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UNCERTAINTY RANGE IN PROBABILISTIC SEISMIC RISK METRICS RESULTING FROM MULTIPLE HAZARD MODELS

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Abstract

Quite frequently, catastrophes impact densely populated areas of the world, and hence mitigation and proper management requires risk evaluations. Because of the uncertain nature of extreme natural hazards and the lack of data, it becomes necessary to forecast the potential damage and losses before the event happens. Therefore, CAT models build on scenarios that represent all possible realizations of the hazard in terms of frequency and intensity. Probabilistic risk models require the characterization of such hazards, the exposure on infrastructure in the evaluated region, and the vulnerability of these infrastructures. The main objective of this research is to compare Loss Exceedance Curves (LECs), Probable Maximum Loss curves (PMLs), and Average Annual Losses (AAL) using four different available seismic hazard models for Chile, denoted hereafter as GAR15, BID, CIGIDEN, and ASLAC. To isolate the effect of changing the hazard model in the risk results, the exposure and vulnerability information is fixed to the one available from the Global Assessment Report, GAR 15 and GAR ATLAS 2017. Results show differences due to the variability on the information used in each model i.e., historical data, estimation of model parameters, the mathematical structure of the model, the value of model inputs and scale of transformation. Imprecise probability theory, logic trees, and frequency and severity blends used by CAT modelers are the approaches applied and compared herein to propose either model blending, or an interval of possible realizations. While uncertainty in risk estimations can be considerable, they need to be understood only as a representation of reality, and hence, uncertainty is just a characteristic needed to deal with correctly in communications and decision making. Moreover, results from models set a risk benchmark used in decisions consistent with that risk.

Keywords: Probabilistic risk assessment, uncertainty quantification, risk model blending, loss exceedance curves, hazard models

1. Introduction

With only few exceptions, very limited information is available about extreme natural events that occurred in the past. Less is known about events that will occur in the future. Therefore, probabilistic risk assessment (PRA) is needed. However, disaster risk assessments have several sources of uncertainty. One of them is the seismic hazard since many aspects of future earthquakes are unknown, such as when time, place, depth, magnitude, path characteristics as waves propagate through the Earth's crust, site effects, buildings and infrastructure inelastic response to strong ground motion, or how damage is associated with economic and human losses.

Catastrophe (CAT) models were first developed by commercial firms in the 1990s, a time when the insurance and reinsurance sector struggled with the arrival to Florida of Hurricane Andrew. Since then, the need to find ways to avoid insolvency in case of low frequency/high consequences events became urgent, boosting research on PRA and applied ruin theory [1, 2]. CAT models have evolved since then and, with more recent disasters, new knowledge has been acquired, allowing for their improvement. It was not until recently that PRA was understood as very useful not only to avoid insolvency in the insurance sector, but to aid decision-making from the governance perspective at the national, subnational, and local levels. Consequently, diverse CAT models have been developed by different research and consultancy firms for different purposes.

Results from different PRA tend to vary considerably, due to the uncertainty present in modeling highly complex natural phenomena, their impact on the built environment, as well as the assumptions, and simplifications used by each model. For instance, the analysis published by Guy Carpenter in 2011 shows that the uncertainty range in U.S. hurricane risk models was "a two standard error interval (a plausible range that has a 68 percent chance of including the true, but unknown value) for a national writer's 100-year or higher probable maximum loss (PML) goes from 50 percent to 230 percent of the PML estimate produced by the model" [3, 4]. Despite the rather normal differences amongst risk models, they tend to converge somewhat in the order of magnitude.

Risk results allow trade-offs between risk and opportunity to be properly measured, valued, and visualized, facilitating a transition between risk-blind public investment towards risk-informed development. They can also be used to design financial protection mechanisms to cover potential losses of the government.

In the case of Chile, at least four seismic hazard models suitable for PRA have been developed in the past. Different techniques as well as hazard representation, leads to different risk assessment results, which give a more complete perspective on the range of potential outcomes. Hence, Transparency Model Blending output is a common practice in the actuarial field and different techniques have been developed for it. However, caution should exist with the models used and assumptions made, since blending inadequate models does not lead an adequate model [5].

Herein, risk results are obtained using four different hazard models for Chile. Their outcomes are compared with one another and then blended using frequency and severity blends, commonly used in CAT models.

