how supply and demand for insurance develops over time and space. A commonly employed model type for this purpose is an insurance supply model, which concerns the pricing of insurance contracts by simulating (risk-based) premiums (e.g., Aerts and Botzen, 2011). On the demand side, partial equilibrium models aim to simulate supply and demand in an insurance market or consider the effect of insurance on equilibrium conditions between marginal cost and marginal revenue for a business. In this way, it is possible to derive insights about insurance uptake (e.g., Tesselaar et al., 2020b) or how insurance can incentivize DRR (e.g., Hudson et al., 2016). Recently, agent-based insurance models have been developed, which aim to simulate the complex interactions in an insurance market between individual autonomous consumers, insurers, and the government (Dubbelboer et al., 2017).

While recent research has reviewed climate insurance studies in a broad context (including sustainability issues; e.g., Nobanee & Nghiem, 2024) there is no systematic review of climate risk models for the insurance sector. Therefore, this paper primarily aims to review and synthesize the current literature about climate risk models for the insurance sector. This process will identify the key building blocks of such models, best practices, and lessons learned. Ultimately, this overview will provide recommendations for future model development, which can aid in closing the overall natural disaster protection gap. Since existing models are already used by the European Insurance and Occupational Pensions Authority (EIOPA, n.d.; Tesselaar et al., 2020b) or the European Central Bank (ECB & EIOPA, 2022), our review will offer valuable insights to policymakers and the insurance sector about how to address future climate challenges and how to close the natural disaster protection gap. This research will further examine real-world climate risk assessment practices in the European insurance industry to identify challenges and areas for innovation. A stakeholder analysis will be used for this purpose and to bridge the current theory-practice gap.

The remainder of this paper is organized as follows: Sections 2 and 3 describe how the review and stakeholder analysis has been conducted, respectively. Section 4 reviews the literature by summarizing our findings in three parts: general model types, the risk component, and the insurance model component. Section 5 presents the findings of the stakeholder analysis systematically based on a developed conceptual framework. Sections 6 and 7 discuss the main research findings, policy implications and recommendations for future research according to the literature review and stakeholder analysis. Section 8 concludes the paper.

2 Methods of literature review

2.1 Paper selection

For this paper, a systematic literature review was conducted building on existing reviews (e.g., Aburto Barrera & Wagner (2023); Nobanee & Nghiem (2024)) by following three steps (Figure 1): (1) selecting keywords for querying articles, (2) querying articles within a literature database (Scopus), and (3) screening the queried articles for their suitability.

2.1.1 Keywords

For our review, we have addressed three keyword types: “hazard-related keywords,” “model keywords,” and “insurance keywords.” Using combinations of the three keyword types in the query with “AND” and “OR” Booleans ensures that only papers with abstracts that mentioned a hazard type, a model type, and an insurance-related word were selected. This action was undertaken with the intent of refining the query to encompass papers within the area of interest. However, to make the query more exhaustive, the keywords were often kept a bit broader. For example, in the hazard type keyword list, words such as “disaster” were also chosen. The selected keywords for the hazard, model, and insurance types are summarized in Table 1 of the Appendix.

2.1.2 Query

The “advanced search” function by Scopus was used to query the articles. We used Scopus because it was often used in similar literature reviews (Khatib et al., 2022; Nobanee et al., 2022; Nobanee & Nghiem, 2024). First, the potential search strings were tried to obtain several articles that were large enough to contain all the suitable papers but small enough to be feasible. Keywords consisting of multiple words were put between quotation marks to make sure Scopus would only look for instances where the entire keyword was present. The language was limited to English, and the document type was limited to peer-reviewed articles. The query was carried out over the title, abstract, and keywords of each article. The final query had 2,067 hits, which is comparable to similar reviews such as Aburto Barrera and Wagner (2023). The search string used can be found in the Appendix.

2.1.3 Screening

In the last step, the 2,067 articles selected by Scopus were screened using the AI-assisted screening tool Rayyan (Johnson & Phillips, 2018). Since the review focuses on the state of the art of insurance modeling, papers published before 2010 are excluded. Additionally, papers related to index or parametric insurance contracts were excluded because these types of insurance are deemed too dissimilar to the insurance under consideration in this study. After the manual screening, 50 papers were deemed within our scope and selected for a thorough review. During this process, 14 papers were deselected because they were out of scope, leaving 36 papers for the final analysis. The final 36 papers were analyzed based on the type of the model (Table 2 of the Appendix), the risk component of the model (Table 3 of the Appendix) and the insurance component of the model (Table 4 of the Appendix).

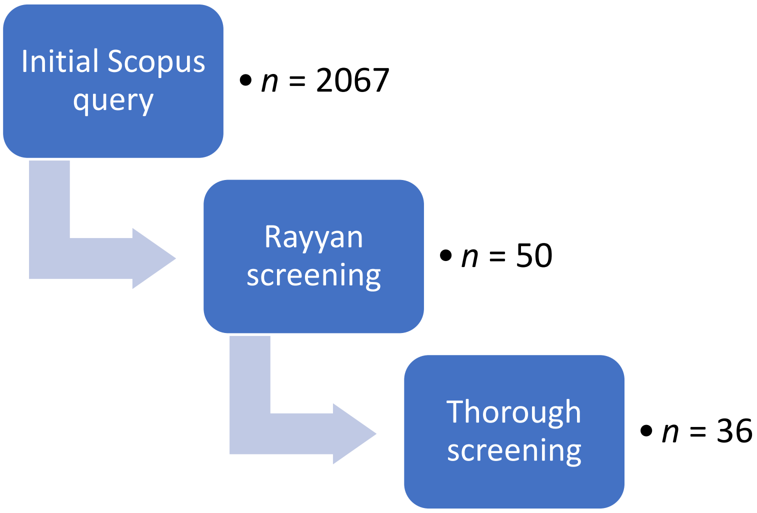

Figure 1: Selection process

3 Methods of stakeholder analysis

For the stakeholder analysis, this paper develops a conceptual framework that will ensure systematic analysis of the insights shared by experts in the field. This is followed by an elaboration of the methodology. That is, first the sampling procedure for the expert interviews is motivated. Second, the approach in which data is collected is clarified. Third and last, the systematic approach to data analysis is described, which eventually shapes the results that follow from all insights collected.

3.1 Conceptual framework

The three concepts of climate-related risk information, other model data inputs, and uncertainty factors are considered in climate risk modeling. Climate-related risk information is dependent on climate-related risk and climate data. Climate-related risk is a function of the hazard, the exposure of the portfolio, and vulnerability factors. A double arrow is drawn from climate-related risk to climate-related risk information as both affect the other, due to adaption and mitigation practices. Additionally, information on changing climatic factors can be used to improve understanding of the natural hazards and the impact that they might have, which is necessary to set accurate parameters in the models. Furthermore, several other data inputs can be used to evaluate risks, depending on the model type. These data inputs can include historical losses, which allow for projecting trends of economic impact based on past hazard losses. For forward-looking models, future data based on climate forecasting and projections can be incorporated. Additionally, socio-economic factors need to be considered. For instance, population density, political decisions, or high inflation potentially affect damage outcomes (Landreau et al., 2021). Third, uncertainty factors reflect the unknown elements of climate change and natural hazard risk for which the models try to account. These can be, for example, tipping points, which are critical thresholds where small changes can lead to dramatic shifts in the climate system, or compound effects, which refer to the interaction of multiple climate hazards that amplify the overall risk.

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Next, several types of climate risk models can be applied. Such models can be built in-house or bought from an external vendor party. The latter can be attractive since external parties might have more climate-related risk information and model-building resources. However, these models are often less transparent. The following step results in model outputs, which can consist of potential damage and risk distributions in the form of economic losses or natural hazard damage scenarios (Botzen, 2021). Concluding, this information is used in insurance decision-making on risk pricing, the development of insurance products, and long-term strategy of the insurance firm. The type of insurance product naturally depends on the type of natural hazard it relates to. Also, proper insurance products can foster the development and implementation of DRR measures by encouraging risk awareness and providing capital for risk reduction measures (Jarzabkowski et al., 2019).

The conceptual framework provides the basis for developing a deductive coding scheme around which the interview data and results are systematically organised.

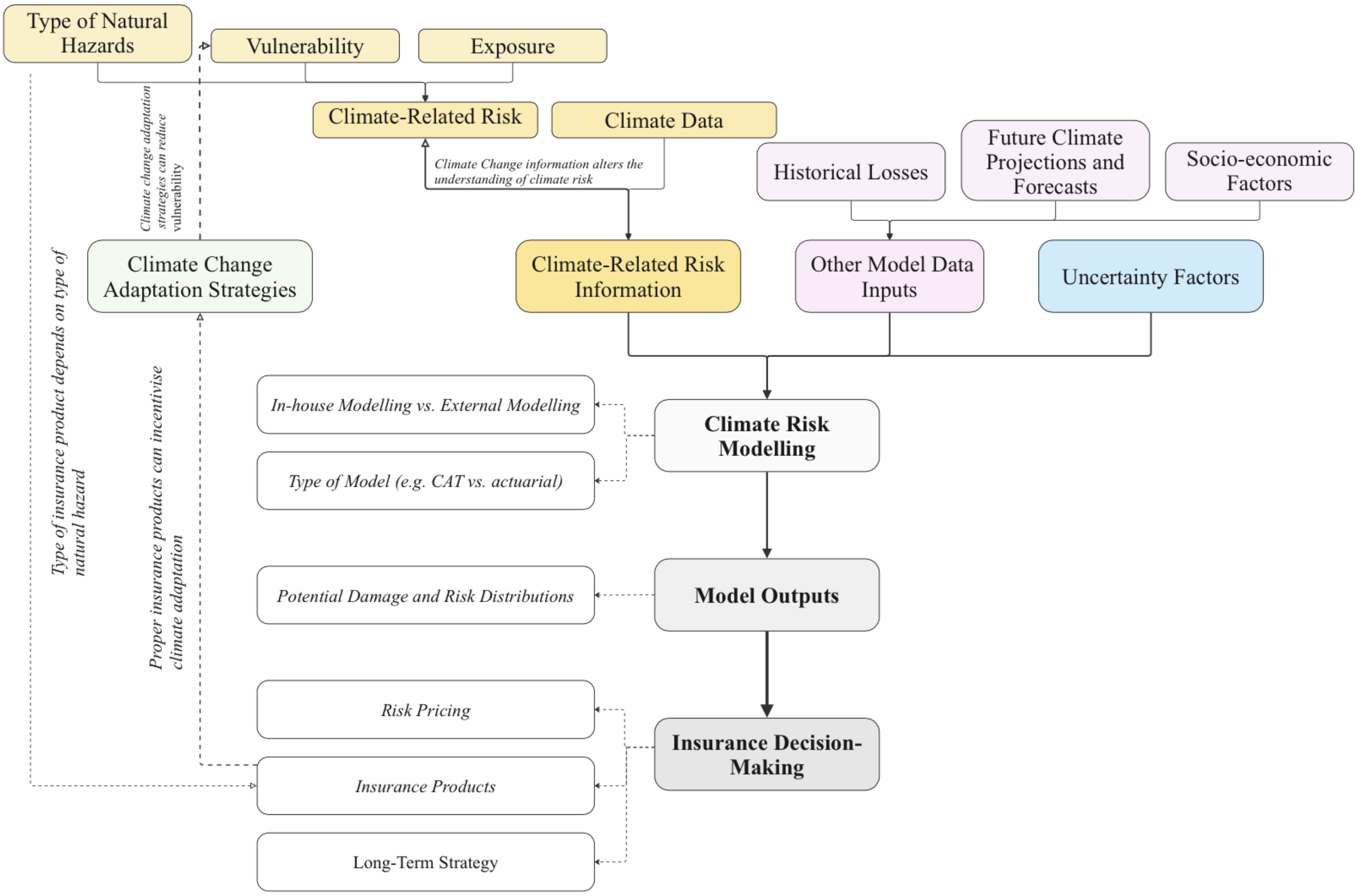

Figure 2: Conceptual framework

3.2 Sampling

To collect primary data from interviews, purposive sampling was used. Purposive sampling is a form of non-probability sampling in which participants are selected based on their expertise according to the research objectives. Participants are therefore chosen by judgment of the researcher, as only a specific type of candidate can properly serve as a primary data source due to the nature of the research objectives and the required expertise (Bell et al., 2019). The interview participants in this study are all experts in natural hazard risk modeling, climate risk insurance, and actuarial services in Europe. General role descriptions can be found in Table 5 of the Appendix. Professional networks within the Piloting Innovation Insurance Solutions for Adaptation (PIISA) project were leveraged to reach out to potential candidates. Also, participants were asked to refer other possible candidates in their network with expertise on the topic. A third method of participant recruitment was reaching out to potential participants on LinkedIn. Suitable candidates were contacted after looking at their field of work and relevant experience. A total number of sixteen participants were recruited for the interviews successfully.

3.3 Data collection

The data for this research was gathered through in-depth semi-structured interviews. This approach allows for a flexible exploration of pre-defined questions while leaving room for further exploration of unique experiences, viewpoints, or other themes. A total of twenty-four questions were formulated with help from focused discussions and peer-review by experts in the field that are connected to the PIISA project and institute of the lead researcher (Appendix). The questions start by discussing the use of climate risk information in insurance modeling and product design. Next, the questions cover model inputs, model outputs, the types of models used, and the adoption of forward-looking climate models. Lastly, the uncertainties of natural disaster risk modeling were discussed, as well as potential advancements in risk assessment approaches.

The interviews were conducted online during a period between the start of April and mid-May 2024, and lasted between 30 and 45 minutes. Prior to the start of the interview, confidentiality was promised, and consent to record the interview was confirmed. A test pilot interview was conducted in preparation of the expert interviews to test the materials and correct formulation of the questions. In addition, an ethics check by the Research Ethics Review Committee (BETHCIE) of the Faculty of Science at Vrije Universiteit (VU) Amsterdam was completed to ensure ethical practices throughout the data collection process.

This research prioritizes ensuring the validity of its findings by adhering to the four key criteria established by Whittemore et al. (2001): credibility, authenticity, criticality, and integrity. Credibility and authenticity focus on accurately interpreting the meaning of the results and accurately representing participant experiences. To mitigate threats to validity such as distortion, bias, and inadequate representation of relevant constructs, the research employs several strategies. First, anonymity was guaranteed to encourage participants to speak freely. Second, interpretations of their experiences have been repeatedly confirmed with participants to ensure accuracy. Finally, a neutral and objective approach was maintained throughout the research process. Criticality and integrity are further ensured by thorough and objective interpretation of the data. As more data was collected and few new insights emerged, the findings became more trustworthy as a point of data saturation was reached.

Moreover, an online focused discussion was held with approximately fifty stakeholders involved or interested in climate risk modeling in April 2024 to understand in greater detail: (1) key perceived uncertainties in natural disaster risk modeling – participants could select up to four uncertainties (identified prior as key uncertainties) through a multiple-response question or could select an "other" option. The non-other options were future climate conditions, future population and economic growth, limited past data availability and difficulties of including adaptation dynamics; and (2) what is needed to advance natural disaster risk modelling – participants could state five needs in a multiple-response question or could select an "other" option. The non-other options were scientific insights, methods that include adaptation dynamics, methods to deal with multi-hazard risk, better ways of addressing model uncertainty and more refined risk maps. The discussion aimed to assess how closely these stakeholder views aligned with the uncertainties and methodological needs identified during the interviews.

3.4 Data analysis

The data analysis process for the interviews consisted of several stages. First, the audio recordings of the sixteen interviews were used to transcribe the interviews. Transcribing the interviews was necessary for the coding process, while it also presented an opportunity to review the information that was given. During the transcription process, interpretations were made in some cases to exclude pauses and filler words and to correct grammar. Before conducting the data analysis, the first stage of Wright and Nyberg's (2017) detailed reading of the collected data was applied. During this process, emphasis was placed on familiarising with the initial qualitative data, structuring the information, and cleaning the data. Next, all transcripts were imported into Atlas.ti. This program facilitates consistent and organized coding of large amounts of qualitative data. To systematically analyse the data, a preliminary coding scheme was developed deductively based on the conceptual framework. Figure 3 presents the initial codes, including their grouping.

In accordance, one or more codes were applied to relevant data segments of the interview transcripts. During the coding process, the coding scheme was continually revised and refined to capture emerging themes and ensure consistency. For three overhead codes, namely "Hazard", "Uncertainties & Challenges", and "Innovation Potential", sub-codes were derived inductively, inspired by the Gioia methodology (Gioia et al., 2013). A detailed description of this process can be found in the Appendix. Types of hazards mentioned in the interviews were registered for context purposes. In addition, topics concerning challenges and innovation potential that emerged during the interviews required special attention as they are the focus of this research. Figure 4 presents an overview of the sub-codes. After the first round of coding was completed, a second round of coding was initiated to re-examine and re-analyse the codes and categories applied thus far. The Appendix presents an example of the coding process of part of an interview.

Atlas.ti's features were used to create a visual representation of code co-document networks and code-occurrences. Visualising the data structure is pivotal for qualitative research design as it facilitates increasing levels of abstraction by capturing relationships between groups and codes. Identified relationships were subsequently used to create a narrative and to interpret the significance of outcomes in relation to the research question and existing literature (Gioia et al., 2013; Miles et al., 2014).

