Probabilistic Regional Conditioning of Natural Hazard Loss Models

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Abstract

Natural hazard risk models underpin decisions from insurance pricing to infrastructure investment, yet their accuracy depends on vulnerability functions rarely calibrated to local conditions. The most accurate vulnerability functions capture regional building characteristics through multi-variable models or large engineering-based loss-function databases, but need detailed asset-level data that is rarely available. This paper introduces a method that condenses such models and databases into single-variable loss functions tailored to a region, without asset-level data collection. Rather than weighting all loss functions equally, as conventional blending does, the method assigns each a probability based on how well it matches the regional building stock, inferred from samples or expert judgement, and updates these probabilities using Bayes theorem as building data becomes available. Applied to a wind loss-function database and a multi-variable flood loss model, regional conditioning reduces absolute and bias errors versus equal-weight blending, especially where building stock differs most from the original model context.

1. Introduction

Models that estimate losses caused by natural hazards are used for a wide variety of risk management actions, including the pricing of catastrophe insurance contracts (e.g. Grossi & Kunreuther, 2005) and informing decisions about infrastructure investment (e.g. Kind, 2011). These modeled losses are determined by combining hazard, vulnerability, and exposure information for a particular region or site. Hazard information, such as flood or wind maps, have improved substantially in recent years with the availability of higher-resolution remote sensing data and greater computational power. However, estimating risk also requires understanding how these hazards affect the built environment, which depends on exposure and vulnerability data. These data are increasingly becoming the dominant source of uncertainty in natural hazard risk assessments.

Traditional loss models for natural hazards have relied on so-called loss or damage functions (Merz et al., 2010). These functions typically relate a hazard variable, such as water depth for flooding, peak ground acceleration for earthquakes, or gust speed for wind, to losses for individual properties. Different property types may be represented by different loss functions. However, a key limitation of this approach is that a single variable typically has limited power to explain losses across broad property-type categories. For example, water depth typically correlates weakly with losses (Pistrika & Jonkman, 2009; Thieken et al., 2005; Wagenaar et al., 2017). Studies comparing flood loss models therefore often find large unexplained differences between models (e.g. Jongman et al., 2012; Gerl et al., 2016). Wagenaar et al. (2016) reasoned that missing contextual information in flood loss models is likely an important part of these differences, implying that variables other than water depth are also important.

Relatively few loss models are available because of limited historical data and the high cost of engineering-based studies. As a result, studies typically rely on loss models that are not tailored to local conditions; instead, a loss model developed for one study is often used in another. In other words, loss models are transferred both spatially, between regions, and temporally, by applying historical observations to present-day conditions. These transfers are especially problematic when the context of the models is not considered (Cammerer et al., 2013). This issue is particularly important for single-variable models, which rely on many implicit assumptions about the local context.

For these reasons, flood loss modelling has increasingly shifted toward more complex models that explicitly include contextual information. Starting with Merz et al. (2013), models have used multiple variables and machine learning techniques to represent loss processes in greater detail. These methods have been widely adopted in the academic literature (e.g. Amadio et al., 2019; Ganguly et al., 2019; Sieg et al., 2017; Spekkers et al., 2014; Wagenaar et al., 2017). They appear to transfer better to new locations and perform better in validation studies (Schröter et al., 2014; Wagenaar et al., 2018). However, in practical applications, such as insurance pricing or infrastructure investment decisions, these models are often difficult to use because they require extensive contextual information for each asset, which is often infeasible to collect.

For wind, loss models tend to rely on engineering-based approaches, in which thousands of curves are produced for a wide range of buildings and engineering details (e.g. Vickery et al., 2006; FEMA. 2012). Rather than using multi-variable models in which building characteristics are included as variables, individual single-variable damage functions are produced for each combination of building characteristics, resulting in a large database of damage functions. The differences between these curves can be very large, even for relatively small differences in building design. This again shows that building context, such as construction details and building occupancy, is important, and that gust speed alone produces highly uncertain results. However, despite the explicit modelling of many input variables, these databases of wind damage functions have the same practical drawbacks as multi-variable flood loss models, because complex engineering-based approaches often require details that are rarely available (e.g. presence of shutters, roof material, etc.).

One method often applied to develop loss functions with limited contextual information is loss model blending (e.g., Huizinga & De Moel, 2017; Wagenaar et al., 2016). In this approach, a database of loss functions is compiled from the literature, and an average loss function is computed, often conditioned on region and/or building occupancy type. This method treats all loss functions found in the literature as equally applicable and therefore assumes that the average conditions represented in the literature provide a good approximation of the contextual situation in the study area. Given the transferability issues discussed above, this assumption is unlikely to hold except by coincidence.

This equal-weight blending approach produces practical loss functions that are widely used (e.g., Huizinga & De Moel, 2017), but is likely to result in models with large, unquantified errors. Complex multi-variable models and engineering-based damage-function databases, on the other hand, can produce more accurate loss estimates, but are often not usable in practice because of their input requirements. In this paper, we introduce a probabilistic blending approach that condenses damage-function databases or complex multi-variable loss models into simple single-variable damage functions. This makes it possible to develop simple models that outperform conventional single-variable approaches without requiring infeasible amounts of input data. It also makes many currently available multi-variable loss models and damage-function databases usable in practice, by translating them into a form that does not require extensive asset-level data. The method assigns a probability to each loss function reflecting how likely it is to be appropriate for a specific building in the region, based on information about how well each function matches the regional context. These probabilities are derived from regional contextual information represented probabilistically, using either samples of individual buildings or expert judgement, and can be updated incrementally using Bayes' theorem as additional building-level information becomes available. When the starting point is a multi-variable model rather than an existing loss function database, the method first converts the range of possible inputs into a database of single-variable loss functions. The resulting probabilities can either be combined as a probability-weighted sum to produce a mean loss function or they can be used directly as a probabilistic loss function. Here, we apply this method to two case studies: one using a large database of wind loss functions (FEMA, 2012), and one using the multi-variable flood damage model developed by Wagenaar et al. (2017).