2. Probabilistic Risk Assessment

Given the short history of disaster records, it is rather evident that the "worst-case" scenario is unlikely to have occurred yet. Therefore, for large losses, exceedance rates are difficult to be estimated statistically. An analytical approach, that rationally incorporates and propagates the inherent uncertainty in the occurrence of loss and impact, is required to fully represent the catastrophe risk problem. PRA, which all CAT models implement, is the most appropriate tool for this. As the occurrence of hazardous events cannot be predicted, CAT models use sets of events to represent all possible ways in which the hazard phenomenon may manifest in the area under analysis in terms of both frequency and severity. The vulnerability of the exposed elements is represented with functions that provide the probability distribution of the loss as a function of increasing hazard intensity. Event-based PRA have been extensively applied for different hazards at different scales (e.g. [6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16]).

PRA are composed by hazard, exposure, and vulnerability. These components are defined as follows:

- Hazard model: for each phenomenon, a set of events is defined along with their respective frequencies of occurrence, forming an exhaustive representation of the hazard. Each scenario contains the spatial distribution of the parameters to characterize the intensities as random variables;
- Exposure model: an inventory of exposed elements, specifying the geographical location of each asset, its replacement value, and its building class;
- Vulnerability model: for each building class a vulnerability function is defined for each type of hazard. This function characterizes the structural behavior of the asset with each hazard intensity. Thus, vulnerability functions provide the probability distribution of the loss as a function of hazard intensity.

In general terms a probabilistic calculation follows this sequence: *(1)* For a given scenario, the probability distribution of losses in each of the exposed assets is determined; *(2)* the probability distribution of the sum of these losses is determined taking into account the correlation between them; *(3)* the probability of exceedance of a given loss value p is calculated; *(4)* the contribution of any particular scenario to the overall loss exceedance rate is calculated by multiplying the probability determined in step 3 by the annual frequency of occurrence of the event.

These steps are then repeated for all events, resulting in the loss exceedance rates for the integrated hazard. For further details on the probabilistic risk assessment methodology please refer to [17, 18, 19].

The main risk metric obtained from a fully PRA is the Loss Exceedance Curve (LEC), which is recognized to be the most robust tool for representing catastrophe risk [17, 18, 2]. The LEC provides an exhaustive probability quantification of the risk problem. Although it is not possible to know the exact losses of a future disaster, it is possible with the LEC to know the probability that any loss amount will be exceeded within any time frame and use this information to support the decision-making process for risk reduction. From the LEC, different metrics are obtained such as the Average Annual Loss (AAL) and the Probable Maximum Loss (PML). The AAL is a compact metric with low sensitivity to uncertainty. It expresses the expected average loss per year considering all the events that could occur over a long timeframe, including large losses over long return periods.

The modular nature of PRA allows modifying or replacing any portion of it for comparison purposes. Consequently, four different hazard models for Chile are used herein together with a single exposure and vulnerability model.

2.1. Seismic Hazard Models

The seismic hazard is represented by means of a stochastic set of events (realizations). These events must be mutually exclusive (they cannot occur simultaneously), collectively exhaustive (combined, they represent all the ways in which the hazard may manifest), have a mean annual occurrence frequency rate and consider at least the first two probability moments for the hazard intensities (expected value and variance). This representation includes events that have not yet occurred but that are feasible to occur.

Failing to represent mutually exclusive hazard scenarios leads to an incongruence when adopting the Poisson process to model the occurrence of loss in time (as inherently considered in CAT models and ruin theory [19]). On the other hand, the set of scenarios being collectively exhaustive does not necessarily mean a large number of them. Few scenarios may be enough to represent exhaustively a hazard, if such scenarios cover the ones that can occur. In some other cases, a large number of scenarios does not guarantee fulfilling this requirement. The above mentioned features must be implemented in a seismic hazard model for it to be suitable for catastrophe risk evaluations. All hazard models used in these calculations herein fulfill these requirements.