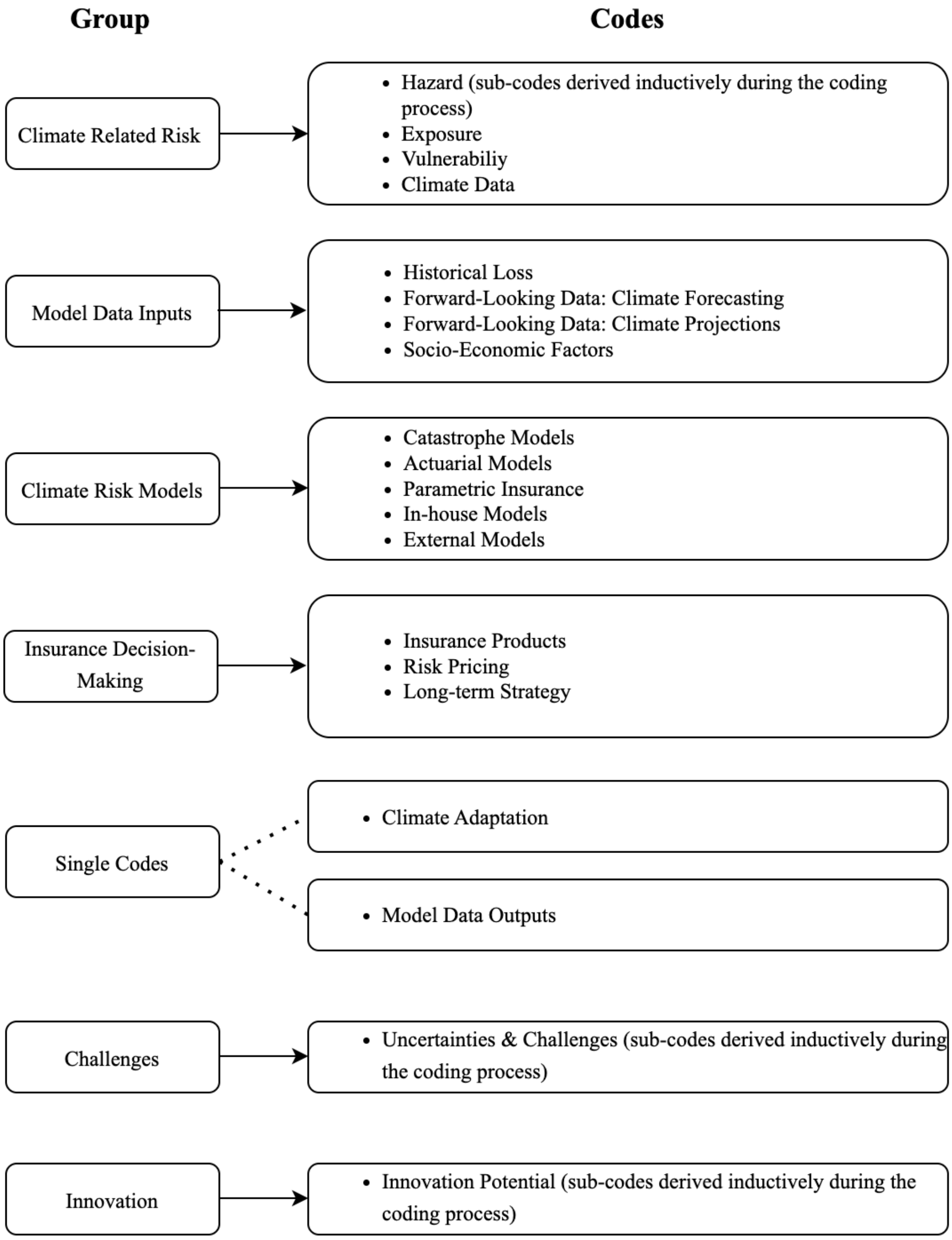

Figure 3: Coding scheme

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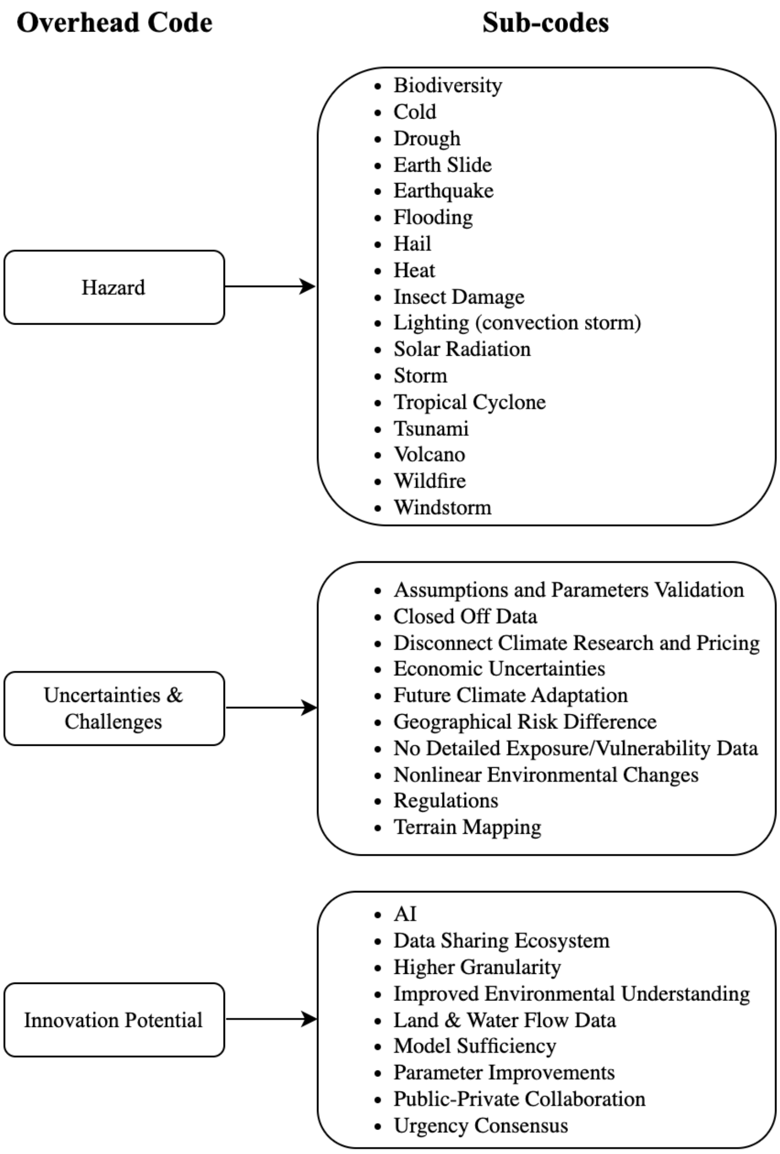

Figure 4: Inductively derived sub-codes

4 Results of literature review

The commonality among all papers in this review is that they compute an insurance premium based on a climatic risk. In accordance with the 3 tables defined in the method section 2 (model type, risk component, insurance component), the results section will review these three aspects.

4.1 Model type

Based on our review, we distinguish three methods of operationalizing risk assessment: catastrophe modeling, actuarial modeling, and theoretical modeling. When the climatic hazard is operationalized as a risk via either catastrophe modeling, an actuarial approach, or a probabilistic/theoretical approach, the estimated risk can be used in an insurance model. We distinguish four types of insurance modeling: insurance supply models, partial equilibrium models, agent-based models, and "other models," which comprise model types that are less prevalent in the literature. This section summarizes the findings about the three risk component types and four insurance component types. Figure 5 indicates the number of papers per model type. For information about the reviewed models, refer to Table 2 of the Appendix.

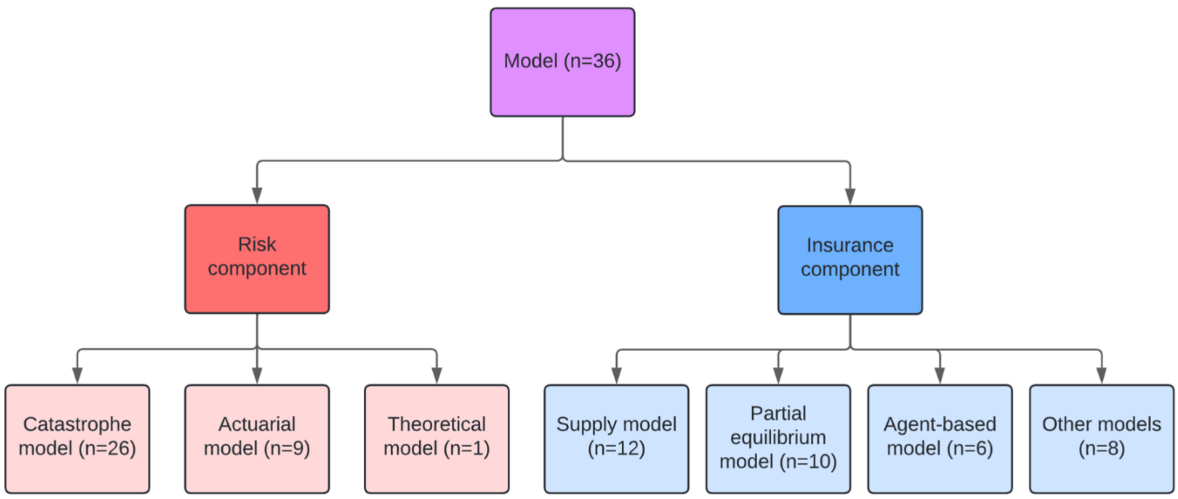

Figure 5: Number of papers per model type

4.1.1 Risk model

Catastrophe models

In catastrophe modeling, risk is simulated by combining information on hazard impacts and associated occurrence probabilities with the exposed elements at risk and their vulnerability (Grossi et al., 2005). Often, hazard impacts and probabilities enable the construction of exceedance probability curves, which illustrate the likelihood of a loss surpassing specific threshold values. However, there are also more simplified catastrophe models that only combine hazard footprints (e.g., flood extent, windstorm field, or areas subject to heatwaves) with exposure data on buildings infrastructure to estimate risk without addressing the probability of such events (Grossi et al., 2005). Most papers employ a catastrophe model because risk related to high-impact low-probability hazards is impaired by a lack of available observed loss data due to this low probability of occurrence. Hence, hazards such as flooding, hurricanes, and earthquakes are mostly estimated via catastrophe modeling (e.g., Tesselaar et al., 2022; de Ruig et al., 2022; Aerts & Botzen, 2011; Boudreault et al., 2020; Peng et al., 2014; Perazzini et al., 2022; but see Sidi et al., 2017). An alternative rationale for the frequent use of catastrophe models is their ability to flexibly accommodate future climatic and socioeconomic conditions. A potential drawback of catastrophe modeling is that it requires an often computationally expensive multi-layered approach with data on hazard probabilities, exposure, and vulnerability (e.g., Boudreault et al. (2020), de Ruig et al. (2023), or Ermolieva et al., 2017). The resulting outputs of a catastrophe model (loss or risk) can be plotted in a spatial manner using maps showing risk per pixel or per administrative unit.

Actuarial models

A subset of papers uses an actuarial base for their model. Instead of being simulation based as with catastrophe models, actuarial models estimate risk based on actual events with loss data (Boudreault et al., 2023). Actuarial models are mostly applied to windstorm (El-Adaway, 2012) and wildfire hazards (Barreal et al., 2014; Brunette et al., 2015; Pinheiro & Ribeiro, 2013, Thompson et al., 2015). Using empirical loss data, the risk can be estimated using econometric methods such as regression models. Examples are Pinheiro and Ribeiro (2013), who used the expected annual average burned area per municipality based on historical fire occurrences and the annual average burned area and Barreal et al. (2014), who used regression models to estimate wildfire risk based on socioeconomic, geographical, and climate-related variables. El-Adaway (2012) showed that actuarial models can be combined with bootstrapping to enhance loss observations; in this application, three datasets of 5,000 observations were created from 2,000 actual windstorm observations. An advantage of an actuarial approach is the possibility to elucidate potential trends that do not yet have a physical understanding (Boudreault et al., 2023). On the other hand, given the high-impact low-probability nature of climatic disasters such as flooding, there is often a lack of historical data on these events to apply a statistical analysis (but see Islam et al. [2021] for an actuarial model applied to flooding).

Theoretical models

One reviewed paper does not apply its model to a case study (Brunette et al., 2017). This model treats risk as a simple stochastic variable. Therefore, the model does not simulate risk using an underlying catastrophe model and is not based on empirical data. We classify this model as a purely theoretical model, as there is no underlying risk model specified.

4.1.2 Insurance model

Insurance supply models

The most common insurance application is the insurance supply model. An insurance supply model concerns the pricing of insurance contracts. An example of such a model is applied in Aerts and Botzen (2011), which calculated the future evolution of risk-based premiums for flooding in the Netherlands using a catastrophe model, considering several socioeconomic and climate change scenarios. The premium was calculated per administrative area based on its expected annual damage (EAD) divided by the number of houses per administrative area. This risk estimate, together with a loading factor that represents the operational costs of providing insurance as well as a profit margin, provided an estimate of the premium per household. Using this method, a stark increase in insurance premiums over time was found due to climate change and socioeconomic developments and the fact that the uncertainty around these future developments complicates the insurers' rate-setting of long-term contracts. Another example is Brunette et al. (2015), who estimated premiums for multi-hazard forest insurance using an actuarial approach in combination with an insurance supply model. With this method, it was found that the most efficient procedure is to assume independence between the natural hazards, which in reality cannot be a fair assumption, in particular in the case of compound events.

Most insurance supply models incorporate spatially explicit, risk-based premiums, relying on catastrophe models or actuarial methods to assess spatial risk. Examples of models that employ a model with spatially explicit, risk-based premiums can be found in Boudreault & Ojeda (2022), Boudreault et al. (2020), El-Adaway (2012), Kalfin et al. (2022), and Sacchelli et al. (2018). Generally, the premium's spatial resolution is limited by the complexity of the underlying risk module. Some models calculate premiums with a high spatial resolution, such as Boudreault et al. (2020), in which premiums are calculated per individual house, aiming to explore methods for mitigating adverse selection. Calculating risk-based premiums at a high resolution has the advantage of accurately reflecting the risk of the area and potentially incentivizing DRR effort. However, according to Botzen (2021), risk-based premiums can lead to unaffordability in high-risk areas and may influence location decisions. This means that a pricing application alone is often not enough to answer all insurance-related challenges. More intricate insurance applications such as partial equilibrium models not only compute premiums but also leverage these premium data in subsequent modules to, for example, obtain insights into insurance demand or DRR efforts.

Partial equilibrium models

Partial equilibrium models assess equilibrium conditions in a particular market, *ceteris paribus* (Varian, 2014). There are no feedback effects that alter the fundamental supply and demand relationships defined in advance (Mas-Colell et al., 1995). A partial equilibrium application is useful for determining equilibrium outcomes in an insurance market or considering the effect of insurance on equilibrium conditions between marginal cost and marginal revenue for a business.

By simulating insurance market conditions, insights about insurance uptake, such as the uninsured portion of risk or the unaffordability of insurance, can be obtained. These insights are showcased by studies on the European flood insurance market. An example is Tesselaar et al. (2020b), who found that insurance unaffordability will increase due to climate change and socioeconomic development by simulating premium prices and insurance demand for various scenarios. Another area in which partial equilibrium applications prove useful is when the effect of insurance on (agri) businesses is considered. For example, Brunette et al. (2017) analyzed the effect forest insurance can have on the implementation of DRR efforts by examining the marginal cost and benefit of insurance in different situations. Results showed that including DRR efforts in forest insurance contracts is a beneficial tool to promote DRR efforts, especially if the type of DRR effort is unobservable to the insurer. In a similar study, Barreal et al. (2014) examined the effect of insurance on the net present value of forest investments by analyzing the equilibrium between marginal DRR cost and benefit. Results showed that insurance plays a larger role in increasing the net present value of forest investments when restoration costs are included in the insurance policy. When insurance supply systems are considered, a partial equilibrium application can also be used to compare different insurance supply systems on key characteristics such as premiums and demand (Hudson et al., 2019; Tesselaar et al. 2020a, 2020b). Thereby, the model can be used to obtain insights into the desirability of insurance market reforms through evaluating both their supply and demand side effects.

Agent-based insurance models

Agent-based models (ABMs) subdivide complex systems into a flexible simulation framework of individual autonomous, heterogenous, and active components (agents), which is useful for investigating complex and emerging agent behavior (Crooks & Heppenstall, 2012). ABMs offer valuable insights for climate risk insurance modeling by simulating the intricate interactions and dynamic behaviors among consumers and insurers in the market, thus providing valuable insights into (emerging) consumer behavior. It is noteworthy that all reviewed papers with an ABM application consider flood insurance. One example is a study by Dubbelboer et al. (2017), which applied an ABM to simulate U.K. housing market to assess the viability of the FloodRe scheme. Another example is a study on the U.S. flood insurance system by de Ruig et al. (2022), investigated the societal benefits of risk-based premiums in a changing climate. The type of consumer behavior that is modeled in ABMs usually comprises insurance uptake (Crick et al., 2018; de Ruig et al., 2022, 2023; Dubbelboer et al., 2017; Jenkins et al., 2017;Tanaka et al., 2022), implementing DRR methods (de Ruig et al., 2022, 2023; Crick et al., 2018; Dubbelboer et al., 2017; Jenkins et al., 2017), and the decision to purchase property (Crick et al., 2018; Dubbelboer et al., 2017; Jenkins et al., 2017; Tanaka et al., 2022).

The interactions in the ABMs depend on the modeled agents and the focus of the model. Interactions are commonly modeled between consumers and the development of risk (de Ruig et al., 2022, 2023) or impact (Crick et al., 2018; Dubbelboer et al., 2017; Jenkins et al., 2017) of a flood event. In de Ruig et al. (2022) and de Ruig et al. (2023), households evaluate the risk of flooding and base the decision to take DRR measures or insurance on the severity of the risk they face. In studies by Dubbelboer et al. (2017), Jenkins et al. (2017), and Crick et al. (2018), households base the decision of taking DRR measures on whether a flood event occurred.

Another common interaction addressed in ABMs is an interaction between households and the insurance market. In studies by de Ruig et al. (2022) and de Ruig et al. (2023), households decide each year whether to purchase insurance or not. This decision is linked to a subjective expected utility function that takes the (risk-based) premium calculated by the insurance sector, the budget of the household, and a deductible into account. In studies by Dubbelboer et al. (2017), Jenkins et al. (2017), and Crick et al. (2018), households are mandated to take flood insurance but can influence their premium by moving to another location or undertaking DRR measures. Tanaka et al. (2022), Dubbelboer et al. (2017), Jenkins et al. (2017), and Crick et al. (2018) also modeled an interaction between households and the housing market. In Tanaka et al. (2022), households decide whether to move or not based on a utility function that considers flood risk reflected by the insurance premium.

Allowing for individual agent behavior is useful concerning the implementation of DRR measures (Crick et al., 2018; de Ruig et al., 2022, 2023; Dubbelboer et al., 2017; Jenkins et al., 2017). Furthermore, de Ruig et al. (2022) and de Ruig et al. (2023) showed that modeling interactions between consumers and the insurance market leads to useful insights about insurance uptake and affordability. Another strength of an ABM is its suitability for integrating climate change and socioeconomic development scenarios. This is also reflected in the fact that all reviewed agent-based models include at least one climate change scenario. Moreover, since an ABM often includes data on the characteristics of agents such as income, socioeconomic development scenarios are often applicable (de Ruig et al., 2022, 2023; Tanaka et al., 2022). A typical caveat, though, of these models is that the modeler can define virtually any type of rules for the agents to follow, and hence ABM offers a powerful approach to diagnose and better understand mechanisms underlying the model assumptions, but it is less effective in helping discovering general patterns and mechanisms that are beyond the model assumptions.