2. Results

2.1 Theoretical framework

The fundamental idea of this approach (Fig. 1) is to address the lack of input information about the context of loss models by representing that context probabilistically. This probabilistic representation can be much cheaper and easier to produce than collecting information for every building, because it can rely on samples or expert judgement.

The starting point is a database of single-variable damage functions with explicit assumptions, such as those produced in engineering-based studies or derived from multi-variable loss models. Functions inconsistent with the available asset-level information for a given building are excluded. The remaining functions are then weighted by the probability that their underlying assumptions apply to that building. This produces probabilistic damage functions tailored to particular regions based on samples of the local building stock.

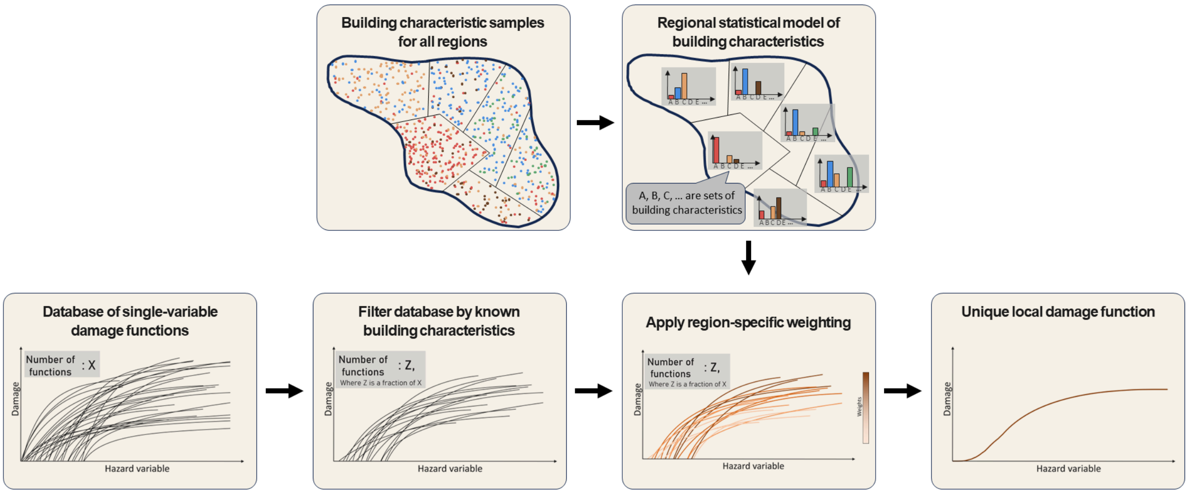

Figure 1. Overview of the approach to condense a database of loss functions into a simple single variable loss function.

2.2 Application to engineering based wind loss functions

HAZUS (FEMA, 2012) is a US loss-modelling framework provided by the Federal Emergency Management Agency (FEMA). For tropical cyclone wind loss functions, it provides a database of 6,115 loss functions that relate gust speed to loss ratios. Each loss function depends on 20 building characteristics (see Table 2), although not all combinations are available. Of these 20 characteristics, our regional building samples provide information on six, and the probability distributions used to describe regional context are defined over these six variables. We collected samples of buildings from different regions around the world to condition these wind loss functions to particular regions.

2.2.1 Regional loss functions

Figure 2 shows the resulting loss functions derived for different regions based on local building samples. The difference between the lowest and highest regional loss functions is about 10–30% for single-family homes and about 50–100% for (large) engineered buildings depending on the gust speed. This shows that regional samples describing the local context significantly change the loss functions, with a larger effect for (large) engineered buildings than for single-family homes.

In general, the largest driver of differences between regions among the variables considered in our study is the presence of shutters. Shutters appear to be more common in the US according to our samples, and this is reflected in US buildings typically being less vulnerable to wind than buildings in Asia. In particular, according to our dataset, shutters for commercial engineered buildings are extremely rare outside the US, which appears to drive the additional wind resilience of engineered commercial buildings in the US. One driver of differences between regions for single-family houses is the primary construction material. According to our data, wood is a much more common construction material for single-family homes in Asia (all three regions) than in Australia and the United States. Masonry is more resilient to wind according to HAZUS, and therefore Australia and the United States have somewhat more resilient single-family homes than Asia.