The hazard models used are: *(i)* The probabilistic hazard model based on smooth seismicity developed for the Global Risk Assessment in the framework of the Global Assessment Report, GAR 2015 for 216 countries and territories of the world [10, 20]; *(ii)* the probabilistic hazard model based on detailed information of the subduction and crustal sources of Chile developed in the framework of technical cooperation with the Interamerican Development Bank, IDB for Chile, developed by Ingeniar Ltda [21]; *(iii)* the CIGIDEN "in-house" probabilistic hazard model which is based on detailed information of the subduction sources and an updated recurrence model [22]; and *(iv)* the regional model for Latin America and the Caribbean, ASLAC, developed using the state-of-the-art representation of both crustal and subduction sources [23, 24].

This paper does not aim to describe the methodology of each hazard model but to present risk results using each model, present a comparison among them, and analyze different model blends (severity and frequency) as well as to obtain a range of losses. The conceptual framework and methodologies used for each of the hazard models is deferred to the corresponding references. No preference, or technical judgments on the quality of the selected models are presented herein, and the article focuses on the epistemic uncertainty that arises from these models.

Earthquake scenarios were generated using the computer program CRISIS 2014 and 2015 [25, 26] for GAR15, IDB, and ASLAC, while for the CIGIDEN hazard model, the earthquake scenarios were generated using our own research software, which has been carefully validated with existing models. Seismic hazard assessment was performed at the bedrock level, and the platform used for risk calculations was CAPRA [27].

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2.2. Exposure and Vulnerability Model

The exposure model is a grid of 5x5 km resolution that contains information of buildings (the exposed assets considered in this analysis), such as geographical location, construction class, replacement cost, and occupancy, and the vulnerability functions that relate the intensity with direct losses. A total of 36,397 entries (shown in Figure 1) comprise the GAR15 exposure database for Chile with a total exposed value of million USD 730,000.

There are 383 different building types for Chile, which using the CAPRA vulnerability functions are grouped in 10 macro classes: Reinforced concrete *(C)*; Rubble stone (field stone) masonry *(RS)*,;Adobe block (unbaked dried mud block) walls *(A)*; Reinforced masonry *(RM)*; Steel *(S)*; Unreinforced fired brick masonry *(UFB)*; Informal constructions (self construction) *(INF)*; Wood *(W)*; Unreinforced concrete block masonry; and lime/cement mortar *(UCB).*

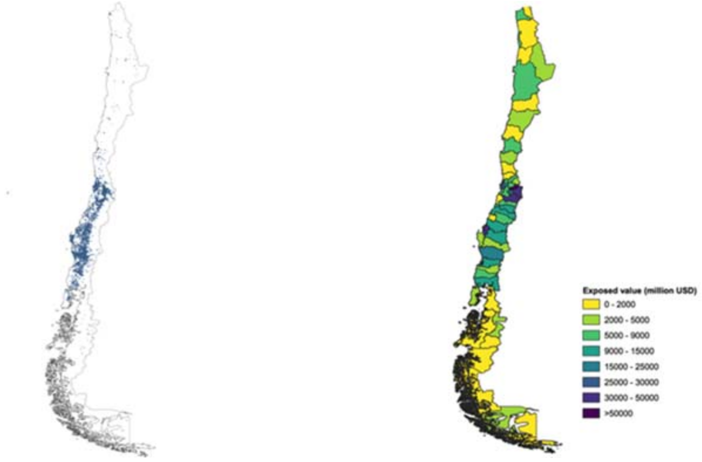

Figure 1. Overview of the exposure model: a) GAR15 exposure database for Chile using a 5x5 km resolution; b) Exposed value in million USD by province (from GAR15 exposure database for Chile).

3. Comparison of Probabilistic Seismic Risk Evaluations

In this section, we present the expected loss obtained using the four different hazard models used and the exposure and vulnerability information included in GAR15. Table 1 shows total AALs in million USD and normalized values relative to the total exposed value (per thousand). Loss Exceedance Curves, LECs for the four models are shown in and Probable Maximum Losses, PML are shown in

Figure *3*.

Results from the annual rated and PML differ among models. While the closer LEC are those of CIGIDEN and GAR15 for small losses, the CIGIDEN and IDB become closer for large losses. For the PML curves, the values are lower by the GAR, while the CIGIDEN and IDB model are quite similar. Moreover, the ASLAC PML curves have lower losses for return periods shorter than 1000 years, while losses are larger for long return periods.