Other insurance model types

There are two other insurance model types that can be distinguished in the literature. Birghila et al. (2022) and Islam et al. (2022) employed an insurance demand model. The goal of an insurance demand model is to obtain an insight into the demand for insurance. Birghila et al. (2022) did this by analyzing the optimal risk layering of insurance contracts per recipient to maximize uptake under ambiguity. Islam et al. (2022) analyzed the willingness to pay for insurance via a logit model based on a field survey. Another insurance model type is a game theoretic model. A game theoretic model shares similarities with an ABM but places a greater emphasis on equilibrium conditions and optimization (De Marchi & Page, 2014). Utilizing game-theoretic models proves useful in capturing the dynamics between the demand and supply sides of insurance. This framework offers valuable insights into the strategic choices made by both insurers and insurance consumers. An example is Peng et al. (2014), who highlighted the existence of policies that include retrofitting and make all actors (households, government, insurers, and reinsurers) better off than a policy that does not include retrofitting. Game-theoretic models can serve as a valuable tool for analyzing the wider implications of insurance, retrofitting initiatives, and the acquisition of high-risk properties on overall losses, as discussed by Guo et al. (2022).

4.2 Risk

Risk can be subdivided into hazard, vulnerability, and exposure (IPCC, 2012), where the hazard is defined as the frequency and intensity of the natural hazard, exposure as the presence of exposed values, such as buildings, property, or crops that can adversely affected, and vulnerability as the susceptibility of these exposed values to losses (Botzen, 2021).

This section reviews the modeling input referring to the risk component of the model. Details about the risk component per reviewed paper can be found in Table 3 of the Appendix.

4.2.1 Hazard

In this paper, we identify five climatic hazard groups: flooding, wildfires, hurricanes, windstorms, and other hazards.

Flooding is overrepresented in the literature, with more than half of the papers being applied to flood hazards. We further divide flood hazards into three subcategories: riverine flooding (Aerts & Botzen, 2011; Boudreault et al., 2020; Boudreault & Ojeda, 2022; de Ruig et al., 2022; Ermolieva et al., 2017; Hudson et al., 2016, 2019; Moosakhaani et al., 2022; Sidi et al., 2017; Tanaka et al., 2022; Tesselaar et al., 2020a, 2020b, 2022; Unterberger et al., 2019), coastal flooding (Aerts & Botzen, 2011; de Ruig et al., 2022, 2023; Ermolieva et al., 2017), and other flooding (which consists of pluvial flooding [Tanaka et al., 2022], surface water flooding [Crick et al., 2018; Dubbelboer et al., 2017; Jenkins et al., 2017], flash floods [Islam et al., 2022], and flooding in general [Perazzini et al., 2022]). Of these types, riverine flooding accounts for more than half of the flood modeling papers. In some cases, a combination is used between riverine flooding and another type of flooding (e.g., Aerts and Botzen, 2011; Ermolieva et al., 2017; Tanaka et al., 2022). Moreover, coastal flooding is used in all but one case (de Ruig et al., 2023), in combination with riverine flooding. Of the other hazard types, hurricanes/cyclones (Guo et al., 2022; Kesete et al., 2014; Kunreuther et al., 2013; Peng et al., 2014; Walker et al., 2016) and wildfires (Barreal et al., 2014; Brunette et al., 2015; Pinheiro & Ribeiro, 2013; Sacchelli et al., 2018; Thompson et al., 2015) occur the most. To a lesser extent, there are models about windstorm insurance (El-Adaway, 2012; Loisel et al., 2020; Sacchelli et al., 2018). The group “other hazards” consists of forest-related damages (Brunette et al., 2015, 2017), earthquakes (Perazzini et al., 2022), debris flows (Ding et al., 2012), drought (Birghila et al., 2022), and natural disasters in general (Kalfin et al., 2022).

Most of the reviewed papers tend to employ models that exclusively focus on addressing individual natural hazards. A few examples of models that allow for a multi-hazard approach are models by Brunette et al. (2015) and Sacchelli et al. (2018). These are both forest insurance papers. Perazzini et al. (2022) explicitly used both a single-hazard and a multi-hazard insurance policy in

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their case study. The low attention to multi-hazard insurance indicates a gap in the climate insurance modeling literature: Compound climate risks are increasing rapidly, and an expanding literature focuses on multi-hazard climate risk assessments (IPCC, 2023), but multi-hazard risks are not often considered in climate insurance models.

The way in which the hazard is operationalized varies by hazard group and risk model type. For flooding, the hazard is commonly determined as the inundation extent with a certain return period in a certain grid cell or area (Aerts & Botzen, 2011; Boudreault & Ojeda, 2022; Crick et al., 2018; de Ruig et al., 2022, 2023; Dubbelboer et al., 2017; Hudson et al., 2016, 2019; Jenkins et al., 2017; Tanaka et al., 2022; Tesselaar et al., 2020a, 2020b 2022). This means that inundation depths are linked to a certain probability each year per grid cell or area. This probability and inundation depth can then be used in combination with exposure and vulnerability data to estimate the expected annual damage. Concerning hurricanes, Guo et al. (2022), Kesete et al. (2014), and Peng et al. (2014) all used a set of probabilistic hurricane scenarios based on historical records first developed by Apivatanagul et al. (2011). These hurricane scenarios comprise a track with certain parameters that determine the intensity and probability of occurrence. Kunreuther et al. (2013) similarly used hurricane scenarios but developed by a climate-catastrophe modeling approach. For wildfires, the hazard is usually determined as a probability per area based on historical wildfire occurrence (Barreal et al., 2014; Pinheiro & Ribeiro, 2013; Sacchelli et al., 2018). These probabilities are more often denoted by region rather than grid cell, in contrast with flooding. Similar to the assessment of wildfires, the evaluation of windstorm hazard usually relies on historical data analysis (El-Adaway, 2012; Sacchelli et al., 2018; but see Loisel et al. (2020), which uses return periods).

4.2.2 Exposure

For flooding, exposure is commonly operationalized via data about land use (Aerts & Botzen, 2011; Boudreault et al., 2020; Crick et al., 2018; de Ruig et al., 2022, 2023; Dubbelboer et al., 2017; Ermolieva et al., 2017; Hudson et al., 2016, 2019; Jenkins et al., 2017; Tanaka et al., 2022; Tesselaar et al., 2020a, 2020b, 2022; Unterberger et al., 2019). However, there are differences in the resolution of this approach. For example, while it is common to use aggregated information about land use, Boudreault et al. (2020) used data for single houses, including characteristics such as number of floors and main usage. Furthermore, forward-looking models often include GDP growth and population growth as a proxy for the growth in exposure (Aerts & Botzen, 2011; de Ruig et al., 2022, 2023; Hudson et al., 2016, 2019; Tanaka et al., 2022; Tesselaar et al., 2020a, 2020b, 2022; Unterberger et al., 2019).

In hurricane-focused insurance models, there is a heavier focus on residential buildings than in insurance models for flooding. Hence, the approach is less land use-based and more focused on the buildings themselves. Exposure can be aggregated by building class (Guo et al., 2022; Kesete et al., 2014; Peng et al., 2014) or be based on the value of assets in an insurance portfolio (Kunreuther et al., 2013) or the value per building (Walker et al., 2016).

Papers considering wildfire insurance models are mostly forestry related. This means that exposure input data for these models are related to forest stand value (Barreal et al., 2014; Brunette et al., 2015, 2017; Sacchelli et al., 2018). It is common to relate this value to the age of the forest stand.

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Concerning windstorm insurance models, the approach is similar to wildfire insurance models, as both categories are mostly applied to the forestry sector (Brunette et al., 2015; Loisel et al., 2020).

4.2.3 Vulnerability

For flooding, vulnerability is commonly depicted by depth-damage curves (Aerts & Botzen, 2011; Boudreault et al., 2020; Boudreault & Ojeda, 2022; Crick et al., 2018; Dubbelboer et al., 2017; Ermolieva et al., 2017; Hudson et al., 2016, 2019; Jenkins et al., 2017; Tesselaar et al., 2020a, 2020b, 2022; Unterberger et al., 2019). A depth-damage curve relates inundation depth to monetary damage (Huizinga et al., 2017). In this manner, vulnerability can be operationalized by assigning distinct depth-damage curves to various buildings or land-use categories. For riverine and coastal flooding, protection standards such as dykes and levees are often considered (Aerts & Botzen, 2011; Hudson et al., 2016, 2019; Tesselaar et al., 2020a, 2020b, 2022; Unterberger et al., 2019).

Concerning hurricanes, Kunreuther et al. (2013) differentiated between two vulnerability conditions, one with risk limitation standards compliant with local building codes and one with the current observed risk limitation standards. Similarly, (Walker et al., 2016) differentiated between two vulnerability conditions: current practice and more stringent design. Other examples include modeling the building resistance level as a parameter and dividing buildings into classes based on location and category (Guo et al., 2022; Kesete et al., 2014; Peng et al., 2014).

Since wildfire insurance models are mainly targeted to forestry insurance, modeling input concerning vulnerability to wildfires is also mostly targeted to forestry practices. One way in which vulnerability is translated for the forestry sector is as a forest management parameter. This parameter stands for the level of preventative measures that are taken and is inversely related to the risk (Barreal et al., 2014). Another paper makes use of empirical vulnerability functions based on the age class of the trees and the probability of destruction (Brunette et al., 2015).

Similar to wildfires, windstorm vulnerability is also mainly targeted to forestry insurance. The empirical vulnerability functions in Brunette et al. (2015) are also applied to windstorms. Concerning trees, the effect of age on vulnerability is more apparent for windstorms than for wildfires (Loisel et al., 2020). Loisel et al. (2020) operationalized this vulnerability by examining age-dependent tree characteristics, specifically diameter and height. They posited that an increase in the percentage of damaged trees occurs when these characteristics attain higher values.

4.2.4 Location

There is only one paper that did not apply its model to a location-based case study but rather considered a generic forest and forest owner (Brunette et al., 2017). More than half of the reviewed papers applied their model to a case study that occurs in Europe (e.g., Barreal et al., 2014; Birghila et al., 2022; Dubbelboer et al., 2017; Hudson et al., 2019; Loisel et al., 2020; Sacchelli et al., 2018; Tesselaar et al. 2022; Unterberger et al., 2019). Of the remaining papers, most of the case studies take place in the United States (e.g., de Ruig et al. (2022), El-Adaway (2012), Guo et al. (2022), Kesete et al. (2014)). A few papers feature a case study in Asia (e.g., Ding et al., 2012; Sidi et al., 2017; Kalfin et al., 2022; Islam et al. 2022). Boudreault & Ojeda (2022) and Boudreault et al. (2020) conducted a case study in Canada. Walker et al. (2016) applied their model to a case study in Australia. The predominant pattern here is that climate risk insurance models are most often applied to western and developed countries compared to less-developed countries. For instance, no model is applied to Africa or South America, which are areas that are more vulnerable to climatic hazards (IPCC, 2023) and might, therefore, benefit from insurance coverage. A possible explanation for the lack of case studies in these regions is the requirement of high-level input data, which are often harder to acquire in less-developed countries. Innovations in the usage of satellite imagery might offer a solution for this problem (Islam et al. (2022). For non-forestry applications, El-Adaway (2012) used actual loss events to link the expected loss to a geographical location.

4.2.5 Scenarios

Models that are forward-looking use projections of how the risk develops over time. This is often done by using a climate change scenario in the risk component of the model. Due to the uncertainty of climate change, it is common to use multiple climate change scenarios in estimating future natural disaster risk.

About half of the reviewed papers can be classified as forward-looking. These papers considered at least one climate change scenario in their approach. The scenarios considered are often the Representative Concentration Pathways (RCPs). RCPs are radiative forcing trajectories until 2100 for different climate change scenarios, ranging from 2.6 to 8.5 W/m^2 (van Vuuren et al., 2011). These trajectories can be employed to simulate future climate conditions in a model and, if multiple RCPs are used, compare the model under different climate change scenarios. If multiple climate change scenarios are employed, such as a low RCP and a high RCP, it becomes possible to set a lower and upper bound on the possible outcomes of a model, capturing the uncertainty around climate change. There are, however, several papers that can be considered forward-looking but only employ one climate change scenario.

More than half of the papers that applied a climate change scenario to their model also applied a socioeconomic development scenario. There are no instances where only a socioeconomic development scenario is applied. The socioeconomic development scenarios often used are the Shared Socioeconomic Pathways (SSPs). SSPs describe different socioeconomic development trajectories such as sustainable development and fossil-fueled development (Riahi et al., 2017). The SSP2 (middle of the road) and SSP5 (fossil-fueled development) scenarios are often paired with the RCP4.5 and RCP8.5 scenarios, respectively, as they have similar traits (e.g., de Ruig et al. (2022), and Tesselaar et al. (2020a)). Another way in which socioeconomic development scenarios are being used is in the form of simulating future land use (for example, Tesselaar et al. (2022) or Aerts and Botzen (2011)). Tanaka et al. (2022) incorporated income and house prices that increase over time, reflecting a constant economic growth rate.

4.2.6 Disaster risk reduction (DRR)

DRR measures to reduce climate risk are often accounted for. More than half of the reviewed papers include some form of DRR. Often, these papers employ a forward-looking model by means of a climate change scenario, as modeling DRR measures is especially interesting for forward-looking models.

In reality, DRR is usually financed by governments and consumers of insurance. Of the papers that included DRR, most did so for DRR financed by households (e.g., Hudson et al., 2016; de Ruig et al., 2023; Tesselaar et al., 2022) or by both households and the government (e.g., Peng et al., 2014; Jenkins et al., 2017; Guo et al., 2022). A subset of the reviewed papers included DRR measures financed by agribusinesses, such as Barreal et al. (2014), Birghila et al. (2022), or

Brunette et al. (2017). Furthermore, Aerts and Botzen (2011) and Unterberger et al. (2019) considered DRR financed by only the government. Models that consider insurance against wildfires and/or storms generally did not include DRR (but see Barreal et al. (2014)). However, DRR measures against these hazards do exist (Manocha & Babovic, 2017; Paveglio et al., 2018).

When a premium is risk-based, investing in DRR measures can potentially lower this premium. This not only incentivizes proactive risk management but also promotes broader societal engagement in resilience-building efforts. This ultimately fosters a more economically viable and secure environment for both insurers and policyholders. An important question is how insurance arrangements can incentivize investment in risk reduction measures (Botzen, 2021). The idea of using insurance to stimulate DRR is explored in multiple papers and across hazard type (e.g., Brunette et al., 2017; Hudson et al., 2016; Jenkins et al., 2017; Peng et al., 2014). For example, Hudson et al. (2016) showed that correctly incentivizing DRR via insurance can lead to a reduction in household flood risk of 12% in Germany and 24% in France by 2040.

4.3 Insurance

This section summarizes findings about the insurance component of the model. Details per reviewed paper can be found in Table 4 of the Appendix.

4.3.1 Recipient and the decision to insure

About two-thirds of the reviewed studies concerns insurance for households. Two papers included insurance for households in combination with insurance for another entity; Moosakhaani et al. (2022) used a model where both households and the government are insured, and Ermolieva et al. (2017) used a model where households and firms are insured. Furthermore, some papers modeled insurance for structures such as civil infrastructure developments (El-Adaway, 2012; Unterberger et al., 2019) or insurance for buildings in general (Sidi et al., 2017). Multiple papers modeled agricultural insurance, of which two papers concerned some form of crop insurance (Birghila et al., 2022; Islam et al., 2022), and six papers focused on insurance for forestry (Barreal et al., 2014; Brunette et al., 2015, 2017; Loisel et al., 2020; Pinheiro & Ribeiro, 2013; Sacchelli et al., 2018). While agricultural insurance can be considered as insurance for firms, Ermolieva et al. (2017) is the only paper that considered insurance for general firms alongside households by using land-use maps.

Models that are not only supply-focused also often incorporate a consumer decision component. This decision component indicates, if applicable, the way in which the decision to purchase insurance is made. Insurance uptake can be summarized into two categories: mandatory uptake and voluntary uptake. Concerning mandatory uptake, the premium can be risk-based when a solidarity market structure is concerned (Hudson et al., 2019; Tesselaar et al., 2020a, 2020b, 2022). There are also examples of papers that use mandatory uptake but do connect the premium to the risk. These papers either assume that all constituents purchase insurance (Aerts & Botzen, 2011; Crick et al., 2018; Dubbelboer et al., 2017; Jenkins et al., 2017) or a given percentage of households (Tanaka et al., 2022). For voluntary uptake, the decision to insure is based on expected utility maximization. In this way, the insurance recipient (commonly households) makes the decision based on a (subjective) utility curve. In essence, the insurance recipient determines whether acquiring insurance provides greater value than not obtaining insurance by weighing the prospective loss against the premium payment. The way in which this decision method is employed varies mostly in the degree of rationality that is assumed. In Kesete et al. (2014), the insurance recipient is assigned a risk aversion coefficient based on the risk region but has no specific rationality constraint. This differs from the model employed by, for example, Hudson et al. (2019) and Tesselaar et al. (2020b), where a subjective expected utility framework is used. The subjective expected utility framework incorporates variations in risk perception from the objective risk to account for bounded rationality. Subjective expected utility is also used in studies by de Ruig et al. (2022) and de Ruig et al. (2023), where households are assumed to overestimate their risk after a flood event and underestimate their risk after a period of no floods. Other models that make use of an expected utility curve but do not include a rationality constraint can be found in studies by Ding et al. (2012), Peng et al. (2014), and Brunette et al. (2017).

4.3.2 Insurance sector modeling

Climate risk insurance is organized differently across countries and hazard types (Le Den et al., 2017). Moreover, insurance can be arranged privately, publicly, or a combination of the two (Hudson et al., 2019).

Insurance supply models predominantly concentrate on the pricing aspect of an insurance contract and typically omit explicit consideration of the insurer as an agent (e.g., Boudreault et al., 2020; Brunette et al., 2015; Sacchelli et al., 2018). More often, the insurer as an agent is incorporated, but only one representative insurer is assumed to exist (e.g., Kalfin et al., 2022; Birghila et al., 2022; Kesete et al., 2014). Not including an insurer as an agent or assuming the insurer to be a single agent is a common modeling assumption. This assumption is also frequently employed in models focused on insurance demand (e.g., Birghila et al., 2022; Islam et al., 2022). An alternative format involves modeling an insurance market wherein a public entity assumes the role of providing insurance, as opposed to a private company. This approach is frequently employed in partial equilibrium and agent-based models, where multiple market forms are simulated and considered (e.g., Crick et al., 2018; Hudson et al., 2019; de Ruig et al. 2023).