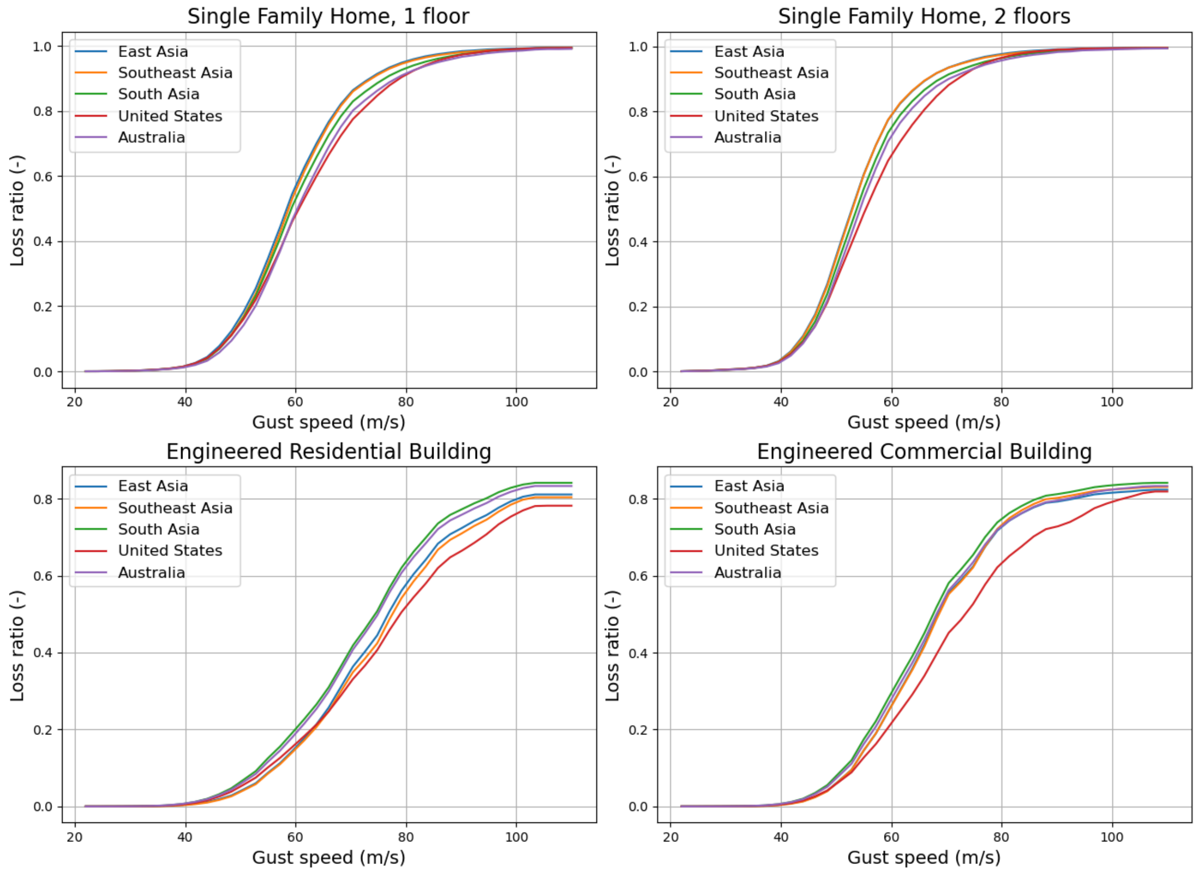

Figure 2. Regional vulnerability functions for wind damage derived from local building samples. Curves show the mean loss ratio as a function of gust speed for (a) single-family homes with one floor, (b) single-family homes with two floors, (c) engineered residential buildings, and (d) engineered commercial buildings.

2.2.2 Uncertainty reduction contextual information

Our method is probabilistic by nature, because each damage function in the database is assigned a probability. This allows us to derive probabilistic vulnerability functions. In our case, the results show, consistent with expectations, that the more contextual information is available for a building, the more confident we can be in the loss estimates. However, additional contextual information does not only reduce uncertainty; it also shifts the mean damage functions as information is added.

Figure 3 provides a clear example of this phenomenon. After conditioning the loss database on all US buildings, the 95th percentile loss is 13.2 times larger than the 5th percentile at a gust speed of 60 m/s. After providing the model with the contextual information that the building is a single-family home made of wood, this difference decreases to 6.8. When four additional variables (1 floor, gable roof, shingle roof cover, no shutters) are added, it decreases to 3.1. Considerable uncertainty remains because many variables are not provided to the model and are considered unknowable for the purposes of this study.

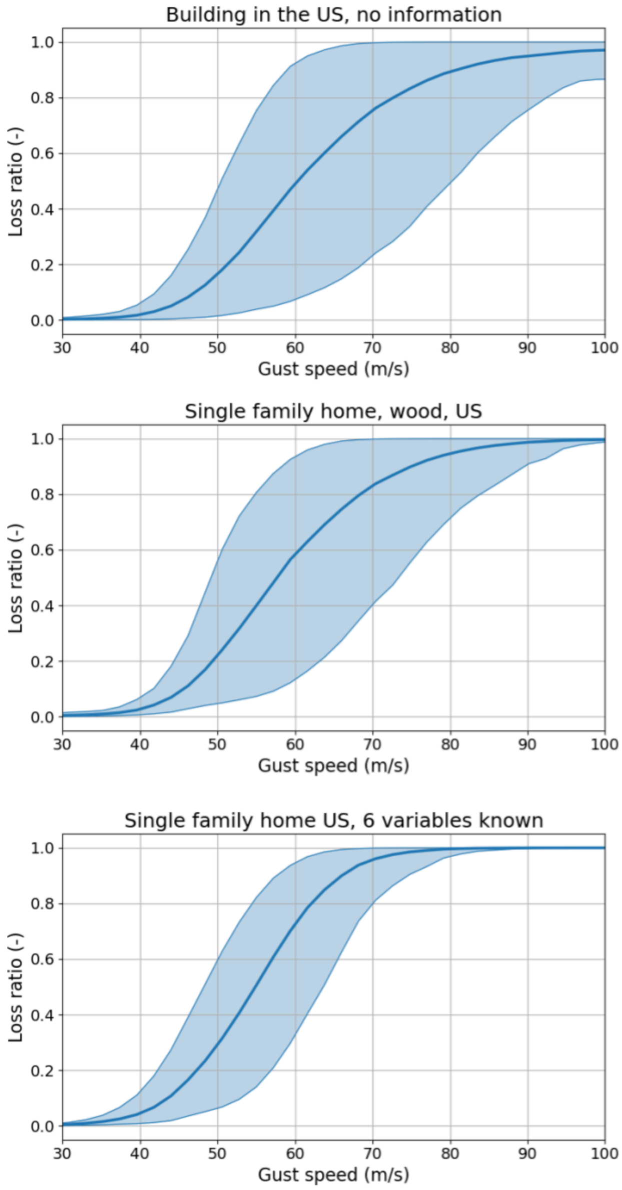

Fig 3. Probabilistic wind damage functions for a single-family wood-frame house in the US, showing how uncertainty narrows as contextual information is added. The blue line shows the mean loss ratio and the shaded region the 5th-95th percentile range. From top to bottom: (a) no building information provided, (b) building identified as a single-family wood construction, (c) six building variables identified.