Table 1. Average Annual Loss in millions of USD and normalized to the exposed value (‰)

Hazard model	AAL (million USD)	AAL (‰)
CIGIDEN	2,410	3.29
GAR15	2,397	3.27
IDB	7,139	9.74
ASLAC	3,008	4.11

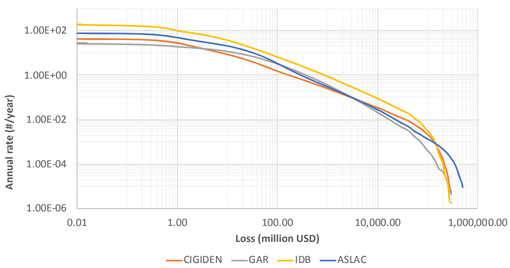

Figure 2. Seismic Loss Exceedance Curves (LECs)

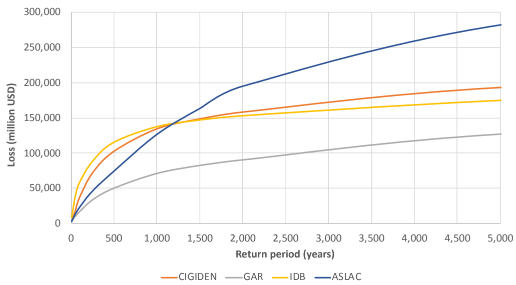

Figure 3. Probable Maximum Loss (PML) curves

It is well known that more frequent losses will contribute more to the AAL. While the IDB and CIGIDEN curves are similar, results vary due to the first part of the curve where more frequent losses contributed more importantly to the IDB curve. Such is the case also with the ASLAC model that presents less frequent losses, reflected on a lower AAL, despite the larger losses for less frequent events.

It is also apparent that the shape of the GAR curve is different from the other three curves. As mentioned earlier, this model is based on smooth seismicity, which implies that it may limit the influence of additional factors such as local faults or seismicity conditions that may not necessarily be properly accounted for in the set of events. Because it is based on coarser information, all input parameters and results are smoothed over larger regions, which may not capture specificities as the other three more detailed models.

4. Use of Multiple Risk Models

In a broad sense, uncertainty is inherent to any approach to model complex dynamic systems under stochastic inputs and parameters. It can be understood as the gap between the outcome of the model and the real behavior of the system. This gap is composed by the uncertainty on the available observations, the estimation of model parameters, and inputs the functional form of the model itself (typically simplifying the phenomena), the transformations of scale (commensurability), and the natural randomness. This last source of uncertainty is usually referred to as *aleatory*. All the other mentioned sources compose the *epistemic* uncertainty. It is widely recognized that epistemic uncertainty is reducible as more data or knowledge is added to the problem (e.g. by incorporating multiple hazard models). However, we have shown in this paper the variability of results obtained by changing just one of the model components. This process has either increased the epistemic uncertainty of the overall risk model or revealed to us a new source of uncertainty that is usually neglected when using a single hazard model. In any case, we have a broader range of results rather than single-valued metrics [28].

In CAT risk practice, and considering the involved models as reliable, impacts due to the limitations can be minimized by using multiple models in order to gain a broader view of risk [29].[1] Furthermore, the use of multiple models allows comparing and contrasting results, as well as seek an explanation of why models produce different results. The use of more than one model provides different views of the same risk [5].

While some rating agencies have a positive view on the use of multiple models in assessing risk others are more cautious about this matter. Standard & Poors believes that a multi-model approach would add transparency, since risk can differ significantly between models depending on how data is interpreted. The approach would give a better perspective on the range of potential outcomes. AM Best expects companies to justify the use of certain risk outputs obtained from adjusting to a weighted average in cases where more refined information is available.

[1]Available at: https://www.artemis.bm/news/sp-report-highlights-need-to-understand-risk-modelling-uncertainty/

Multi-model techniques include bending (adjusting specific modules to develop a customized view of risk), blending (averaging) the model outputs, or morphing outputs from one model into another model to reflect the characteristics of the first model. In each case, it is important to consider the correct selection of specific weighting parameters and methodologies. Whatever is the technique used, considerations and assumptions need to be informed by adequacies and shortcomings of each model [3, 4]

Four hazard models are available for this analysis as mentioned above, from which risk results for seismic hazard were obtained. Model blending and loss exceedance intervals are used in this study. A frequency versus severity blending results comparison and analysis is presented. Also, the interval of losses resulting from using the lowest LEC and the largest LEC, this result assumes that there is a range of losses with no knowledge of a probability distribution within. In this study, the hazard module varies, while the exposure and vulnerability modules remain the same. The motivation to do this is to dissect in modules the complete probabilistic risk model to observe how models differ significantly only by changing input information in one of the models. Later on, in this line of research, different databases of exposure will be used and combined with the different hazard models used herein.