Another representation of the insurance sector is delineating the insurance component as a public-private market, wherein the government assumes the role of a risk-neutral reinsurance agent providing support to insurers (e.g., Perazzini et al., 2022; Hudson et al., 2019; Aerts and Botzen 2011) or a publicly organized insurance market in which a public agent provides insurance instead of a private company (e.g., Crick et al., 2018; de Ruig et al., 2023).

Certain models offer an evaluation of the effectiveness of diverse insurance structures, spanning from private to public configurations. Hudson et al. (2019) evaluated six different insurance systems in the EU on their ability to cope with trends in flood risk and found that introducing elements of public–private partnerships can improve the affordability of insurance. In a study conducted by Unterberger et al. (2019), three distinct insurance systems are analyzed with regard to their fiscal impact on forthcoming governmental budgets and the associated variability in disbursements for public infrastructure insurance. As another example, Kunreuther et al. (2013) differentiated between hard and soft insurance market conditions to evaluate how the supply system for hurricane insurance behaves under these different conditions. In a similar fashion, Tesselaar et al. (2020a) analyzed the effect of climate change on premiums, affordability, and insurance uptake in soft and hard reinsurance conditions.

A select number of models integrate the consideration of insurer competition, each employing distinctive methodologies in their approach. One model type that is well suited for modeling competition is the game-theoretic model type. For example, Guo et al. (2022) simulated multiple insurers that participate in a perfect information Cournot–Nash noncooperative game to calculate the premium. Another way in which competition is considered is by assuming Bertrand competition among the insurers. This is done by omitting a premium profit margin (e.g., Hudson et al., 2019; Tesselaar et al., 2022; Tesselaar et al., 2020a; Kalfin et al., 2022), indicating that the insurers cannot earn a high profit due to the market being competitive. A general observation is that none of the reviewed ABMs explicitly model competition among insurers. Most ABMs either use a public insurance agent (de Ruig et al., 2022, 2023) or assume only one insurer in the model (Crick et al., 2018; Dubbelboer et al., 2017; Jenkins et al., 2017). Tanaka et al. (2022) employed an ABM that does not include an insurer as agent but uses a given insurance premium.

4.3.3 Premium calculation

Insurance premiums are often computed using various methodologies such as a solidarity system or capped premiums via a public-private partnership. However, the most prevalent approach is the usage of risk-based premiums. This type of premium is designed to mirror the inherent risk associated with the insured entity. The utilization of risk-based premiums holds significance, as it facilitates alignment between premium revenue and projected indemnity disbursements, thereby contributing to the financial viability of an insurance scheme. Furthermore, the deployment of risk-based premiums serves as a means to convey information pertaining to risk, as evidenced by the studies conducted by Botzen and van den Bergh (2009) and Kousky and Kunreuther (2013). Additionally, these premiums can serve as a mechanism to incentivize the implementation of DRR measures, as elucidated by Botzen and Van Den Bergh (2009).

Examples of models that use risk-based premiums for wildfires can be found in the study by Sacchelli et al. (2018). Examples of models that use risk-based premiums for hurricanes are those by Kunreuther et al. (2013) and Walker et al. (2016). Alternative methods for computing insurance premiums include the application of the distortion premium principle, as proposed by Birghila et al. (2022). Another approach involves representing the premium as a random variable, a concept explored by Sidi et al. (2017). Additionally, a quantile-based methodology, as outlined by Ermolieva et al. (2017), offers an alternative perspective on premium calculation. In some models, premiums are determined via aggregated risk in a solidarity market (e.g., Hudson et al., 2019; Tesselaar et al., 2020b).

Studies addressing multiple insurance supply systems frequently employ diverse methodologies in premium calculation. An illustration of this multifaceted approach is evident in the work of Hudson et al. (2019), where premiums are determined through various models. These models encompass scenarios where premiums are unrelated to risk, fully risk-based, or risk-based with an imposed cap. A similar instance is illustrated in the research conducted by de Ruig et al. (2022), where the determination of premiums varies across several approaches. These include premium calculations based on outdated risk maps, fully risk-based assessments, computations grounded in updated risk maps following a flood event, and premiums derived from periodically updated risk maps. The adoption of diverse premium calculation methods proves to be a valuable strategy, facilitating comparisons among distinct market types or risk assessment methodologies. This comprehensive approach contributes to novel insights within the field of climate risk insurance modeling. As an example, by performing a multi-criteria analysis on different insurance market types, Hudson et al. (2019) found that a public–private partnership system can reduce the unaffordability of insurance by performing a multi-criteria analysis on different insurance market types.

5 Results of stakeholder analysis

The elements of the conceptual framework served as the initial structure around which the results have been organized. This section consists of three parts. First, it begins by outlining the context of climate risk assessments within the EU insurance industry. Second, uncovered uncertainties and challenges are highlighted. Last, potential innovation opportunities that emerged from the stakeholder interactions are elaborated upon. All the parts are paired with supporting quotes.

5.1 Context setting

This analysis begins by examining common insurance products relating to climate risk. Next, it explores how climate data is utilized. The analysis then extends to other model data inputs, including historical losses, projections, and socio-economic factors. Finally, the focus shifts to strategic insurance decision-making.

5.1.1 Insurance products

From the interviews, it became evident that climate risk assessments are mainly relevant for property-related impact and non-life insurance. One participant explains: "It's mostly related to Property and Casualty (P&C) business because natural perils have material or property related impact." Property risks encompass any type of physical damage. For instance, damage to buildings due to floods and earthquakes was mentioned in fifteen and eight interviews, respectively (out of sixteen interviewees). Interestingly, forest risks associated with storms and insect infestations were mentioned twice.

Beyond property-related impact, business interruption emerged as a recurring theme in eleven interviews, highlighting its importance in insurance coverage for natural hazards: "We look into different things. The first one is the damage to buildings, damage to facilities, damage to machines. This is straightforward damage to our end customers. We are also looking into the impact on supply chains that have to do with business interruptions."

The interviews revealed a variation of clients, with participants offering full property coverage for commercial, public, and individual clients, only commercial clients, or commercial and public clients. One participant's quote effectively summarizes the key applications of climate risk assessments in insurance products: "We use it for all property insurance, motor, and homes. Both residential, commercial, industrial, and agricultural. It covers buildings and their contents, but also business interruptions. We also use climate/natural hazard risk information with business lines that are exposed like marine and aviation transport and for engineering risks and construction risks."

5.1.2 Climate-related risk information

Hazard

Understanding the range of hazards is crucial for developing a comprehensive understanding of climate risk assessments. Figure 6 illustrates the frequency of hazards mentioned during the interviews. The numbers indicate the number of times each hazard was discussed in separate interviews. Flooding was mentioned in all but one interview, making it the most prevalent natural hazard. It became apparent that there are several types of floods that require specific modeling approaches due to varying root causes: "You have fluvial floods, which comes from rivers. Pluvial flood, which relates to precipitation risk. Storm surge, which is when the water level rises because of wind. Then you have flash floods, which is a city problem. You can also have dam breaks and glacial outbursts."

After floods, windstorm risk was highlighted most frequently and emphasized by one participant as the largest risk in the Netherlands. Wildfire, hail, and earthquake risks were subsequently underscored. Interestingly, hail was often discussed in conjunction with both motor vehicle and greenhouse damage.

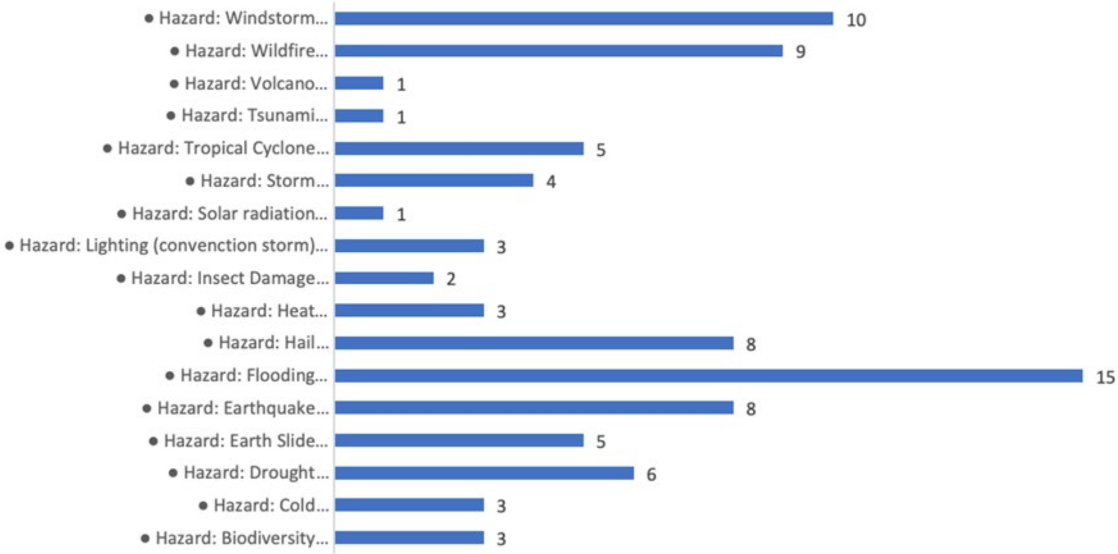

Figure 6: Frequency of hazards mentioned

Exposure

The second element in the risk equation is exposure. Exposure refers to the value and risk profile of insured property. The discussions revealed that exposure data is used as an input to the models: "The model reads an input, which is a monetary input. This is your total exposure. It gives a distribution of the percentage of that exposure that is at risk, given different thresholds of probabilities."

The importance of understanding an insured property's exposure and its future development is essential. Participants highlighted the value of enhancement techniques for improved exposure data comprehension, recognising that models perform better with better-calibrated data. Specifically, geocoding was mentioned three times: "Creating a modeling output goes with knowing where your risks are located, which is the geocoding. Information on the location of assets is intersected with what kind of perils they're exposed to. […] The better your geocoding and the better the information on the type of structure, the more accurate your model becomes."

Depending on the type of hazard, exposure data needs to be granular enough to determine the expected portion of the total limit an insurer is at risk with.

Vulnerability

Beyond exposure, vulnerability determines how the hazard translates into losses. The interaction of hazard and vulnerability yields a destruction rate as a fraction of the total value, which is then applied to the exposure. Consequently, having a good understanding of both an area's vulnerability and the vulnerability of specific insured clients is crucial, as was highlighted in seven interviews. One participant illustrates: “A vulnerability function translates, for example, wind speed or hailstone size into the mean damage ratio for a certain area or a postcode.” In another interview, this was elaborated upon: “The vulnerability model looks at your portfolio and how, for example, a hailstone or a windstorm impacts a wooden structure versus a concrete structure.”

Risk models can incorporate data on certain protective measures in the built environment that reduce vulnerability if this information is provided by a broker or client.

Climate data

To model a potential loss distribution, the development of frequency and severity of a hazard needs to be well understood. Public data plays a vital role in hazard modeling, with openly available information from public entities and research institutes serving as the foundation. An important distinction needs to be made: “We have short-term horizon weather data from different data providers. But when we talk about climate change, it's a medium to long time horizon. There are different research institutions currently working on it. So that's why we get data at different levels. Sometimes it's from IPCC, so the international level. Sometimes we get the data from a local institute in different geographies.”

Weather institute data appears to be a frequently utilized source to obtain short-term meteorological and hydrological data. In addition, eight participants mentioned how climate change data is gathered on various climate parameters through reports by the IPCC. Expertise is also leveraged through collaboration with research institutes and commercial entities, as one participant highlights: “Our science team works on models for climate change with universities in Europe, sometimes in the USA. Besides, we sometimes use data provided by commercial companies. […] Airbus, for example, is a good company. They produce satellite data. We can use this to see what, for example, the drought evolution is, pictured by soil moisture.”

Acquiring satellite data is further streamlined as openly available for utilization: “They’ve created structured processes to download satellite data from free open-source satellites, like ESA and NASA Science. They've got a whole platform dedicated to quickly being able to download that data.”

By combining data from public entities, research institutions, and commercial companies, insurers aim to build hazard models that reflect the evolving climate as accurately as possible.

5.1.3 Other model data inputs

Historical losses

Analysing past events is crucial for understanding the frequency and severity of natural hazards. By incorporating and analysing historical claim data categorized by risk maps, insurers can build and validate model parameters that effectively predict potential loss distributions in the event of a natural disaster. One participant explains: “The company has recorded weather, climate, and hazard data and claims worldwide. I think it started in the 60s, so they have a detailed long-term history of data they can use for that.”

Less frequent hazards require longer historical datasets for a more accurate understanding of the risk profile. While historical loss data provides a valuable foundation for natural disaster risk modeling, climate change may cause past events to be less representative of current and future risks. To address this limitation, two participants address techniques like detrending to remove long-term trends from the data, isolating the present risk profile: “We detrend the climate data so that we know that we're looking at data that's now, and not taking into account maybe a less risky history.”

Furthermore, the future is factored in. Another participant highlights: “Historical data is detrended based on scientific research. If you look for example at hurricane models, they are based on historical data, but they are updated every year based on the data, the context, and the weather conditions.”

Forward-looking data

Incorporating scientific forecasts and future projections of climate scenarios allows insurers to develop better forward-looking models. However, the interviews revealed an equally divided approach among participants regarding the use of these techniques. Forecasts, which extrapolate from historical data, offer a more predictive element, making them valuable for pricing purposes and short-term risk assessments. One participant explains: “Climate forecasts are based on the best understanding of what the situation is now and try to go forward with it. With the scenarios that the IPCC generates, which are different from forecasts, it can be a + 1,5 degrees world or a +4 degrees world. I would say in that sense, climate forecasts are the ones that influence the insurance industry more than the scenarios. […] because a forecast starts from the current situation and environment to show how it will evolve. Depending on what IPCC scenario proves to be true, the basis of the forecast changes.”

Climate projections, on the other hand, are more often used when looking at long-term climate risks, particularly those concerning assets. These scenarios, which look twenty, thirty, or more years ahead, allow insurers to see how climate change will affect the risk in the longer run due to their ability to capture non-linear climate effects that might be more severe than a linear extrapolation of historical trends: “In my view, the projection models are more appropriate because with historical trends, it's always dangerous and difficult to extrapolate them into our future pattern. […] I think with projections you've got a better understanding because we see that climate change is developing faster than what the historical trends might suggest.”

The projections mostly seem to be based the Representative Concentration Pathways (RCPs), which were cited seven times: “We use different scenarios of the RCP. RCP 8.5 for the worst-case scenarios. We use the 4.5 as a benchmark. Sometimes we also use the optimistic 2.5, but we use that less often because our job, unfortunately, is to alert our client.” Another participant confirms: “Mostly if you are using RCP, you are using RCP 4.5 and 8.5. 2.6 is very optimistic and no one uses 6.0 that much. They say that 4.5 is most common, 8.5 is very pessimistic.”

Nevertheless, eleven participants brought up that the non-life insurance contracts have a horizon of one year, which is why long-term projections are not top of the agenda of insurance companies. Short-term volatility is not driven by average annual warming. Instead, intra-annual fluctuations play a more significant role: “We are only talking about intra-annual variability that might be driven by whether next year is going to be an El Niño or a La Niña year, or in what mode the North Atlantic oscillation is. These are very different questions about climate. […] That huge volatility you see you on year are the things that insurers are interested in, more so than the background warming.”

Although forward-looking climate models are not yet widely integrated due to the short-term focus of many insurance products, these models hold significant potential for promoting DRR strategies and putting pressure on, for instance, governments.

Socio-economic factors

Although socio-economic factors were thought to be an input factor to the risk models, most participants excluded them entirely. Yet, one participant indicated the following: “We are using estimates of future climates under the assumptions of future human-related activities such as socioeconomic and technical development.” Nevertheless, socio-economic circumstances seem more of a consequence rather than an input, which depends on geographies, population, and the protection gap: “The impact of climate change is not distributed equally to people. I believe that the impact of vulnerable people is more important than the middle and upper class. This needs some actions from governments to not act and react too late. We need to understand that the impact to different countries and different populations are different.”

5.1.4 Climate risk models

Climate risk assessments are generally modeled through Natural Catastrophe (Nat Cat) models that incorporate hazard, vulnerability, and exposure data to generate event-loss tables using a stochastic approach. A participant highlights the complexity: “If you want to know the likelihood of your house and your neighbour’s house being impacted by the same flood event, then you need a refined stochastic model. This provides several scenarios of events that could happen, which allows for quantifying the aggregation of the risk coming from a certain pattern.”

Furthermore, Monte Carlo simulations are used to model a wide range of potential natural disasters or other insured events. This results in a probability distribution for hazard frequency and severity, in which inherent uncertainties are included. Nat Cat models are further highlighted by seven participants in informing both solvency requirements and reinsurance strategies for insurers. They focus on high-impact, low-frequency tail events that uses one in 100-, 200-, or 1000-year scenarios. These tail events are particularly relevant for solvency calculations under Solvency II regulations: “We use a 1-in-200-year scenario, as it is important for Solvency II. Solvency II is the requirement for the solvency calculations for insurers in the EU. […] For every risk type, there is a formula. Then you can add it together to get the total capital requirement, the Solvency II capital requirement.” Another participant confirms: “We are using it for our solvency internal model. When we want to run our model for Solvency II, we need the 99,5-percentage quantile. You need something that's rather robust at exactly this quantile.”

Twelve participants confirm they (partly) rely on external vendors and reinsurers for Nat Cat models, leveraging their expertise of the hazard and vulnerability component, and translating exposure into economic risk distributions: “We make use of models developed by model vendors. We get the information from the reinsurance brokers. They run the models to be able to negotiate with the reinsurers and advise us on the reinsurance program, but we can also use these models for internal risk management purposes.”

Although the external models may lack transparency due to their proprietary nature, developing models in-house would require significant expertise, time, and financial resources. Instead, insurers aim to gain a thorough understanding of the model’s methodology through testing and validation in which their expertise and experience is leveraged: “We do investigations on those external models. We are using a scorecard with all different types of tests we do on those third-party models. […] We validate the methodology that they used especially relating how fast climate shocks are translated to economic impact. Then we read the report, we check it for plausibility, we reference it to other reports that we know of. Sometimes you need to adjust for opinions or methodologies."