2.2.3 The importance of the local context

One way to test the importance of local context in the method is to assess how much accuracy is lost when regional context is replaced with global or equal-weight statistics, relative to a known, region-specific truth. We do this by randomly generating a dataset of buildings using the statistics of a particular region. Each building in the hypothetical dataset is randomly assigned a damage function that, for the purposes of this test, we consider true.

Of the 20 characteristics in the FEMA database, we have collected regional sample data for six characteristics. We therefore define a benchmark model as one in which these same six characteristics are known directly for each individual building. This represents a theoretical best case, since knowing all six characteristics for every asset removes the need for probabilistic conditioning in the first place. We then construct three more realistic models, in which only one of the six characteristics (building occupancy) is known directly for each building, and the remaining five are represented using regional statistics, global statistics, or equal weighting across damage functions, respectively. The equal-weight approach represents the standard way to summarize single-variable loss-function databases (e.g. Huizinga & De Moel, 2017).

The remaining 14 characteristics are drawn randomly for the test environment. This keeps the test realistic, since even in the best-case scenario many building characteristics remain unknown, and ensures that these unmeasured characteristics do not contribute to regional bias by construction.

The results are shown in Figure 4. Conditioning on regional statistics consistently outperforms equal-weight blending and conditioning on a more generic (global) context. Regional conditioning can reduce the error by as much as nearly 50% (for East-Asia) on the Mean Absolute Error (MAE) metric but for the United States and Australia the MAE reduction is much lower.

First, the loss function database was developed in the USA and represents typical US building types, so equal weights approximate the US context reasonably well but Asia poorly. In addition, global conditioning draws on samples that may likewise be more similar to US building characteristics than to Asia. This highlights that transfer can sometimes work quite well by coincidence, even without conditioning on the local context.

Even with regional conditioning, however, errors remain about significantly higher than under the six-characteristics-known benchmark, showing that local context narrows but does not eliminate the error introduced by not knowing all six characteristics directly.

Mean bias error (MBE) shows a stronger pattern than MAE: conditioning on regional statistics substantially outperforms equal-weight blending and global conditioning. A small number of cases deviate from this pattern; in these instances, positive and negative errors across different characteristics may coincidentally cancel out, leading to unexpectedly low bias (or the opposite, if errors coincidentally compound), despite the model's underlying ignorance of those characteristics.

In general, we find very large improvements in MBE when we condition on the local context, compared with using global contexts or equal weights. Errors are generally up to 2–4 times smaller when conditioned on the local context rather than on a global context or equal weights. For many applications, bias errors are what matter most, because models are applied to aggregate losses, such as an insurance portfolio for reinsurance or a town or region for infrastructure improvements. Our method therefore seems to be most beneficial in these cases, rather than where individual buildings are concerned.