4.1. Model Blending

Models blending has different versions. A natural one is “to adopt the best bits of each component model”, say, to produce a new model using model X for the hazard module, model Y for the exposure module, and model Z for the vulnerability module. This was called Model Fusion by Guy Carpenter (2011). Another interpretation of model blending is with outputs, which is not uncommon in the insurance world.

Different modelers use different platforms, assumptions, models, which give different views of risk. Recognizing that models are different, it is not necessarily objective to justify that one model is better than another. Assuming that they are carefully constructed and that they all have a strong scientific basis, choosing one model or another is not the aim of this study, but to discuss changes on outputs using various hazard models. The blending of model outputs is a practical approach, even if it falls short of the ideal model fusion.

Blending models, as treated in this study, involves the mixing of event results from multiple models to develop a final view of risk. Two commonly employed ways of blending outputs of CAT models are severity blending (or commonly known as a weighted approach – [30]) and frequency blending (an alternative weighted approach – [30]). Both alternatives are applied on the results of each model by blending either the frequency or the severity of them. Thus, no changes are introduced on the hazard models. What it is important to keep in mind is that blending two inadequate models or assumptions does not imply an adequate model.

For the model blending presented next, different alternatives of blending were considered. For the four available models, two different sets of weights were used. One assumes equal weights for all models; i.e. 25% for each. The second alternative assumes unequal weightings that match better the level of resolution of the models: 10% for the GAR model given its lower resolution, 20% IDB because it is outdated, 35% CIGIDEN because it is the “in-house” model and its resolution is acceptable, and 35% ASLAC due to the high-resolution version of the hazard model (it is an update of the IDB model) that considers crustal and subduction sources, and it is the most recent model developed for commercial purposes. This article includes the results of the second alternative only (different weights).

4.1.1. Severity Blending

In the severity blending approach, for each exceedance probability, a weighted average of the corresponding loss is performed. Figure 4 shows the PML curves resulting from the severity blending compared with the PML curves of the original models: CIGIDEN, GAR15, IDB, and ASLAC using equal (light blue line) and different (dark blue line) weights for all models.

Using severity blending does not allow to construct a consistent additively coherent CAT model. Also, the approach does not deal with epistemic or model implementation uncertainty, which frequency blending

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does. Conversely, severity blending attempts to establish that having two "good" models, the loss would be somewhere in-between. The blended model output gives an average or a weighted average of the expected losses when it is believed for example, that one model might understate severity of loss while other might overestimate it. By taking a weighted average of the losses, the results are "less wrong" than using a single model. In other words, severity blending attempts to manage the consequences of getting the estimate wrong [5].

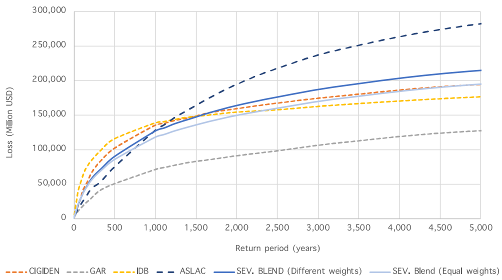

Figure 4. Severity blending using the four available models

4.1.2. Frequency Blending

In the frequency blending approach, for each magnitude of loss severity, a weighted average of the exceedance probability is performed. Figure 5 shows the PML curves resulting from the frequency blending compared with the PML curves of the original models: CIGIDEN, GAR15, IDB and ASLAC using the same weights (light green line) and different weights (dark green line).

Frequency blending allows working with simulated events of the models used. As suggested by [30], in this way, frequency blending gives a proper CAT model that has its own event set and associated portfolio losses [5].