In two instances, catastrophe models were noted as inputs for actuarial calculations. For specific risks where external vendor models are unavailable, such as floods in certain regions, insurers may choose to develop their own actuarial models in-house: "Mainly we work with third-party vendor models. But that's not the case for flood risk. […] For flood risk, we have made a model that's built on our own account using the different advisory companies in the Netherlands. […] There's no external flood model available, but we've seen it as an important material risk, so we've created a model ourselves."

In contrast, four participants offer parametric insurance solutions. Parametric insurance specifically targets acute natural perils, as chronic perils are challenging to insure parametrically due to their extended duration. Unlike Nat Cat models, parametric models focus solely on the hazard itself, triggering pay-outs based on pre-defined parameters: "In parametric insurance, you negotiate the terms, the parameters, of the event very precisely. You set space, you set the time, and you set a certain metric. For example, if an earthquake happens in the 100-kilometer area around the centre of Zurich and this earthquake is more than 6 on Richter, then the insurance policy is triggered and you get immediate pay-out based on the agreed-upon value, but if the magnitude is 5.9, you get nothing." Naturally, this type of insurance requires very good knowledge of the natural perils which is leveraged through different data sources including weather stations, drones, and satellite images, so that claims can be released quickly.

5.1.5 Insurance decision-making

Risk models generate probability distributions of potential financial losses, which then serve as inputs for underwriters when determining policy pricing: "Based on hazard, vulnerability, and exposure, you make a loss model that is taken for pricing. Then you have a technical price, which tells you the minimum price that we're willing to sell this insurance for. Then people called underwriters take it. They negotiate with the client to get the final price."

Climate change, however, introduces significant uncertainties, potentially necessitating premium increases in regions experiencing uncharacteristically high losses for events that might fall outside the current models. On the other hand, as mentioned before, most non-life insurance products have a duration of one year, which limits the application of long-term climate effects in pricing. Climate change is very gradual, and insurers are only interested in how climate change is going to affect the coming year: "I don't know how much climate modeling is necessary when it's one-year policies. You want to isolate what's going to happen this year. You don't care what's going to happen 2030."

While long-term climate effects are not critical for pricing due to their one-year nature, the contrary seems true for strategic considerations. Besides solvency and reinsurance, six participants recognise the increasing influence of climate change on investment decisions, such as bonds, equity shares in companies, or real estate: "We have an asset portfolio consisting of government bonds, equity shares, bonds from companies, real estate, and mortgages. Those are worldwide and we analyse it on two levels. First, on a granular level top down. We look at how our portfolio is roughly distributed around the world and what the climate risks are to GDP and so on; […] we analyse the companies we invest in. In that analysis, we use a climate analysis for the specific asset to assess how much material risk it has."

Since some investment portfolios hold assets for decades, a long-term strategy that incorporates climate considerations is required, since these assets are exposed to potential climate risks over their lifetimes. One participant elaborates on their strategy: "We have a best-in-class strategy where companies that do well in climate risk reduction are preferred over companies that not do as well, and the bad ones we don't want to invest in. We're hoping that by doing this, we limit our climate risks and have more of an impact."

Although climate risk reduction is reflected in the vulnerability component of the risk model, it is not directly used as an input in the model. Nevertheless, four participants highlighted that they inform clients of measures that could reduce their risk of specific natural perils: "We can show clients: this is your flood risk today, this is how it would look in 2030, and this is how it would look in 2050. Those assessments are passed on to the risk consulting department. They are the ones who best advise the client what they could do, what measures they could take to reduce the risk."

One interviewee emphasized the challenge of long-term planning for climate risk reduction considering frequent leadership changes among boards, CEOs, and ministers.

5.2 Uncertainties and challenges

Uncovering the main uncertainties and challenges of climate risk assessments is crucial to this study. Ten distinct categories emerged from the interviews. Figure 7 summarizes the codes for "uncertainties and challenges," highlighting their frequency (left vertical axis, bar chart) and the number of interviews where each challenge was discussed (right vertical axis, line chart). The relative percentage indicates the proportion of each challenge code within the total "uncertainties and challenges" category. It suggests a correlation between the frequency of a challenge and the number of interviews it arose. Notably, "Nonlinear Environmental Changes" is the most evident challenge. Participants noted that there are uncertainties that come from climate evolution that we are not aware of because the whole system is changing. The nonlinear nature of these changes, with potential tipping points and unforeseen triggers, significantly complicates future climate modeling: "These effects are nonlinear and kind of increase. Small errors at the very beginning increase in size and become huge errors in and like in 30-40-50 years projections."

Three participants continue to address the interaction between tipping points of biodiversity and climatic perils, highlighting its uncertainty: "The escalation that will be caused by lack of biodiversity through climate change and global tipping points, those are the big climate events that make a difference in what the result will be. […] The tricky part of is that you don't have a history of how a change in biodiversity will trigger natural catastrophes. That's a completely new scenario. You have to model it somehow with a very high uncertainty."

The primary challenge associated with nonlinear environmental change lies in modeling such unforeseen scenarios. As one participant pointed out: "There's way more that we don't know than we know. Despite all our attempts to capture this in the most sophisticated climatologist models."

This argument is supported by "Assumptions and Parameter Validation" being the second largest challenge. From hazard to exposure to vulnerability to loss, the uncertainty compounds if any previous assumptions are incorrect. Wrong assumptions can therefore corrupt the entire model, highlighting the need to validate parameters against other models, historical data, and scientific literature. An example of flood risk modeling illustrates its complexity: “The elevation of the riverbed is a big assumption in the model. There's very little validation data for these tools because we don't have enough observations of real flood events measured to any useful degree of accuracy for us to compare the model representation of these floods to an observed reality, which makes it hard for us to understand if anything that we're doing is any good ultimately.”

Two participants further emphasized the need for geographically specific models due to “Geographical Risk Differences” across regions. This necessitates global data, as the impact of a hazard can differ significantly depending on location.

“Economic Uncertainties” include capturing future inflation impacting labour and construction costs or material shortages that could drive up prices, which leads to concerns about the future insurability. Seven participants expressed concern about the ability to set high enough premiums to cover potential risks: “The real issue is that at some point, even with the tools we have, we start realizing that the price that we have is not sufficient. It is not just a matter of calculating what your expected loss is, it is also a matter of making sure you can charge that amount to your customer. I see the effect of climate change being a larger threat to the market dynamics than being a threat as a shock for the industry because I think the shock component is considered in the modeling already. But the inability to place your cover in the market and to find the customers is what is going to cause a bit of an impact on society. It becomes a market failure more than a failure on the modeling side.”

Translating damages into an economic effect is where there is a “Disconnect”, according to six participants. Several issues come to light. First, a gap exists between academia's recent recognition of climate risks in insurance and the industry's decades-long experience managing these risks. In addition, meteorological institutes' risk assessments may not align with the specific measures needed by the insurance industry. Finally, actuaries responsible for pricing may lack the expertise to integrate climate scenarios, such as those provided by the IPCC, into their models.

Furthermore, “No Detailed Exposure and Vulnerability Data” seems to be a prevalent concern, as information is often wrong or lacking. Property details, such as exact location, type of structure, height, and materials are essential to assess a risk. Similarly, “Terrain Mapping” data on the form of the landscape and defences such as flood protection measures are fundamental: “You need to know not only the height of the building but also the material of the building. Depending on if your property is on top of the hill or if you are at the bottom of a mountain, the water has a different speed. To know this, you need a meteorologist and engineering, with that science you can build something more intelligent.”

Beyond data gaps, the additional concern of “Closed Off Data” due to restrictions by vendor companies or governments was highlighted, with three participants advocating for more transparency. Uncertainty of “Regulation” regarding climate change adds another layer of complexity. Four participants expressed concern about the lack of clear government action in response to rising climate costs. One participant proposed a role for academia in guiding governments towards public-private partnerships. Additionally, three participants emphasized the uncertainty surrounding “Future Climate Adaptation” measures and the level of international cooperation.

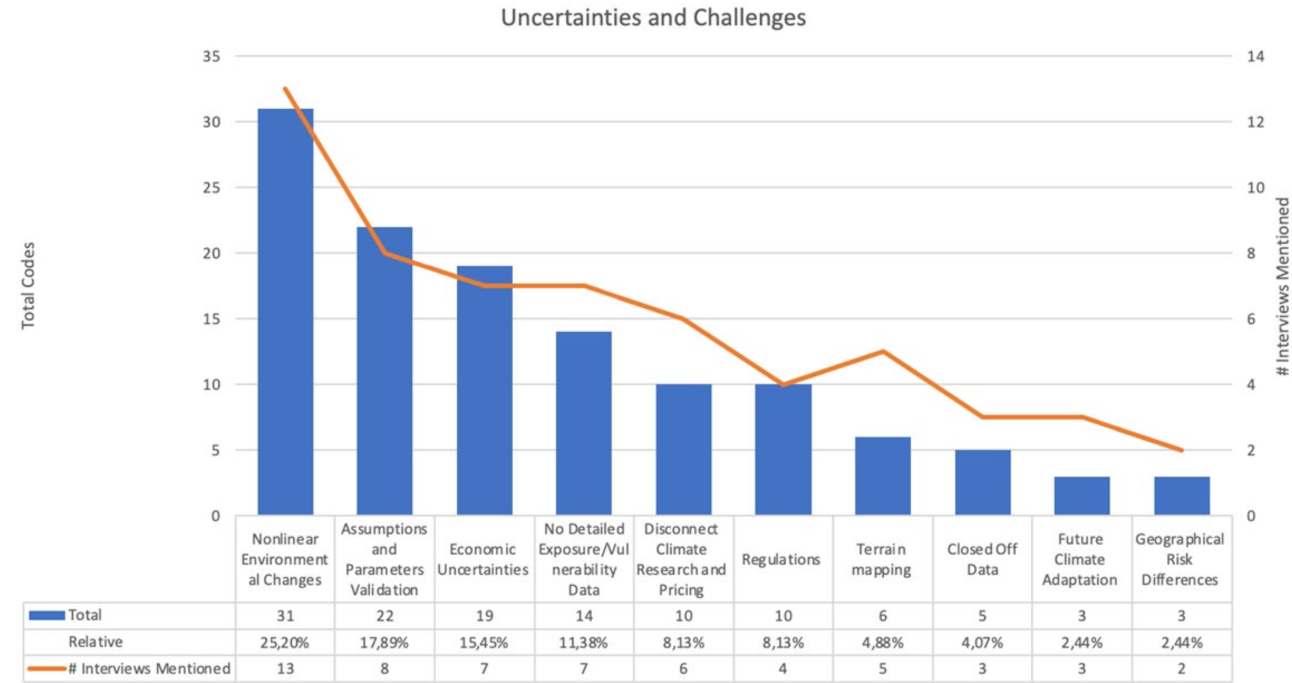

Figure 7: Uncertainties and challenges overview

The focused discussion highlighted some broad perceived uncertainties that may influence the accuracy of natural disaster risk modelling. The largest number of participants (sixteen) highlighted uncertainties around future climate change conditions as the key challenge. This is in line with the frequency that the specific uncertainty relating to climate change elicited from the interviews was mentioned, i.e. the nonlinear nature of this change, and therefore unforeseen future climate conditions. Less participants selected limited past data availability (eleven) and uncertainties about future population and economic growth (nine) as key challenges, which is also generally consistent with how often related uncertainties were mentioned in the interviews. Thirteen participants highlighted uncertainties about how to include adaptation dynamics. Therefore, this point received a higher focus in the discussion, compared to the interviews. Participants highlighted the feedbacks that may occur between vulnerability, hazard experience and adaptation behaviour, as well as the role that social sciences could play in assessing adaptation behaviour over time for facilitating more accurate natural disaster risk modelling. It was also mentioned that adaptation is often included statically across time using protected versus unprotected hazard maps.

5.3 Innovation potential

Ten areas for innovation potential were uncovered. Figure 8 represents a similar graph as seen before for uncertainties and challenges. Correlation between the frequency an innovation emerged and the number of interviews they were mentioned seems, however, less prevalent.

“Parameter Improvements” within the model is where most improvements could be made. This innovation addresses the second largest challenge “Assumptions and Parameter Validation”. One participant pointed out that climate-related parameters are currently hard-coded in the model. However, they should be adjustable to changing conditions to form scenarios on, for instance,

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future biodiversity or tipping points. An improved understanding of the perils through more research is discussed as a solution, in line with the third most frequently mentioned innovation “Improved Environmental Understanding”: “Only as research gets better and discovers new things and improves our understanding of the perils, it will slowly get added into the models.”

An improved understanding of natural phenomena could be directly incorporated into models, leading to better projections. New insights, for instance, the projected impact of a 3.5-degree temperature rise on storms and floods, would enable adjustments in these projections. One participant contested this view, arguing that the focus should be on evolving how models are built, not just on climate research. Another participant agrees, advocating for the creation of more models to ultimately achieve marginal improvements through model convergence: “You simply need as many people as possible creating these models, so it’s easier to do the validation. Over time things are going to converge towards some optimal solution that everyone kind of agrees is the best way to do it. The uncertainty will decrease as more people create these models, especially global models. […] Per solution, we have a better solution in the future and the sooner we reach it, the better. For that, we need brain power, funding for model building, and more companies building their own models.”

On the other hand, through the code “Model Sufficiency”, positive and constructive sentiments about the current models were noted. Participants mentioned they are “getting more sophisticated with a higher resolution” and “very advanced”. It was pointed out that nonlinear models are never perfect while acknowledging the potential added value of combined risk and tipping point modeling. Yet, eleven participants expressed reasonable confidence in current models for informing climate policy and balance sheet analysis: “I think the models are great. However, I think that all models are wrong, some models are useful. As long as we keep thinking and challenging what we see coming out of the models and look at what possible scenarios there are, we can at least try to define the grey swans. Black swans, those are out there. We simply don't know and that's why they are called black swans.”

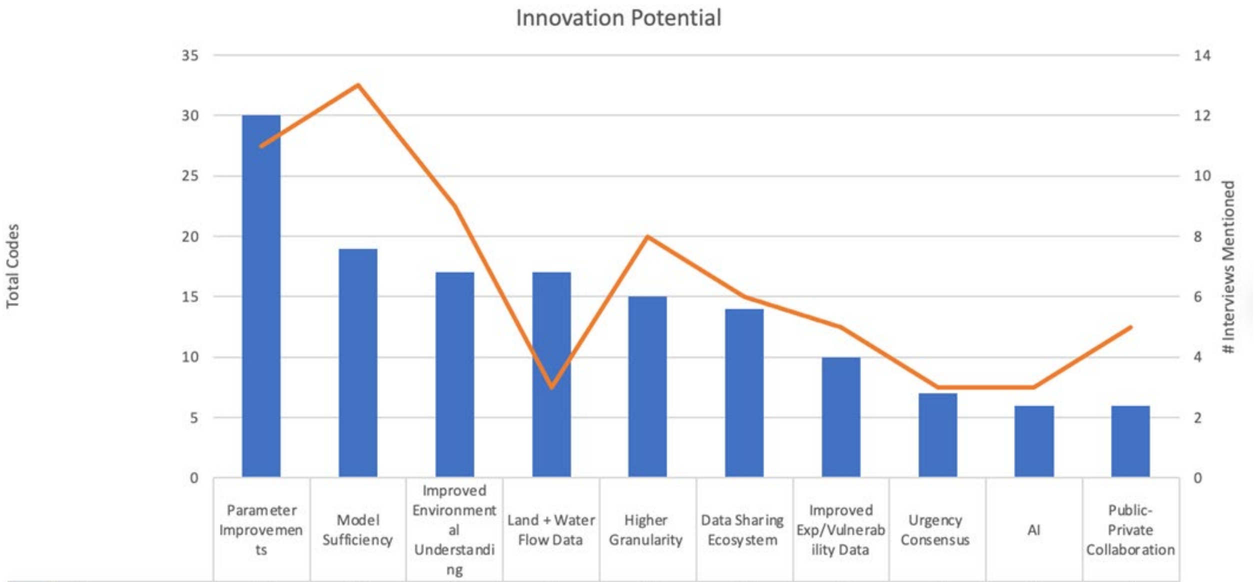
The key challenge lies in the quality of data feeding the models. Two areas were identified for improvement: "Land and Water Flow Data," and "Higher Granularity," These categories address the challenge “Terrain Mapping” from different angles. Floods were a particular concern, highlighting the need for more detailed data on landscape shape and property characteristics: “We need models that can see not only the extent and the depths of a future flood in an area but also the flow dynamics. For example, how fast the water will be, or how long a building will drown in the water. Therefore, strong meteorological knowledge is needed and combined with building engineering deep learning.”

Additionally, landslides, hailstorms, and windstorms are emphasized to require specific data to predict how local exposures are affected. Currently, most models need downscaling to obtain a higher granularity. Yet, the more detail you can get on a granular level, so far as the model becomes robust, the more accepted it is. Radar-based satellite data was mentioned to offer a promising solution. By providing more precise elevation data, it can predict water flow patterns, potential pooling areas, and flood damage to buildings and infrastructure. Additionally, LiDAR technology, which uses laser measurements from airplanes to map ground surfaces, was mentioned as a significant innovation. Also “AI” applications in model building and downscaling emerged in three interviews, claiming that AI is “quite strong in modeling nonlinear effects when it’s benchmarked against experience and expertise from physicists and meteorologists.”

An expert in flood mapping highlighted the importance of freely available, state-of-the-art elevation data in model development, which introduces a “Data Sharing Ecosystem” as an innovation. This ecosystem would address the challenge of "Closed-Off Data" by promoting the open sharing of valuable data, including satellite imagery and climate change knowledge while increasing transparency and dialogue. The concept involves breaking down data silos and establishing a common data-sharing platform. One participant shares his view: “The idea is to create an ecosystem because everyone is strong in their domain of expertise. This infrastructure can be created with two things. The first one is the collaboration of different key actors in different in industries. The second one will be the support from European governments to create a working group so that people can work together.”

Relating to the challenge of “No Detailed Exposure and Vulnerability Data”, acquiring that data would significantly improve loss estimations. While acquiring data on building characteristics and protective measures is technically possible, the sheer volume of individual properties across Europe makes comprehensive data collection impractical. To address this challenge, one participant proposed the creation of a standardized European index cataloguing all structures. Additionally, the potential role of AI in identifying flood defences and building structures was noted.