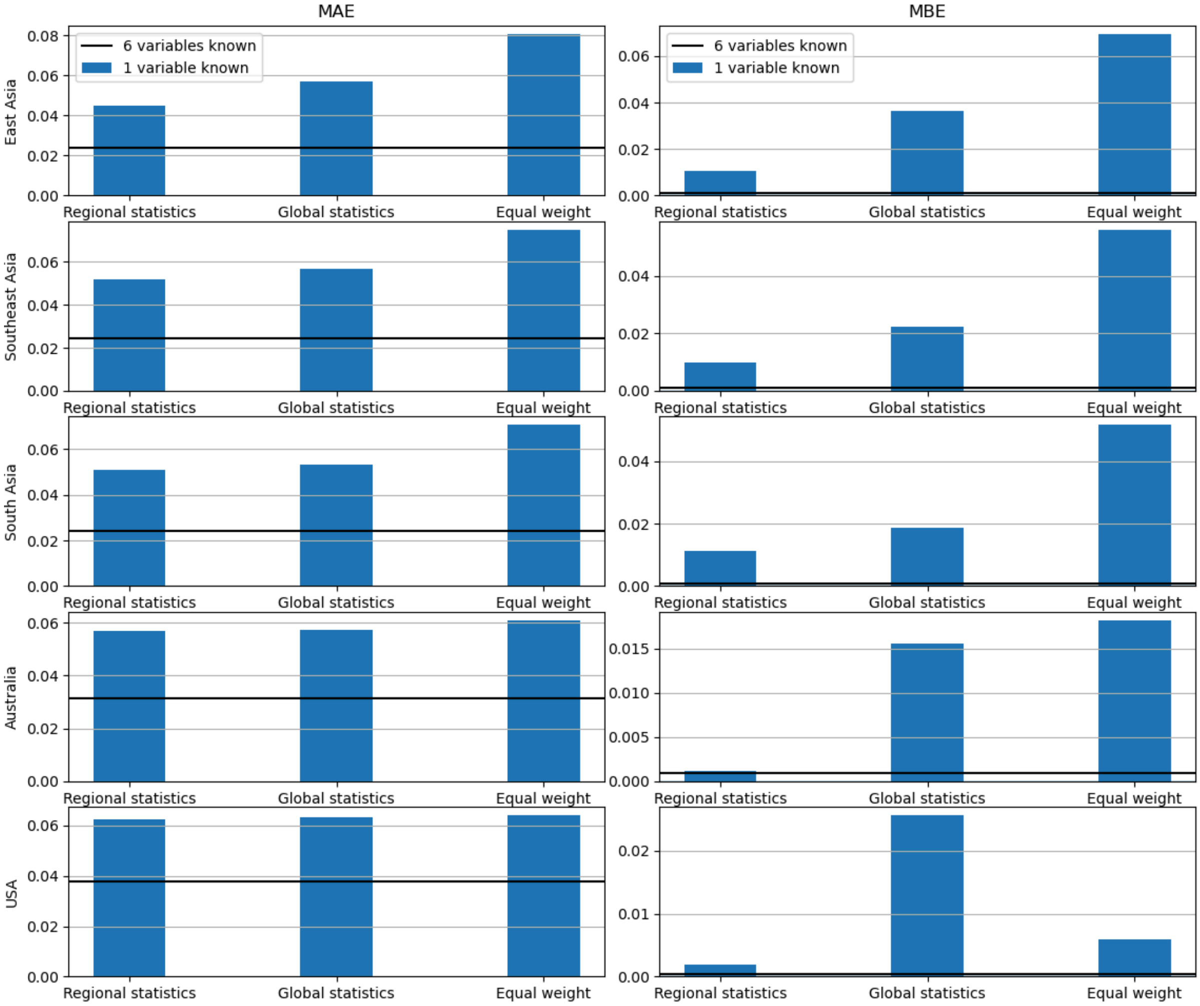

Fig 4: Mean Absolute Error (MAE) and Mean Bias Error (MBE) in loss fractions of a model tailored to the local context, versus a model tailored to global building statistics and a model where each vulnerability function receives equal weight. The black line is the error for the run when all variables the environment was conditioned on are known. For this test we only considered Single Family Homes.

2.3 Application to a multi-variable flood loss model

For the application to the multi-variable flood loss model, we used data from Wagenaar et al. (2017). When a multi-variable loss model is used instead of a database of single-variable loss models, the method is adjusted by first implementing the multi-variable loss model over the entire spectrum of possible inputs other than water depth. This results in a database of single-variable loss functions that can then be treated as the database in the previous case study. It would also be possible to combine different multi-variable loss models or to combine them with a database of single-variable loss functions.

To compare the performance of the condensed models with reference models we need test data that was not used to train the model. To obtain this, we split the original data from Wagenaar et al. (2017) into training and testing subsets. Because the input data for Wagenaar et al. (2017) is relatively homogeneous, and because our goal is to apply the method in a contextual transfer setting, we used the k-means algorithm to split the data into two maximally different groups replicating the difficult case of applying a model far outside the conditions it was trained on. All models were trained on the training subset and validated on the test subset. We repeated this setup many times, taking bootstrap samples within each subset to capture sampling variability.

Four models were created for this test. The first is the original random forest model of Wagenaar et al. (2017),treated as the full complex model ("RF" in Fig. 5). The second and third are condensed, single-variable depth-damage functions produced using the method introduced in this paper, differing only in how they are conditioned: one is conditioned on the probability distribution of the test environment's context ("Con. RF. test"), representing the regional conditioning this paper promotes; the other is conditioned on the context of the training environment ("Con. RF. train"), deliberately mismatching the model to the region it is applied in. The fourth is a reference single-variable model ("Sqrt"), produced by fitting a square-root function between water depth and loss; unlike the other three, it is not derived from the random forest.

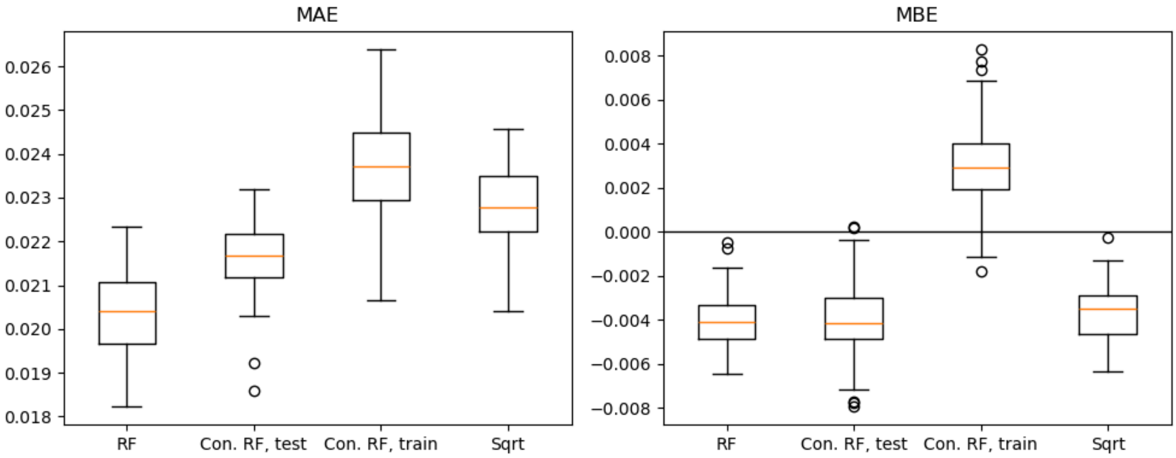

Fig 5. Performance comparison of four models for flood damage prediction. Box plots show the distribution of (a) Mean Absolute Error (MAE) and (b) Mean Bias Error (MBE) across 50 bootstrap samples.“RF” = original random forest model; “Con. RF. test” = condensed random forest conditioned on test data; “Con. RF. train” = condensed random forest conditioned on training data; “Sqrt” = reference square-root depth-damage function. The condensed random forest conditioned on test context performs between the reference function and the full random forest, suggesting the method successfully captures the main drivers of loss variation while simplifying the model. On the MBE its performance is similar to the original full random forest model.