Lastly, three participants displayed a clear consensus on the urgent need to address climate change and arrive at a consensus on how the industry should position itself. “Public-Private Collaboration” could aid by mobilizing broader public support for climate change mitigation and DRR initiatives as this is not a topic that can be solved by the industry alone. Additionally, two participants emphasized the need for governments to establish effective regulatory frameworks for the insurance sector. These frameworks should promote financial resilience within the industry while ensuring that insurance remains accessible and affordable for policyholders: “You need to have a public-private cooperation. It needs to be a market solution that needs regulation from the government. Then there is a much broader set of people that are needed to find a solution that works. Academia can play a role here.”



	Parameter Improvements	Model Sufficiency	Improved Environmental Understanding	Land + Water Flow Data	Higher Granularity	Data Sharing Ecosystem	Improved Exp/Vulnerability Data	Urgency Consensus	AI	Public-Private Collaboration
Total	30	19	17	17	15	14	10	7	6	6
Relative	21,28%	13,48%	12,06%	12,06%	10,64%	9,93%	7,09%	4,96%	4,26%	4,26%
# Interviews Mentioned	11	13	9	3	8	6	5	3	3	5

Figure 8: Innovation potential overview

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The focused discussion further highlighted some general methodological innovations that are needed to advance natural disaster risk modelling. Specifically, the largest frequency of participants selected new or better methods of including multi-hazard risk (seventeen) and adaptation dynamics (sixteen). This is generally in line with the interview results that places a high focus on parameter improvements, which may be achieved via improved understanding of perils, adaptation dynamics and the interrelationships between perils in a multi-hazard risk environment. The discussion emphasized the importance of multi-hazard risk and compounding events in the context of adaptation. That is, modeling innovations need to account for the fact that individuals often need to adapt to multiple perils in one location. The occurrence of single hazards can trigger other hazards and cascading effects, resulting in more severe consequences than the sum of the impacts of individual hazard occurrences. Furthermore, less participants selected addressing model uncertainty (eight) and more refined risk maps (eleven times). The aforementioned interview findings highlight specific points related to the latter issue on a specific data need, e.g. on the types of data, granularity and data sharing.

6 Discussion of literature review

6.1 State of the art and directions for future research

Climate risk insurance models can be subdivided into two components: the risk module and the insurance module. The shape of these components generally depends on the model type, the climatic hazard, and the application of the model. In terms of model type, we distinguish three primary categories: insurance supply models, partial equilibrium models, and agent-based models.

Insurance supply models are useful for premium calculations, which may include premium development over time under different socioeconomic development and climate change scenarios (e.g., Aerts and Botzen, 2011; Boudreault et al., 2020). However, most supply models are not forward-looking (e.g., Boudreault & Ojeda, 2022; Brunette et al., 2015; El-Adaway, 2012; Sacchelli et al., 2018). Partial equilibrium models allow for analyzing the interplay between insurance supply and demand. This makes partial equilibrium models useful for insurance market type assessments (e.g., Hudson et al., 2019) or for investigating inquiries pertaining to the affordability and uptake of insurance (e.g., Tesselaar et al., 2022; Tesselaar et al., 2020b). Agent-based models allow for the simulation of complex agent behavior. This is useful for analyzing decisions that reduce climate risk (e.g., de Ruig et al., 2022; Dubbelboer et al., 2017; Jenkins et al., 2017).

The risk component of a model estimates the risk used to calculate an insurance premium. This component can -with one exception in the reviewed papers, (Brunette et al., 2017)- be divided into catastrophe models and actuarial models. Most of the reviewed papers estimate risk using a catastrophe model. A catastrophe model simulates the risk based on hypothetical events and is, hence, useful for estimating the risk of low-probability high-impact events such as flooding. On the other hand, actuarial models use loss data about actual events to estimate the risk. Therefore, the actuarial approach tends to be more applicable to hazards that happen more commonly such as windstorms.

The insurance component of the model translates the risk into an insurance application. While most papers focus on household insurance, it is worth noting that forestry insurance modeling is also a well-established and developed field (e.g., Barreal et al., 2014; Brunette et al., 2017; Loisel et al., 2020; Sacchelli et al., 2018). Multiple papers include a modeled insurer, often in agent-based models (e.g., de Ruig et al., 2023; Dubbelboer et al., 2017; Jenkins et al., 2017), partial equilibrium models (e.g., Hudson et al., 2019; Tesselaar et al., 2020b), or game-theoretic models (e.g., Kesete et al., 2014; Peng et al., 2014). The premium calculation predominantly follows a risk-based approach, wherein the premium is designed to mirror the level of risk inherent to the insured entity. The usage of risk-based premiums is common for climate risk insurance.

More than half of the papers about climate risk insurance models capture flood hazards. This means that the other climatic hazards are relatively underrepresented in the literature. Insurance for climatic hazards such as drought and windstorm damage tends to be relatively understudied in comparison to flooding. This is despite windstorms accounting for a substantial 40% of the total losses attributed to climate-related events, while flooding constitutes 25% (Hoeppe, 2016). The disproportionate attention to flood-related research compared to the distribution of overall losses highlights an imbalance in the focus on various climatic perils.

Another key research gap is the application of climate risk insurance models to underdeveloped countries. Of the models considered, only a small subset is applied to Asia, and none of the models are applied to locations in Africa or South America. A potential reason for this is the lack of available data. However, since these areas are relatively more vulnerable to climatic hazards than most developed areas (IPCC, 2023), insurance and, therefore, insurance modeling are relevant there. Utilizing remote-sensing techniques to assess the risk for insurance purposes (Islam et al., 2022) can potentially prove useful in locations where data collection is difficult.

A small subset of models concerns insurance for the commercial sector, of this small subset all papers considered only agribusinesses, except for Ermolieva et al. (2017). However, the commercial sector also experiences substantial damage from climatic hazards due to direct impact and business interruptions as a consequence of these direct impacts. Business interruptions can have significant and widespread consequences, potentially resulting in outcomes such as unemployment and product shortages (Koks et al., 2019; Sultana et al., 2018; Taguchi et al., 2022). Therefore, amidst a shifting climate, it is imperative to assess the feasibility and resilience of climate risk insurance for businesses. Achieving this goal will necessitate increased modeling efforts within this domain.

A significant research gap exists in the observation that merely half of the climate risk insurance models can be categorized as forward-looking. This implies that only half of these models integrate future scenarios to evaluate insurance mechanisms in the context of a changing climate and evolving socioeconomic development scenarios. Evaluating risk based on the experience from past events is no longer sufficient to capture the uncertainties around future risks (Adger et al., 2018). Future premium setting is impeded by the uncertainty around climate change (Botzen, 2021). This calls for a thorough forward-looking approach to climate risk insurance setting, which is currently not happening enough, indicating a research gap. This gap is evident for both the inclusion of climate change scenarios, such as RCP scenarios, and the inclusion of socioeconomic development scenarios, such as SSP scenarios. Furthermore, not all papers that are categorized as forward-looking include multiple scenarios. Utilizing multiple scenarios enables a more comprehensive capture of the uncertainties associated with the future.

Furthermore, wildfire and windstorm insurance models do not include DRR (but see Barreal et al. (2014)). Even though DRR for these perils does exist (Manocha & Babovic, 2017; Paveglio et al., 2018), the incorporation of DRR into insurance models for these climatic hazards remains limited. Consequently, there is a potential avenue for enhancing the robustness of insurance models by integrating DRR elements specific to wildfire and windstorm risks.

Another gap is the limited attention to multi-hazard modeling. Multi-hazard risk modeling is an emerging field that poses a more thorough approach to risk management than traditional methods (Stalhandske et al., 2023; Tilloy et al., 2019). Multi-hazard modeling is especially relevant in the context of compound hazards, which largely exacerbate the potential damages. Currently, there is a small number of papers that specifically consider multi-risk premiums, and they either consider forestry insurance policies (Brunette et al., 2015; Sacchelli et al., 2018) or household insurance against earthquakes and flooding (Perazzini et al., 2022).

6.2 Policy recommendations

Most forward-looking models indicate that climate change and socioeconomic developments highly exacerbate future risk and, hence, lead to increased insurance premiums (Boudreault et al., 2020; Crick et al., 2018; Dubbelboer et al., 2017; Hudson et al., 2016; Jenkins et al., 2017; Kunreuther et al., 2013; Tesselaar et al., 2020a, 2020b, 2022; Unterberger et al., 2019). This suggests that taking climate change and socioeconomic developments into account in insurance models is imperative in assessing the long-term viability of insurance. However, uncertainty about future risks gives some insurers an incentive to charge higher surcharges on insurance premiums and restrict coverage for extreme weather events (Botzen, 2021). Applying a stochastic approach rather than a deterministic approach in climate risk assessment (Walker et al., 2016) and taking the ambiguity between different climate models into account (Birghila et al., 2022) are methods to deal with this uncertainty.

Multiple papers advocate for the implementation of risk-based premiums in natural disaster insurance schemes because they are useful for incentivizing DRR efforts (Brunette et al., 2017; de Ruig et al., 2022, 2023; Dubbelboer et al., 2017; Hudson et al., 2016, 2019; Jenkins et al., 2017; Unterberger et al., 2019). For instance, risk-based premiums may act as a price signal that raises awareness among policyholders of the climate risks they face. Moreover, rewarding policyholders who make their properties resistant to the impacts of extreme weather with premium discounts gives them a financial incentive for taking DRR measures against climate risks. Incentivizing DRR is also a recommendation given in a joint discussion paper by the European Central Bank (ECB) and the European Insurance and Occupational Pensions Agency (EIOPA; ECB & EIOPA, 2023). However, it is also important to consider the affordability of insurance, as fully risk-based premiums might lead to unaffordability and, hence, a reduced uptake among low-income households in areas with a high natural disaster risk (Tesselaar et al. 2020b; Unterberger et al., 2019). A potential policy solution for this unaffordability might be the usage of a voucher scheme, which alleviates the share of the insurance premium that is considered unaffordable. Another option is to consider public-private partnerships or making use of a semi-voluntary structure which makes insurance mandatory to acquire a mortgage for example.

Furthermore, to address increasing climate risk and keep insurance schemes viable, a proactive involvement of the government in the insurance market has been proposed through the establishment of public–private partnerships (Hudson et al., 2019; Tesselaar et al., 2020a, 2020b). In such an approach, the government strives to reach a balance between ensuring the financial viability of insurance companies and keeping premiums affordable for the general public. Another example of this can be found in the model used by Crick et al. (2018), Jenkins et al. (2017), and Dubbelboer et al. (2017), which actively examined improvements in the U.K. public–private partnership FloodRe. The government can also be involved by means of enforcing insurance uptake, thereby increasing the pool of policyholders. Pinheiro & Ribeiro (2013) and Tesselaar et al. (2020a) suggested that the mandatory uptake of insurance can lead to higher resilience, the former for forestry businesses concerning wildfire hazard and the latter for households concerning flood hazard. Mandatory uptake leads to the possibility of spreading the risk across more policyholders, leading to lower premiums and a lower protection gap.

Lastly, multiple studies suggest that developing insurance products that cover multiple climate risks can be attractive for enhancing insurance coverage for climate risks (Brunette et al., 2015; Hudson et al., 2019; Perazzini et al., 2022; Sacchelli et al., 2018). This would require a move from single- to multi-hazard climate risk assessments in insurance modeling. Combining multiple hazards under a single insurance policy has been observed to necessitate a lower amount of capital compared to insuring each hazard individually due to risk diversification (Perazzini et al., 2022).

All these recommendations require close collaboration among stakeholders at different levels (e.g., ECB & EIOPA, 2023). Birghila et al. (2022), Crick et al. (2018), Hudson et al. (2016), and Sidi et al. (2017) emphasized the importance of involving diverse stakeholders (e.g., government, other private partners) to create a more nuanced, effective, and transparent risk management framework. Collaboration between all stakeholders involved can limit uncertainty. Specifically, collaboration between the insurance and public sectors is often crucial (Kunreuther, 2018). An example is a clear communication of the government about post-disaster compensation to limit the crowding out of demand for private insurance, also called charity hazard (Tesselaar et al., 2022). Furthermore, due to the inherent complexity of insurance products, collaboration between insurers and government stakeholders not only widens the spectrum of perspectives but also enhances the adaptability of insurance strategies to different challenges. Examples are combining private insurance coverage with public measures that limit climate risk and introducing public–private insurance coverage when premiums otherwise rise to unaffordable levels.

7 Discussion of stakeholder analysis

This study makes two important contributions. First, it identifies challenges and opportunities to improve climate risk assessment through innovation. Second, its findings inform policy implications for the insurance industry, academia, and governments.

7.1 Bridging the gap to innovation

By analysing and connecting the main challenges and innovation potentials identified through stakeholder analysis, we can pinpoint the most promising areas for advancing climate risk assessment practices. First, the uncertainty that follows from nonlinear environmental changes, such as triggers and tipping points, requires improved environmental understanding for them to be accounted for in the models. In accordance with the responses of participants, Jarzabkowski et al. (2019) confirm insurance policies are a reactive product designed around short-term protection with an annual life cycle that is not directly linked to longer-term climate change. The IMF supports the statement that climate change's physical risks extend beyond typical risk analysis horizons and that there is sizeable uncertainty in climate risk modeling due to the many pathways for future emissions and temperatures (Adrian et al., 2022). The stakeholder analysis revealed that improved environmental understanding is necessary for more accurate hazard projections. To address this, Zscheischler et al., (2018) advocate for a refocused approach, in which research should consider a climate-related hazard as a combination of multiple factors, rather than a single event. This approach could offer a deeper understanding of the underlying physical processes, ultimately guiding the development of more accurate climate models and, hence, better risk assessments.

Second, assumptions and parameter validation and their improvement reveal a top area where advancements can be achieved. As one participant explained, this requires changing from hard-coded climatic factors in models to adjustable ones. Participants further suggested creating a larger pool of alternative models for robust comparison and validation. Molinari et al. (2019) support these insights by identifying effective validation techniques such as comparing model results with observed data, benchmarking with other models in the same area, and leveraging expert knowledge. The need for higher-quality data to perform validation and benchmarking was a recurring topic. This could be addressed using varied data sources including historical weather data, satellite imagery, and climate projections. In addition, participants highlighted the potential of AI in model building through downscaling complex geographical data, using deep learning methods that can handle high-dimensional data, and recognising patterns between relationships, which aligns with findings from Lin et al. (2023).

Third, a big concern seemed to be a lack of exposure and vulnerability data of the insured portfolios. While the need of improving such data emerged in nine out of sixteen interviews, the question remains how to accomplish this. Participants emphasized that, in many cases, detailed records of building characteristics are missing. Therefore, updated tools are needed to monitor financial solvency, as the number of exposures in hazard-prone areas is growing (Nicholson, 2019). The interviews identified AI as a solution for vulnerability assessments by identifying building structures and flood defences. Combined with blockchain and the Internet of Things (IoT), AI unlocks further possibilities for insurers, as it could deliver secure, real-time data collection and remote monitoring, leading to more accurate risk assessments (Tinianow, 2019). While blockchain was not explicitly mentioned during the discussions, LiDAR technology was addressed as a promising solution for ground surface mapping by one of the participants. Pinelli et al. (2020) support this, highlighting machine learning combined with LiDAR or drones to produce reliable and complete exposure datasets. Additionally, Stone (2017) suggests a combined approach of omnidirectional imagery collection (e.g. Google Street View) with virtual surveying methodology to collect building data. Yet, this method was not discussed in the stakeholder analysis.

Fourth, as became evident in the results, physical risk exposure is highly location-specific, which is why there is a need for high-resolution climate models (Adrian et al., 2022; Zscheischler et al., 2018). The stakeholder analysis indicated the need for improved terrain mapping, stressing expertise in water flow dynamics and knowledge of the geological makeup of the insured property's surrounding land. Gathering of high-quality field data therefore requires improvement, which could be achieved through institutional collaboration, according to Pinelli et al. (2020). In addition, similar to improving exposure data, AI combined with LiDAR technology could refine the understanding of geographical risk.

Fifth, a common data-sharing ecosystem across Europe could address challenges caused by siloed or closed-off data, particularly from government sources currently unwilling to share. A report from The Geneva Association (2018) affirms that insurers cope with limited access to risk information, which hinders accurate pricing. As a response, three participants called for an ecosystem that could serve as a central hub for comprehensive meteorological data, currently collected on a country-by-country basis, to foster a more unified climate risk assessment framework across the continent. Open-source initiatives and risk data, along with standardized hazard maps, would reduce the cost of risk analysis and underwriting (Warner et al., 2013), ultimately leading to improved risk assessment and the development of innovative new insurance products.

Sixth, public-private collaboration presents an avenue for reducing economic and regulatory uncertainty. While not explicitly identified as a clear-cut solution during the interviews, five participants emphasized the benefits of cross-sector collaboration. These include incentivizing DRR strategies (Pattberg, 2010), fostering innovation and resilience through knowledge sharing, and facilitating resource mobilization (Drejer & Jørgensen, 2005). In addition, clarity on future regulations ensures better alignment across sectoral incentives, allowing the industry to proactively integrate this consideration into their risk management strategies (The Geneva Association, 2018).

7.2 Policy implications

To effectively address climate risk, innovations should be made beyond the short-term focus of non-life insurance as large climate shocks pose an increasing challenge to the industry, as well as society. Therefore, improved environmental understanding is crucial for supporting the development of more sophisticated climate risk assessment methods and ongoing research is required to enhance the comprehension of climate-related impacts. To accelerate progress, the insurance industry should foster stronger, more coordinated engagement with the scientific community (Golnaraghi et al., 2016). Internationally coordinated research programs and operational initiatives can bridge the gap between climate research and risk pricing, through which a mutual understanding of needs can be fostered and a disconnect between institutions can be decreased. Furthermore, progress in scientific research and scenario analysis, combined with technical innovations, such as big data, digital mapping, and advanced computing offers novel opportunities for developing advanced climate-risk modules. Evaluating the success of industry-science initiatives could be measured by factors like knowledge transfer, increased research output, technological innovation, and ultimately, the improvement of Nat Cat models themselves.

From a governmental perspective, a strong regulatory framework could foster innovation in climate risk assessments by creating supportive regulations for data-sharing ecosystems and supporting the development of climate-risk models, which are needed to improve parameter validation. Systematic collection and availability of publicly funded environmental and socio-economic data should be promoted and alternative remotely sensed datasets should be implemented in insurance solutions (Warner et al., 2013). Regulations facilitating public-private partnerships can further leverage combined expertise to accelerate progress and address economic uncertainties. As such, governments, policymakers, and regulators across sectors should work in a more coordinated fashion to build socio-economic resilience to climate change.

7.3 Limitations and future research

The qualitative research methodology used for conducting semi-structured interviews is limited by some inherent challenges. The reliance on participant responses raises potential concerns as the qualitative nature of the data makes it challenging to objectively verify participants' responses.

Besides, the research design allows for a degree of participant control over the content (Queirós et al., 2017). Moreover, recruiting a more diverse group of experts, particularly those from Nat Cat model vendor companies, could have yielded a wider range of perspectives. This possible lack of representativeness could lead to sampling bias, where individual views disproportionately influence the findings, reducing their generalisability and credibility (Gobo, 2004). Additionally, a larger sample may achieve further data saturation, elaborating on important themes and nuances (Hennink et al., 2017).

It should be acknowledged that this research takes an explorative approach to identifying innovation areas in climate risk assessments. Building upon these insights, future research could look deeper into the practical application of proposed innovations by evaluating the feasibility and challenges associated with implementing the innovations in collaboration with industry leaders. Furthermore, improved modeling of climate risks has the potential to increase premiums and the number of assets defined as high-risk is growing, partly due to the increasing frequency and severity of climate-related events (Jarzabkowski et al., 2019). Future research should look into the long-term insurability of natural hazards to prevent a market failure where people cannot afford the increasing costs of insurance, or where insurers can't price policies high enough to cover the risk.

8 Conclusion

This article has synthesized the literature on climate risk insurance models and their characteristics in a literature review. Climate risk insurance models range from simple pricing applications to more complex partial equilibrium and agent-based models that can be used to assess research questions about insurance uptake and affordability. All models can be subdivided into two components: the risk module and the insurance module. The risk module can either be a catastrophe model that simulates the risk approached from hazard, exposure, and vulnerability aspects, or it can be based on historical data via an actuarial approach. Catastrophe models are typically more effective in assessing the risk of climatic hazards characterized by a low probability of occurrence but high impact, such as floods. On the other hand, actuarial approaches prove more beneficial in evaluating risks associated with climatic hazards that occur more frequently, such as windstorms or wildfires.

Most forward-looking models indicate that climate change and socioeconomic developments exacerbate future risk and, hence, lead to increased insurance premiums. Various studies recommend introducing risk-based premiums to incentivize DRR efforts that limit this increase in climate risks, combined with policy strategies that address affordability issues among low-income households. Other findings point toward introducing public–private insurance to cope with climate change and enhance risk spreading by introducing insurance purchase requirements or insurance products that cover multiple climate risks.

Moreover, the research identifies key challenges in current climate risk assessment approaches and explores innovative solutions through stakeholder analysis with insurance industry experts. Firstly, the reliance on historical data limits the accuracy of climate risk models in predicting natural hazards. This research highlights the need for integrating long-term and adaptive views of climate risk, incorporating non-linear environmental changes. Improved risk data and analysis of the impact of climate change are essential to increase understanding of event frequency, severity, and potential financial losses.

Secondly, climate risk models depend heavily on assumptions and parameter validation, which relies on benchmarking against other models and underlying data, including exposure and vulnerability information, which is often lacking. This gap necessitates updated tools and institutional collaboration to improve data gathering.

Thirdly, emerging technologies and open-source initiatives have the potential to enhance climate risk models significantly. Leveraging AI, digital mapping, and advanced computing can improve the granularity of terrain data and, in turn, the accuracy and reliability of risk assessments. Public-private initiatives could facilitate these advancements and further reduce exogenous uncertainty. Based on the stakeholder analysis, we suggest that future research should focus on the practical application of proposed innovations and exploring long-term insurability of natural hazards to prevent market failure.

Furthermore, other knowledge gaps were identified and a research agenda was suggested based on the literature review to improve modeling techniques to aid decision-making in insurance policy design. First, flood insurance tends to be highly overrepresented in the climate risk insurance modeling literature. Second, most models are applied to case studies in developed countries, despite the potential for developing countries to experience a more substantial increase in natural disaster damages, making them potentially more significant beneficiaries of insurance coverage. Third, the coverage for non-agricultural commercial sector insurance is limited, even though a sizable portion of the climate-related damages can be found in this sector, also through business interruption.

Merely half of the reviewed papers applied forward-looking climate risk analyses by utilizing climate change scenarios to examine the impact of climate change on risk. With climate change increasing the frequency and severity of natural hazards, this indicates a considerable research gap. Furthermore, an even smaller number of studies incorporated socioeconomic development scenarios to consider their effects on future risk. This suggests that only a subset of the reviewed papers is truly valuable for evaluating the ability of insurance to cope with future climate change.

The field of climate risk insurance modeling is growing, and the current state-of-the art models are certainly capable of addressing pivotal inquiries related to climate risk insurance. Addressing the research gaps identified by our review is imperative for delivering insights into how the insurance sector can proactively adapt to the challenges posed by climate change. By refining models, expanding geographical and hazard coverage, improving the inclusion of the commercial sector, and embracing a forward-looking perspective, the insurance industry will be better equipped to fulfil its role in mitigating the financial impacts of climate-related losses and fostering resilience.

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10 Appendix

Supplementary table 1: keywords used in query

Keyword group	Subgroup	Keywords
Hazard	Perils	flood, river, coastal, inundation, pluvial, storm, hail, hurricane, cyclone, tornado, sea level rise, tsunami, landslide
	Synonym	disaster, catastrophe, climate hazard
Model type	Type	catastrophe model, damage model, actuarial model, insurance supply model, econometric model, agent based model, ABM, machine learning model, machine learning, deep learning
	Data	geospatial model, GIS
Insurance	-	insurance, compensation system, compensation arrangement, reinsurance, microinsurance, actuarial

The final search string has the following form:

TITLE-ABS-KEY (**flood*** OR **river*** OR **coast*** OR **inundation** OR **pluvial** OR **storm*** OR **hail** OR **hurricane** OR **cyclone** OR **tornado** OR **"sea level rise"** OR **landslide** OR **wildfire** OR **drought** OR climat*) AND TITLE-ABS-KEY (**model*** OR **abm** OR **"machine learning"** OR **"deep learning"** OR **gis** OR **"geo information science"** OR **ai** OR **"artificial intelligence"**) AND TITLE-ABS-KEY (**insur*** OR **"compensation arrangement"** OR **"compensation system"** OR **reinsur*** OR **microinsurance** OR **actuar***) AND (LIMIT-TO (LANGUAGE , **"English"**)) AND (LIMIT-TO (DOCTYPE , **"ar"**))

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Supplementary table 2: risk and insurance model types

Paper	Risk model type	Insurance model type
Aerts and Botzen (2011)	Catastrophe	Pricing (supply model)
Barreal et al. (2014)	Econometric	Partial equilibrium
Birghila et al. (2022)	Catastrophe	Demand model
Boudreault and Ojeda (2022)	Catastrophe	Pricing (supply model)
Boudreault et al. (2020)	Catastrophe	Pricing (supply model)
Brunette et al. (2015)	Econometric	Pricing (supply model)
Brunette et al. (2017)	Theoretical	Partial equilibrium
Crick et al. (2018)	Catastrophe	Agent based
Ding et al. (2017)	Catastrophe	Principal agent
Dubbelboer et al. (2017)	Catastrophe	Agent based
El-Adaway (2012)	Econometric	Pricing (supply model)
Ermolieva et al. (2017)	Catastrophe	Partial equilibrium
Guo et al. (2022)	Econometric / catastrophe	Game theory
Hudson et al. (2016)	Catastrophe	Partial equilibrium
Hudson et al. (2019)	Catastrophe	Partial equilibrium
Islam et al. (2021)	Econometric	Demand model
Jenkins et al. (2017)	Catastrophe	Agent based
Kalfin et al. (2022)	Econometric	Pricing (supply model)
Kesete et al. (2014)	Econometric / catastrophe	Game theory
Kunreuther et al. (2012)	Catastrophe	Pricing (supply model)
Loisel et al. (2020)	Catastrophe	Partial equilibrium / game theory
Moosakhaani et al. (2022)	Catastrophe	Game theory

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Peng et al. (2014)	Econometric / catastrophe	Game theory
Perazzini et al. (2022)	Catastrophe	Partial equilibrium
Pinheiro and Ribeiro (2013)	Econometric	Pricing (supply model)
De Ruig et al. (2022)	Catastrophe	Agent based
De Ruig et al. (2023)	Catastrophe	Agent based
Sacchelli et al. (2018)	Catastrophe	Pricing (supply model)
Sidi et al. (2017)	Econometric	Pricing (supply model)
Tanaka et al. (2022)	Catastrophe	Agent based
Tesselaar et al. (2020a)	Catastrophe	Partial equilibrium
Tesselaar et al. (2020b)	Catastrophe	Partial equilibrium
Tesselaar et al. (2022)	Catastrophe	Partial equilibrium
Thompson et al. (2015)	Econometric	Pricing (supply model)
Unterberger et al. (2019)	Catastrophe	Partial equilibrium
Walker et al. (2016)	Catastrophe	Pricing (supply model)

Supplementary table 3: risk characteristics of the models

Paper	Hazard type	Multi-hazard / single-hazard	Country/region	Climate change scenario(s) inclusion	Socioeconomic development scenario(s) inclusion	Risk reduction inclusion (by household/government/business)
Aerts and Botzen (2011)	Flooding (coastal and riverine)	Single-hazard	The Netherlands	Yes, four climate change scenarios	Yes, future land-use maps based on two economic growth scenarios	Yes (g)
Barreal et al. (2014)	Wildfire	Single-hazard	Spain	No	No	Yes (b)
Birghila et al. (2022)	Drought	Single-hazard	Austria	Yes, RCP4.5	No	Yes (b)
Boudreault and Ojeda (2022)	Flooding (riverine)	Single-hazard	Canada	No	No	No
Boudreault et al. (2020)	Flooding (riverine)	Single-hazard	Canada	Yes, RCP4.5 and RCP8.5	No	No
Brunette et al. (2015)	Wildfire, wind throw, insect outbreaks	Multi-hazard	Slovakia	No	No	No
Brunette et al. (2017)	Damage to forest in general	Single-hazard and multi-hazard	-	No	No	Yes (b)
Crick et al. (2018)	Flooding (surface water)	Single-hazard	UK, London	Yes, a baseline and high-emission scenario	No	Yes (g [and developers])
Ding et al. (2017)	Debris flows	Single-hazard	Shengou Basin, China	No	No	No
Dubbelboer et al. (2017)	Flooding (surface water)	Single-hazard	UK, London	Yes, high-emission scenario	No	Yes (h + g)
El-Adaway (2012)	Windstorms	Single-hazard	United States, Mississippi	No	No	No
Ermolieva et al. (2017)	Flooding (riverine and coastal)	Single-hazard	The Netherlands, Rotterdam	No	No	No
Guo et al. (2022)	Hurricanes (flood and wind)	Single-hazard	United States, North Carolina	No	No	Yes (h + g) (government does buyouts and offers subsidies)
Hudson et al. (2016)	Flooding (riverine)	Single-hazard	France and Germany	Yes, SRES A1B greenhouse gas emission scenario	Yes, socioeconomic projections at the national level from CIESIN	Yes (h)
Hudson et al. (2019)	Flooding (riverine)	Single-hazard	European Union	Yes, SRES A1 scenario	Yes, ensemble mean of SSP scenarios	Yes (h + g)
Islam et al. (2021)	Flooding (flash floods)	Single-hazard	Bangladesh	No	No	No
Jenkins et al. (2017)	Flooding (surface water)	Single-hazard	UK, London: Camden	Yes, high-emission scenario	No	Yes (h + g)
Kalfin et al. (2022)	Natural disasters in general	Single-hazard and multi-hazard	Indonesia	No	No	No

Kesete et al. (2014)	Hurricanes	Single-hazard	United States, North Carolina	No	No	No
Kunreuther et al. (2012)	Hurricanes	Single-hazard	United States, Florida	Yes, six future hurricane scenarios	No	Yes (h)
Loisel et al. (2020)	Storm	Single-hazard	Southwest France	No	No	No
Moosakhaani et al. (2022)	Flooding (riverine)	Single-hazard	Iran	No	No	No
Peng et al. (2014)	Hurricanes	Single-hazard (but it covers both wind and flood damage)	USA, North Carolina	No	No	Yes (h + g)
Perazzini et al. (2022)	Earthquakes, flooding (general)	Single- and multi-hazard	Italy	No	No	No
Pinheiro and Ribeiro (2013)	Wildfire	Single-hazard	Portugal	No	No	No
De Ruig et al. (2022)	Flooding (coastal and riverine)	Single-hazard (flooding seen as one type)	United States	Yes, RCP4.5 and RCP8.5	Yes, SSP2 and SSP5	Yes (h + g)
De Ruig et al. (2023)	Flooding (coastal)	Single-hazard	USA, New York City: Jamaica Bay	Yes, sea level rise	Yes, SSP2 and SSP5	Yes (h)
Sacchelli et al. (2018)	Wildfire and storm	Multi-hazard	Italy	No	No	No
Sidi et al. (2017)	Flooding (riverine)	Single-hazard	Indonesia	No	No	No
Tanaka et al. (2022)	Flooding (riverine/pluvial)	Single-hazard	Japan	Yes, 2- and 4-degree temperature rise	Yes, income and house prices increase over time; economy grows at a constant rate over time	No
Tesselaar et al. (2020a)	Flooding (riverine)	Single-hazard	European Union + UK	Yes, RCP4.5 and RCP8.5 and the average of five GCM scenarios	Yes, SSP2 and SSP5 and Winsemius et al.'s (2016) future simulations of built-up area	Yes (h)
Tesselaar et al. (2020b)	Flooding (riverine)	Single-hazard	European Union + UK	Yes, RCP2.6, RCP4.5, RCP6.0, RCP8.5, and the average of five GCM scenarios	Yes, SSP1, SSP2, SSP3, SSP5, and Winsemius et al.'s (2016) future simulations of built-up area	Yes (h)
Tesselaar et al. (2022)	Flooding (riverine)	Single-hazard	European Union + UK	Yes, RCP4.5 (more RCP scenarios in the Appendix), and the average of CMIP5 GCM scenarios	Yes, SSP2 (more SSP scenarios in Appendix), and Winsemius et al.'s (2016) future simulations of built-up area	Yes (h)
Thompson et al. (2015)	Wildfires	Single-hazard	Western USA	No	No	No

Unterberger et al. (2019)	Flooding (riverine)	Single-hazard	Austria	Yes, RCP8.5 and 5 GCM scenarios	Yes, SSP5	Yes (g)
Walker et al. (2016)	Cyclones	Single-hazard	Australia	Yes, maximum wind speeds increase by 5% each year over a 90-year period	Yes, vulnerability curve is shifted such that higher wind speeds cause the same level of damage	Yes (h)

Supplementary table 4: insurance characteristics of the models

Paper	Consumer type	Insurance markets	Competition between insurers modeled	Commercial sector insurance	Premium setting	Decision to insure
Aerts and Botzen (2011)	Households	Private and public–private	No	No	Risk-based with a premium loading factor to account for insurance company costs and profit; insurers pay up to a cap, and the government pays the rest.	Households are obliged to take flood insurance.
Barreal et al. (2014)	Forestry sector	-	No	Yes	The optimal premium is calculated between the difference in expected damage with and without insurance.	Based on the net present value of forest investments
Birghila et al. (2022)	Farmers	One representative insurer	No	Yes	The premium is based on the distortion premium principle, where the loss suffered is multiplied by a distortion risk measure, which leads to higher values for low-probability high-consequence events. The premium also contains a loading factor. The policyholder has a budget of which a proportion is available for the premium (representing a deductible). The government also finances a proportion of the premium.	Only the middle losses are potentially insured; small losses are for the insurance taker, and large losses require outside assistance. How large the proportion of middle losses is is determined via an optimization problem. The optimization problem is based on the loss distribution for the case of only a single loss distribution (non-ambiguous case) or the case of multiple loss distributions (ambiguous case). The policyholder is expected to be risk neutral for small losses and risk averse for large losses. The policyholder has a budget of which a proportion is available for the premium (representing a deductible).
Boudreault and Ojeda (2022)	Households	Two competing insurance companies	Yes	No	The insurance company clusters the households based on similar flood risk and bases the premium on the average annual loss per cluster.	Homeowners choose the insurance contract with the lowest premium.
Boudreault et al. (2020)	Households	One representative insurer	No	No	A base premium times the relative riskiness and the exposure or a risk-sharing parameter (to spread the risk across all policyholders in the portfolio) instead of the relative riskiness; if this is too low, the flood loss does include a deductible and a limit. The relative riskiness is calculated per region.	NA
Brunette et al. (2015)	Forestry sector	One representative insurer	No	Yes	Risk-based + extra premium to insure the forest stand in relation to the total insured area of hectares to reduce the risk of the insurer.	NA

Brunette et al. (2017)	Forestry sector	One representative insurer	No	Yes	The insurer is risk neutral, and the price of insurance is given as the unit price of insurance times the compensation amount. The insurance contract includes a deductible that can be chosen by the insured.	Based on a strictly increasing and concave utility function (risk aversion)
Crick et al. (2018)	Households	Public market with public reinsurance scheme FloodRe	No	No	Risk-based taking risk-reduction methods into account, a deductible, and a base premium. The impact of the reinsurance scheme FloodRe on the premium is also calculated.	Households are obliged to take flood insurance.
Ding et al. (2017)	Households	One representative insurer	No	No	The premium is chosen by the insurance company alongside the rate of compensation based on an income-maximizing problem that considers the risk degree of debris flow, the total insured assets, the premium, the rate of compensation, and the loss caused by debris flow.	The decision to purchase insurance is based on an expected utility curve that takes into account the risk degree of debris flow, the total assets of the insurant, the loss caused by debris flows, the premium, and the rate of compensation.
Dubbelboer et al. (2017)	Households	Public market with public reinsurance scheme FloodRe	No (mentions what could happen if competition was modeled)	No	Risk-based taking risk-reduction methods into account, a deductible, and a base premium. The impact of the reinsurance scheme FloodRe on the premium is also calculated.	Households are obliged to take flood insurance.
El-Adaway (2012)	Civil infrastructure developments	One representative insurer	No	No	Based on running a Monte Carlo simulation on bootstrapped historical loss data.	NA
Ermolieva et al. (2017)	Households and firms	Insurers, governments, reinsurers, and funds are grouped via a risk reserve. In the case study, only one insurer or catastrophe fund operates per region.	No	Yes	Using quantile-based stochastic optimization under a range of safety constraints across stakeholders to produce optimal risk-based location-specific insurance premiums and coverage.	The decision variables, including insurance coverage, is determined via the optimization of the system.
Guo et al. (2022)	Households	A market of multiple insurers, incorporated via a perfect information Cournot–Nash noncooperative game	Yes	No	The premium price is defined as charge per expected dollar loss and varies by region. Hypothetical insurance price levels are first simulated to maximize the insurers' net profits, and these insurance prices are then implemented in the Cournot–Nash equilibrium model to generate the equilibrium risk-based insurance prices.	Based on a mixed logit model using the insurance premium, the deductible, an indicator of whether the home is located inside or outside the floodplain, the house-to-coastline distance, the number of hurricanes experienced by the homeowner, the homeowner's income, age, and years since the last hurricane experienced as covariates. There is also an affordability constraint such that the premium cannot exceed the homeowner's budget expressed as a percentage of the home value.