Figure 5 shows that for the mean absolute error (MAE), the condensed model conditioned on the test context performs best among the simple models performing between the full complex random forest model and the reference square root model. The random forest performs best overall, as expected, because it is the only model that uses all variables explicitly. This shows that the new model we present here can be a better way to construct a depth-damage function than simply fitting a curve on a single variable.

For the mean bias error (MBE), the test-conditioned condensed model performs almost identically to the random forest, both showing a small negative bias, while the model conditioned on the training environment shows a clear positive bias instead, the opposite sign. This confirms that conditioning on the correct (test) environment, rather than a mismatched one, is essential for replicating the random forest's behaviour, since the training-conditioned model's bias reflects the mismatch between the environment it was conditioned on and the one it is applied to. The reference square-root function shows a similarly small bias on MBE, but this should not be read as evidence that the multi-variable random forest model added little value: on MAE, the square-root function performs substantially worse than both the random forest and the test-conditioned condensed model, close to the training-conditioned (mismatched) model's error. This discrepancy illustrates a more general point: MBE alone can understate a model's error, since errors of opposite sign can cancel; MAE is therefore the more reliable metric for judging overall predictive accuracy here.

A second test assessed the accuracy of the probability distributions of the condensed models compared with the original random forest.This tests whether the probability distributions of the loss provided by the model is a realistic representation of the uncertainty. For this, we used the hit-rate metric, which shows the percentage of observations that fall within the 90% prediction interval for each observation. For this metric, values closer to 0.9 are better; values below 0.9 indicate that the model is too confident, while values above 0.9 indicate that the confidence intervals are too wide. Figure 6 shows very good performance for the random forest model, whereas the condensed models appear to be too confident. This suggests that the probabilistic representation inherent in the approach may be imperfect. This is probably because the condensed models capture only the variation within the deterministic version of the complex model, but not the uncertainty beyond that model.

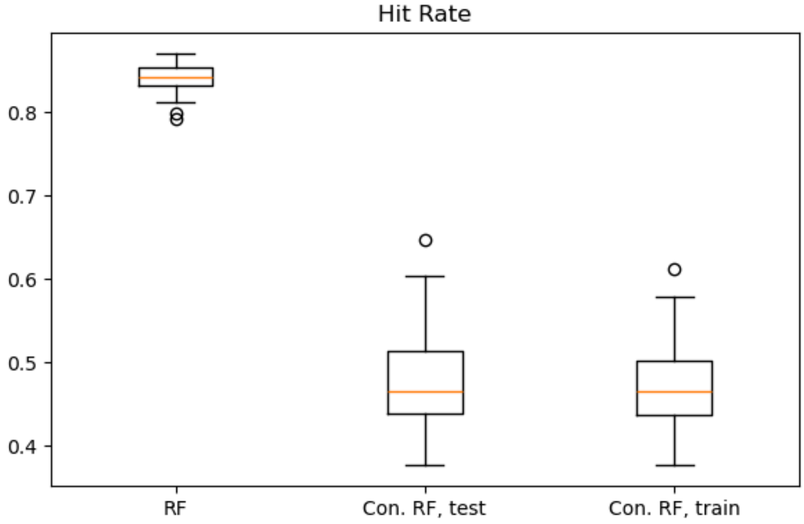

Fig 6. Accuracy assessment of probabilistic predictions. The fraction of observations falling within the 90% prediction interval is shown for each model. Values closer to 0.9 indicate well-calibrated uncertainty estimates; values below 0.9 indicate over-confidence. The original random forest shows good calibration, while the condensed models are over-confident, suggesting they capture variation within the complex model but not the full uncertainty range.

3. Conclusion and discussion

This paper introduces a method for condensing complex multi-variable flood loss models or large databases of single-variable loss functions into regionally tailored single-variable loss models. We demonstrate the method in two very different settings, wind and flood, applied respectively to an engineering-based loss function database and a multi-variable machine-learning model. This diversity, two different hazards and two different types of starting models, suggests the approach has potential applicability beyond the two cases tested here, though further testing across a wider range of hazards and data sources would be needed to confirm this. . Across both case studies, conditioning on regional statistics can substantially improve mean bias error and appears to consistently reduce mean absolute error compared with traditional approaches such as equal-weight blending or fitting a simple reference function. These new single-variable loss models are much more practical to apply and could help bridge the gap between much of the academic literature and practical applications of damage modelling. At the same time, the paper also shows that these simplified damage models have higher errors than their complex counterparts, reflecting the inherent cost of simplification.

The method also inherently provides probabilistic loss estimates, as demonstrated in Figure 3. In the flood case study, however, this uncertainty estimate was generally too confident (Figure 6). This is expected, because the uncertainty only represents the variation captured by the deterministic results from the complex multi-variable model or the loss-function database. In other words, the uncertainty represented by this method is the uncertainty introduced by simplifying the model, not the uncertainty already present in the more complex model or the original loss models. The two would only coincide if the complex model itself made no errors, which is never the case in practice. The results shown in Figure 6 are therefore consistent with expectations. This experiment would not be informative for the wind-damage case-study, because the way that test was set up ensured that we only captured the error produced by the simplification, and therefore one would expect perfect hit rates.