Hudson et al. (2019)	Households	Six market structures, ranging from public to private	Yes (in Appendix)	No	Risk-based and depending on the number of households in a region, the premium includes a loading factor and a deductible; there is an incentive in the premium for DRR methods: The premium gets lower via the effectiveness ratio of the DRR method.	Subjective expected utility that accounts for affordability
Hudson et al. (2016)	Households	A public–private flood insurance scheme	No	No	Various insurance premium rules, including risk-based, risk-based with a risk reduction premium discount, capped risk-based premium, and solidarity premium.	Subjective expected utility that accounts for affordability
Islam et al. (2021)	Crop insurance	Only an insurance premium is calculated.	No	Yes	Damage based for different coverage levels and interest rates	Binary logistic regression approach to elicit the willingness to adopt insurance
Jenkins et al. (2017)	Households	Public market with public reinsurance scheme FloodRe	No (mentions what could happen if competition was modeled)	No	Expected annual loss of the insurers minus the excesses and base flood insurance premium; the remaining loss is spread across the households based on risk. There is an option for reinsurance and risk reduction measures.	Households are obliged to take flood insurance.
Kalfin et al. (2022)	Households	No explicit interaction between insurers	Yes (model that the paper expands on mentions competition)	No	Risk-based with a system that taxes the low-risk areas to provide a subsidy to the high-risk areas	NA
Kesete et al. (2014)	Households	One representative insurer	No	No	Premiums are set via a Stackelberg leader–follower game, where the insurer determines the price of the premium, and the homeowner decides whether or not to purchase insurance based on a utility function. One reinsurer provides reinsurance at a specified price, and the government can set constraints to both the insurer and the homeowners. The premium gets determined via stochastic optimization of this system, where the insurer wants to optimize its profit, avoid insolvency, and maintain sufficient yearly profitability. The premium includes a deductible and loading factor for the insurer's administration costs and profit margin. The premium should be greater than a certain value.	Based on an expected utility function where the homeowners are expected to be risk-averse and have a maximum budget for insurance based on a percentage of the home value.
Kunreuther et al. (2013)	Households	Two different insurance markets: a hard (with capital scarcity and high reinsurance prices) and a soft one (with capital	No	No	Risk-based with a loading factor to cover additional cost (this loading factor is not used in the case study). The premium also considers a risk aversion parameter. The	NA

		abundance and low reinsurance prices). One representative insurer.			premium is calculated for both the insurer and reinsurer.	
Loisel et al. (2020)	Forestry sector	One representative insurer	No	Yes	The insurance premium is a decision variable in the model and can be set by the insurer. The insurer sets the insurance premium by making sure it is more than the future losses multiplied by a discount rate connected to the cutting age of the trees. The premium also includes a loading factor. The cutting age of the trees is determined by the forest owner and determines the forest land expected value (Faustmann value). The insurer sets an upper premium, the premium that is used when the forest owner decides to fully insure their forest.	The decision to insure is given by a decision variable that takes values between 0 and 1, where 1 means full insurance, and 0 means no insurance. The decision to insure depends on the Faustmann value, which stands for the forest land expected value.
Moosakhaani et al. (2022)	Households and government	Three insurers that all have an insurance plan for property owners and an insurance plan for the government	Yes	No	The premium includes a deductible and a fixed number for each loss to cover other costs.	The property owners and the government decide to buy insurance based on their payoff functions. The decision is determined via the Nash equilibrium in a game-theoretic approach where the insurers, property owners, and the government play a role. Government compensation also plays a role, but keep in mind that in this paper, the insurers also offer insurance to the government.
Peng et al. (2014)	Households	One representative insurer	No	No	The premium is based on the expected value of the loss per building type considering coverage of the full home value with a specified deductible. The premium also contains two loading factors: one for the administrative costs, and one for the profit margin per risk region. The insurer is expected to maximize its profit. In this scheme, retrofitting decreases the expected loss and, thereby, the premium charged. There is a minimum premium threshold.	The model is run for five configurations, either allowing or disallowing retrofitting with or without a government subsidy and mandatory or voluntary insurance. Under voluntary insurance, the decision to insure is determined via a Stackelberg game between the insurer and the homeowners. The insurer determines the premiums of various policies and decides how much reinsurance to purchase. The homeowner then decides what policy and/or what retrofit options they want to purchase. The decision-making of the homeowners is ultimately decided via utility maximization. Each homeowner has a maximum budget for homeowner insurance equal to a specified percentage of the total home value; this percentage varies per risk region.
Perazzini et al. (2022)	Households	Private and public–private insurance	Yes (but only mentions)	No	Risk-based plus profit loading, where the risk-based premium should be in the premium the households are willing to pay, and the profit should be adequate.	Willingness to pay calculated using a utility function expecting the homeowners to be rational and risk-averse.

Pinheiro and Ribeiro (2013)	Forestry sector	One representative insurer	No	Yes	There is no explicit premium calculated, but the maximum premium a forest owner is willing to pay is based on the expected risk and size of the forest.	Not explicitly stated but based on the relation between expected loss and the premium
De Ruig et al. (2022)	Households	Public insurance program with four different structures	No	No	Based on old national flood insurance program premiums / risk-based with a risk reduction premium discount	Subjective expected utility function and affordability
De Ruig et al. (2023)	Households	Public insurance program with four different structures	No	No	Based on old national flood insurance program premiums / risk-based with a risk reduction premium discount	Subjective expected utility function that accounts for bounded rationality in forming risk perceptions and affordability
Sacchelli et al. (2018)	Forestry sector	No explicit interaction between insurers	No	Yes	A base premium based on the expected annual loss with a risk premium to allow insurance companies to prepare for extreme years, variable management costs, and fixed insurance company costs.	NA
Sidi et al. (2017)	Buildings	No explicit interaction between insurers	No	No	The premium is calculated as random variable via different methods, via the Esscher principle, based on the proportional hazards approach, Wang's models, Swiss model, and Dutch model.	NA
Tanaka et al. (2022)	Households	No explicit interaction between insurers	No	No	The insurance premium is given per house type per period based on the expected annual flood damage ratio. The insurance rate is multiplied by a markup rate that reflects risk aversion. The flood risk is expected to be perfectly reflected in the insurance premium with the markup rate.	The ratio of households that anticipate flood risk is given; these households will buy insurance. Households take full insurance.
Tesselaar et al. (2020a)	Households	Flood insurance systems that involve a reinsurer: a voluntary system and a semi-voluntary system	Yes	No	The premium is risk-based and includes a deductible of 15% of the loss. The insurer also increases the premium due to the uncertainty of damage by multiplying a risk aversion coefficient with the volatility of damage; 99.8% of damages are considered insurable. The insurer cannot charge a profit loading factor but does charge a cost loading factor. Based on market-structure, there might also be mandatory insurance.	The decision to insure is based on a subjective expected utility function. Households can receive a discount on the premium by implementing disaster reduction measures. The premium should be equal or smaller than the poverty-adjusted disposable income.
Tesselaar et al. (2020b)	Households	Six stylized insurance market structures, ranging from full mandatory to full voluntary and from public to private. Four market	Yes	No	The premium is risk-based and includes a deductible of 15% of the loss. The insurer also increases the premium due to the uncertainty of damage by multiplying a risk aversion coefficient with the volatility of damage; 99.8% of damages are considered insurable. The	The decision to insure is based on a subjective expected utility function. Households can obtain a discount on the premium by implementing disaster reduction measures. The premium should be equal or smaller than the poverty-adjusted disposable income.

		forms are stylized to European insurance markets, and two are hypothetical.			insurer cannot charge a profit loading factor but does charge a cost loading factor. Based on market-structure, there might also be mandatory insurance.	
Tesselaar et al. (2022)	Households	Four market structures, ranging from full mandatory to full voluntary, with either a risk-based or a non-risk-based premium	Yes	No	Based on the market structure. In the voluntary system, the premiums are risk-based, 99.8% of damages are considered insurable, a deductible is set as 15% of the loss, there is a risk aversion parameter that increases the premium, and there is no profit loading factor, but there is a cost loading factor. Households receive a premium discount if they implement risk reduction measures; the premium also contains a reinsurance premium that is calculated in a similar way as the insurance premium but does contain a profit loading factor of 50% of the underwritten risk. In the semi-voluntary system, the premiums are still risk-based, but many households are mandated to take insurance. In the solidarity system, the premiums are insensitive to risk, and all households are mandated to take insurance. In the public–private partnership, the premiums are risk-sensitive up to a certain point; insurance uptake is mandatory for mortgage holders.	If the premium does not cause the household to fall under the poverty line, the decision to purchase insurance is based on maximizing an expected utility curve, which is also dependent on whether the household anticipated government aid after a flood.
Thompson et al. (2015)	Annual wildfire suppression costs	NA	No	NA	The paper couples a wildfire simulation model and a suppression cost model to estimate probability distributions for the suppression costs. The suppression cost of a fire is comparable to an insurance premium. The total suppression costs for a national forest is defined as the sum of all suppression expenditures per escaped large wildfire. The expected value of the suppression cost is calculated by multiplying the expected value of the number of escaped large wildfires in a given fire season by the expected value of the suppression costs per large fire. The variance of the total suppression costs is defined as the expected value of the number of escaped large wildfires times the variance of the	NA

					suppression costs per large fire plus the expected value of the suppression costs per large fire squared times the variance of the number of escaped large wildfires.	
Unterberger et al. (2019)	Public infrastructure	Insurance is organized in three market forms: one where there is just a disaster fund, one where there is risk transfer to a private insurer, and one where there is a public–private insurance mechanism. The insurance sector is simplified to one representative insurer.	No	No	The premiums are based on the expected annual damage with a surcharge that represents the volatility in annual losses, which reflects the risk aversion of reinsurers. On top of this premium, there is a further surcharge that is used to cover administrative costs and generate a profit. The premiums are calculated for both federal and regional governments and include a deductible of 15% of the loss suffered.	There is no decision to take up insurance, but there is a decision to employ dry flood-proofing, which is calculated via the net-present value of the reduction in premiums over 20 years (which is considered as the lifespan of the dry flood-proofing measure).
Walker et al. (2016)	Constructed assets	There is no explicit interaction between insurers; the model works with one hypothetical insurer.	No	Yes	Premiums are calculated based on the average annual risk of loss multiplied by a risk loading factor that reflects the administrative costs and a term that increases the nonlinearity, essentially reflecting the volatility for the insurer.	NA

Supplementary table 5: participant roles

Participant	Role Description
1	Actuary for insurance - Netherlands
2	Expert in climate insurance - France
3	Expert in climate insurance innovation - France
4	Catastrophe expert for commercial insurance - Italy
5	Actuarial consultant - Finland
6	Catastrophe expert for commercial insurance - Germany
7	Expert in public climate insurance - France
8	Actuary for insurance - Greece
9	Mathematician for insurance - Finland
10	Actuary for insurance - Netherlands
11	Reinsurance expert – Netherlands
12	Nat Cat and reinsurance expert - Netherlands
13	Actuary and reinsurance expert – Europe wide
14	Climate data analyst for reinsurance - Switzerland
15	Nat Cat research analyst for commercial insurance – Germany
16	Flood risk modeler - UK

Full list of interview questions

Do you agree to participate in this interview? (yes/no)

Do you give permission for this interview to be recorded? (yes/no)

1. Is your organization using climate change risk or natural hazard risk information? (yes/no)

If no, discontinue.

2. How does your organization gather and store this information?

3. Does your organization use the information for natural disaster risk modeling purposes? (yes/no)

If no, skip to q6.

4. What types of natural hazards are modeled at your organization using climate change risk or natural hazard risk information (e.g. floods, windstorms, heatwaves, etc.)?

5. What types of insurance products are these modeled for (e.g. homeowners' insurance, insurance against business interruption costs, etc.)?

6. Does your organization use climate change risk or natural hazard risk information for any other purpose (if yes, elaborate)?

If no to q3, discontinue.

7. Is your organization using in-house or external party natural disaster risk models?

If in-house, skip to q10.

8. Do you have insights into the components of external party natural disaster risk models so you can well interpret the results or are they a black box?

If they can interpret well, skip to q10.

9. Is it a problem for your organization that they are a black box?

If black box to q8, discontinue.

10. What specific types of climate data and other inputs are used to model the natural hazards?

11. In your opinion, are there other types of data/inputs that would facilitate a more accurate assessment of the natural hazards?

12. What type of outputs result from the natural disaster risk modeling (e.g. damage per event, risk distribution, etc.)?

13. What type of damages/losses are these outputs (e.g. direct damage to buildings, business interruption losses, etc.)?

14. Is climate change adaptation taken into account in the natural disaster risk models?

15. Do you know what types of models are used specifically (e.g. are they catastrophe (CAT) models, econometric/actuarial models, etc.)?

If don't know, skip to q17.

16. What types of hazards are the model types used for?
17. Do you know whether they are forward-looking natural disaster risk models that assess the risk in a future climate? (yes/no)

If no, skip to q21.

18. For these forward-looking models, do you use climate forecasts or climate projections (or both)?
19. Which type of model (forecast or projection) is better in your opinion and why?
20. Do you know what types of climate change and socio-economic scenarios are used in these forward-looking models (if yes, elaborate)?
21. In your opinion, what are the main uncertainties involved in natural disaster risk modeling?

If none stated, skip to q23.

22. Are there ways that natural disaster risk models may better address these uncertainties?
23. How can natural disaster risk modeling approaches be advanced to improve the ability of the insurance sector to cope with climate change related risks?
24. In general, are there any new scientific insights that are needed to advance natural disaster risk modeling approaches?

Use of Gioia Methodology in deriving sub-codes

1 The Gioia Methodology inspired the process of inductively deriving the sub-codes for “Hazard”, “Uncertainties and Challenges”, and “Innovation Potential”. The Gioia Methodology is a systematic approach to new concept development and grounded theory articulation that is designed to bring qualitative rigor to the conduct and presentation of inductive research (Gioia et al., 2013).

2 While the core principles of the Gioia Methodology were adopted, the process was tailored to the specific needs of the research:

1. Open Coding: Similar to the Gioia methodology, the analysis began with open coding, assigning initial codes to relevant data segments.
2. Building First-Order Concepts: As the analysis progressed, a natural clustering of similar topics around these initial codes was observed. These clusters represent the "first-order concepts" in the Gioia methodology. In this study, they formed the foundation for the sub-codes.
3. Refined Sub-Codes: Unlike the Gioia methodology, which progresses to develop second-order themes and aggregate dimensions, the analysis stopped at this point. Since the sub-codes already belonged to a broader overarching theme, further abstraction wasn't necessary. These themes included "Hazard", "Uncertainties and Challenges", and "Innovation Potential".
4. Connecting Challenges to Innovation: The final step involved exploring the relationship between the "Uncertainties and Challenges" sub-codes and the "Innovation Potential" sub-codes. This analysis served as the basis for the discussion section of this research.

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Example of Coding Process

0:22:17.680 --> 0:22:23.360
Participant X
Exactly. We use IPCC scenarios. But what we do internally is that we downscale them. These models or this output from IPCC actually are as coarse as 200 kilometres by 200 kilometres, so they're not granular enough. So what we have done internally is that we have downscaled them to a much smaller grid. We can do at least 25 kilometres to 25 kilometres. For some specific indicators, like flooding, we can do as precise as 10 metres by 10 metres, because flooding is very local. It depends on where the building is. So we believe 25 kilometres as a resolution is not enough.

15:29 These...
Innovation Potential: Higher Granularity

0:23:11.370 --> 0:23:17.490
Jorna, M. (Mandy)
And in your opinion, what are main uncertainties that are involved in natural disaster risk modelling?
0:23:26.320 --> 0:23:53.600
Participant X
So the first main uncertainty comes from the different scenarios. So how will people react to climate change. Because we know we take different CO2 emission scenarios in this natural catastrophe modelings. This is of course linked to regulations. So there's a political consideration behind that, which is uncertain to us, how European Union will pick these strict regulations looking forward.

15:30 So...
Uncertainties & Challenges: Regulations

In what we do, we also need very precise data. So it will be helpful if we have like common platform that we have data from different European countries. For time being, what we do is at country by country level. But I believe there are some world meteorological organisations. Which at worldwide level could have some data.
But we hope that we can have some data at European level with more precise informations. We want to have an understanding on social and business behaviour of this kind under different scenarios so that it helps us to model better.

15:31 it w...
Innovation Potential: Data Sharing Ecosystem
Uncertainties & Challenges: Closed Off Data

So if I summarise that, the main uncertainties are the availability of information and the way businesses and also politics will behave in the future.

15:...
Uncertainties & Challenges: Closed Off Data
Uncertainties & Challenges: Regulations

0:25:28.810 --> 0:25:35.10
Jorna, M. (Mandy)
Do you think there are any ways that the models can better address these uncertainties?
0:25:47.540 --> 0:26:14.340
Participant X
Yes, what we can do internally is we backtest these models. As an insurance company, we have data. So at one side we have this kind of weather data, climate data and on the other side we can collect data from our insured companies.
So we can try to calibrate, back test our models and so on.
And this is one of the thing that we can do because our model is predictive. But this prediction needs to be calibrated with what's happening worldwide. So this something that we can do. But it's not easy because you know data cleaning, as basic as they could be, is not easy.

15:34 So...
Innovation Potential: Parameter Improvements
Uncertainties ...: Assumptions an...ers Validation

What we do is to leverage our strengths as insurance company, try to open our ecosystem to other research institutions, having input from other partners around the world. And that's why we continuously improve our model to solve these kind of solutions.

15:35...
Innovation Potential: Data Sharing Ecosystem
Innovation Potential: Parameter Improvements