Another limitation of this method is that the different contextual variables are treated as independent. This is clearly not true in practice, because building features and hazard-related variables are likely to be correlated. In theory, this limitation could be addressed with Bayesian networks, which explicitly represent these correlation structures. However, Bayesian networks would not be useful for a loss-function library, as in the wind case study, and it remains unclear whether they would add much practical benefit compared with the approach presented in this paper. This is especially true because correlation structures among building characteristics, hazard-related variables, and their interactions are typically very complex, and Bayesian networks often simplify them substantially. If these correlations are not simplified, Bayesian networks tend to produce very large conditional probability tables that cannot realistically be constructed. Finally, Bayesian networks generally underperformed compared with random forests in Wagenaar et al. (2017).

It is also important to distinguish between the local conditioning applied in this approach and the local conditioning that can be achieved with methods such as sample selection bias correction (e.g. Wagenaar et al., 2021). Sample selection bias correction is similar to this approach in that it uses information from the target region, where the model will be applied, during the training of the multi-variable loss model. This produces multi-variable loss models tailored to the region where they will be applied, but it does not simplify the model as in this study. The two methods therefore have different goals and could potentially be applied together, because the approach presented here condenses the existing complex model but does not improve that model.

We tested both the wind and flood models only against data from the same study. This is because cross-model studies (e.g. Wagenaar et al., 2018; Molinari et al., 2020) often require substantial data cleaning and alignment of definitions. This is unlikely to lead to a clean comparison and therefore introduces an additional error signal that has little to do with the new methods themselves. The benefits of the regional statistics are greatest in a transfer setting, and we therefore simulated such a setting in the flood case study by splitting our data using the k-means approach. Ideally, this study should be repeated using a dataset that is homogeneous across multiple regions, in which regions can be isolated in a more realistic way. For the wind case study, we had a much cleaner transfer setting, as we had regional statistics collected from around the world in the same way. However, in that case study, we had no observed loss data.

Currently, the model assigns weights based on the probability that certain building characteristics apply to a given building. These weights could also be scaled using more subjective assessments of the general applicability and quality of a loss function. For example, Stone et al. (2017) demonstrate this approach in the context of earthquake loss functions, using criteria such as author credibility, derivation for a proximate location, and the popularity of the function.

Finally, it is important to stress that, especially in flood loss modelling, substantial uncertainty remains in multi-variable loss models. This uncertainty is caused by complexity that cannot be explained by the collected variables. Instead this leftover uncertainty is probably caused by insufficient data quality, limited sample sizes, variables that aren't collected and the limitations of the machine-learning methods used to extract models from the collected data. The approach presented here does not resolve these uncertainties.

4. Methods

4.1 Method for creating local damage functions

The starting point of our method is a database of single-variable loss functions. These loss functions can be derived by querying every possible combination of inputs in a multi-variable loss model, or they can be produced from engineering-based loss models. The method could also be applied to a heterogeneous, literature-based dataset of loss functions (e.g. Gerl et al., 2016; Wagenaar et al., 2016; Huizinga & De Moel, 2017), but it works best when the loss functions have broadly similar input variables and cover the spectrum of potential inputs relatively well. The damage functions also need to use consistent definitions of both the hazard variable and the loss ratio. This is often not the case among damage functions from different sources in the literature: for example, water depth may be defined relative to the first-floor height or to the terrain elevation, while a loss ratio of one may be defined as full reconstruction costs or to the maximum plausible loss (e.g. excluding implausible losses such as high floors). Such inconsistencies are documented by Wagenaar et al. (2016).

After the database is established, each loss function is assigned a probability. The starting point is an equal probability for each loss function in the database. At this stage, a general damage function for the database can already be produced by weighting all damage functions by their probabilities. This is equivalent to taking the average of the loss functions and it is similar to blending loss functions, as applied in Huizinga and de Moel (2017) and Wagenaar et al. (2016). Similarly, 5th and 95th percentile loss functions can be produced by ordering the functions for each depth or gust speed and taking the corresponding percentiles.

There are two contexts in which these probabilities are updated. The first is through Bayesian updating of prior weights. For example, if we know that 50% of the buildings in a region have a gable roof, 20% have a hip roof, and 30% have a flat roof, we can update the likelihoods of the loss functions to reflect those probabilities. This is done by multiplying the probability of each loss function by the probabilities of the individual variables and then rescaling the resulting probabilities so that their sum remains one. This is shown in Formula 1, as per Bayes' theorem. Note that, in Formula 1, we assume that all building characteristics are independent for simplicity; this simplification is addressed in the discussion section.

$$p_i^* = \frac{p_i \prod_{k=1}^{K} P(a_{ik})}{\sum_{j=1}^{N} p_j \prod_{k=1}^{K} P(a_{jk})} \quad (1)$$

p_i^* = weight for damage function i after updating.

p_i = weight for damage function i before updating.

K = total number of building characteristics used to update the weights.

a_{ik} = value of building characteristic k for damage function i.

N= total number of damage functions.

p_j= weight of damage function j prior to updating.

a_{jk}= value of building characteristic k for damage function j.

The second context to update the weights of the damage functions is when additional information becomes available for a specific building. For example, if we know that the occupancy type of a building is residential, we can set the probabilities of all non-residential damage functions to zero and rescale the remaining weights so that they sum to one. This Bayesian updating is shown in Formula 2. Formula 2 is a special version of formula 1 where weights are binary.

$$p_i^{**} = \frac{p_i^* \prod_{k=1}^{K} I(a_{ik}=b_k)}{\sum_{j=1}^{N} p_j^* \prod_{k=1}^{K} I(a_{jk}=b_k)} \quad (2)$$

$I(a_{ik} = b_k) =$ 1 if $a_{ik} = b_k$ or 0 if $a_{ik} \neq b_k$

b_k = known value of building characteristic k (e.g. residential occupancy type)

K = total number of known building characteristics used in this specific update.

4.2 Case study with HAZUS wind damage functions

Our first case study uses engineering-based wind damage functions from HAZUS. This dataset contains 6,115 damage functions that relate hurricane gust speed to loss ratios. The functions were developed for the United States using an engineering-based model, meaning computer simulations of losses under specified wind conditions. In our study, we used only the structural functions and assumed a fixed roughness length of 0.03, treating roughness length as part of the hazard rather than vulnerability or exposure.

In practice, HAZUS appears to use several engineering models for different building occupancy types, meaning that not all of the 20 building characteristics are relevant to every damage function and not every possible combination of characteristics is represented in the database. Therefore, even when a set of building characteristics is defined, a corresponding damage function may not always be available.

For this case study, we collected building samples from around the world. Sampling was carried out by data collectors, who used street-view maps to identify buildings and record their characteristics. Most data collectors had a basic familiarity with structural engineering and received documentation with instructions on how to label buildings based on HAZUS documentation.

The general sampling procedure was for collectors to sample 10 buildings at a random location and then move to another random location. They were asked to collect approximately 50% single-family houses and 50% other asset types. Apart from that, they were assigned target countries, mostly prioritizing countries with significant tropical cyclone exposure. Countries with limited available street-view data were excluded, because the available data could be biased toward high-income areas and may provide a poor representation of the actual building stock. For this reason, we had to exclude many countries in Africa. Because of these choices and constraints, sample size differs significantly among regions (see Table 1).

Table 1: Sample size per region

Region	**Sample size**
Australia	439
East Asia	695
Europe	764
Latin America	920
South Asia	293
Southeast Asia	927
United States	1639
Other (incl. Africa, Central and Western Asia)	986

From the data collected, six variables were used in this study: occupancy type, primary material, number of floors, roof geometry, roof cover, and shutters. Table 2 shows the full list of variables available in HAZUS, although not all combinations of these variables are available in the database. In some cases, the sampled buildings had combinations of characteristics that were not available in HAZUS. These samples were discarded for the local conditioning. Some building characteristics in the HAZUS database are easy to observe but are captured in only a very small number of damage functions, and were therefore not considered knowable in this study, such as building height.

Table 2: Variables available in the HAZUS hurricane loss model (FEMA, 2012)

Variable name	**Variable options**	**Considered knowable** (used from samples)
Occupancy type	8	Yes
Primary material	5	Yes
Number of floors	7	Yes
Building height	4	No*
Building size	4	No*
Roof Geometry	3	Yes
Roof Cover	5	Yes
Roof Cover Quality	3	No
Roof Attached Structures	3	No
Roof Deck Attachment	9	No

Roof Deck Age	3	No
Roof Frame	3	No
Building openings as fraction of surface	4	No*
Type of garage door	3	No
Shutters	2	Yes
Units per floor	3	No
Masonry reinforcement	3	No
Building tied down	3	No*
Wall type	3	No
Other uplift restraint	3	No

*Not used because it is only used for a few building types in HAZUS despite being observable in principle.

4.3 Case study with a multi-variable flood loss model

For the flood damage case study, the starting point is the random forest model introduced in Wagenaar et al. (2017) based on the data of WL Delft (1994) also described in Wind et al. (1999). This study is based on flood loss observations after the 1993 Meuse floods in Limburg, the Netherlands. The observations are based on amounts paid by the government to compensate households for their losses and consist of 4,398 records. The dataset includes 10 explanatory variables for damage, some of which were collected in 1993 and some of which were added later by Wagenaar et al. (2017).

The dataset records absolute loss values in 1993 Dutch guilders. To convert these to relative losses, we used construction costs per square meter in the Netherlands from De Bruijn et al. (2015). We corrected this value for inflation and converted it to Dutch guilders, resulting in a maximum structure value of 1,846 guilders per square meter for 1993. We then used the building size in the dataset to convert the absolute losses to relative structure losses.

Another change we made compared with Wagenaar et al. (2017) concerns the two water-depth variables used in the original paper: observed water depth and modelled water depth. The observed water depths were collected directly after the 1993 flood in the original survey that also determined the flood losses. Modelled flood depth were only added in 2017 and were generally slightly higher as it is the explicit depth compared to the elevation map whereas the original survey probably measured more relative to the ground floor elevation. For this paper, the modelled water-depth variable was therefore changed to the difference between modelled and observed water depth, which roughly represents ground-floor elevation. The observed water depth is then used to produce the single-variable flood damage models.

For the testing purpose of this study, we split the dataset into training and testing subsets in a biased way. This was done to make the test more realistic, because in practice the samples used to create a model rarely represent the samples to which the model is applied accurately. This split was produced using the k-means algorithm with nine variables, excluding water depth and all loss observations.

We took 50 bootstrap samples from both the training and testing data to illustrate sampling variability in this case study. This bootstrap sampling was performed after the training-test split, because k-means is expected to cluster the same samples together regardless of the bootstrap sample.

We then discretized all variables to create a database of single-variable loss functions by querying every possible combination in the random forest multi-variable loss model. This resulted in a database of 245,760 single-variable damage functions extracted from the random forest trained on the training data. We then assigned probabilities to these 245,760 damage functions based on either the training-data context or the testing-data context.

We compare the performance of these models with a reference damage function produced by fitting a square-root function to the water-depth and damage observations. This is similar to the reference functions used in Merz et al. (2013) and Wagenaar et al. (2017). Because this reference method does not require discretization, we did not discretize the data for this model.

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