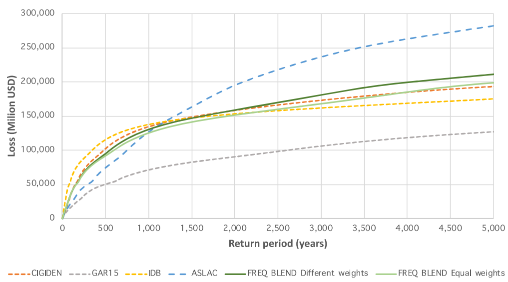

Figure 5.Frequency blending using the four available models

4.1.3. Comparison Between Frequency Blending and Severity Blending

No matter if it is severity blending or frequency blending, both produce a weighted average Loss Exceedance Curve (LEC)[2]. As explained in previous sections, this curve can be obtained by taking a weighted average of the loss at each return period (severity blending), or a weighted average of the frequency of loss thresholds, or frequency of each event of the set (frequency blending).

[2] Or Probable Maximum Loss (PML) curves or Exceedance Probability (EP) curves which can be obtained from the LEC.

Figure 6 shows the PML curves obtained from the severity blending and the frequency blending using equal and different weights. Table 2 shows the AAL in million USD and relative to the exposed value. Both model blending techniques are common; however, in many cases, the severity blending is preferred given its easiest calculation at individual return periods. Strictly speaking, the frequency blending approach has a more consistent implementation that maintains the nature of CAT modeling.

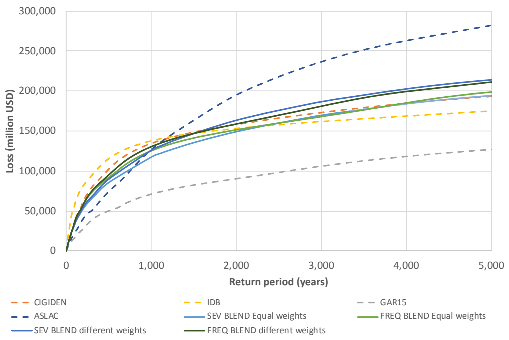

Figure 6. PML curves comparison

Table 2. AAL Frequency and Severity blending using equal and different weights

Weights	Frequency blending million USD	Frequency blending ‰	Severity blending million USD	Severity blending ‰
Equal	3,738	5.10	3,632	4.96
Different	3,564	4.86	3,453	4.71

As it can be observed in Table 3 and Table 4, the frequency and severity blending results are very similar; what it is important to consider is the philosophy of the concepts. When applying a severity blending, the consistence of CAT modeling is lost, and it avoids the additivity coherence of the modeling. “The severity blending attempts to manage the consequences of getting the estimate wrong” [5]. Severity blending focuses on the level of losses and not on the probabilities of exceeding thresholds of losses, which is the nature of CAT modeling. Instead, frequency blending maintains the coherence of a CAT model and maintains the event set and the associated estimated losses. The curve resulting from the frequency blending approach can be obtained from the weighted average of the frequencies of loss thresholds or by combining all the scenarios from the original models available.

Table 3. PML (million USD) for different return periods for the four models available and the severity and frequency blending with equal and different weights

Return period	PML (million USD)							
	CIGIDEN	GAR	IDB	ASLAC	Frequency blending		Severity blending	
					Equal weights	Different weights	Equal weights	Different weights
10	2,907	2,935	8,538	3,068	4,343	4,124	4,362	4,117
25	8,319	6,027	20,046	7,274	10,478	10,173	10,416	9,913
50	17,488	10,083	37,932	13,370	19,462	19,247	19,718	18,777
100	36,495	16,555	57,901	22,867	36,659	36,599	33,454	31,968
250	71,692	33,481	88,222	46,178	66,393	67,510	59,893	58,420
500	102,244	50,111	115,415	74,232	91,708	94,880	85,500	85,659
1000	134,340	71,056	137,539	126,613	125,233	130,368	117,387	124,788
1500	148,515	82,408	147,093	163,334	141,248	146,987	135,337	149,029
2000	158,189	90,319	153,131	195,010	151,429	158,792	149,162	168,801
5000	193,192	126,869	175,025	281,978	198,731	211,165	194,266	227,320
10000	212,814	148,955	199,360	346,378	240,312	259,121	226,877	270,519

4.2. Loss Exceedance Intervals

As discussed, the CAT modeling complexity, the uncertainty involved in modeling, the assumption on the information and on the models, will generate different outputs from different modelers. The degree to which resulting curves could differ is very high nevertheless, experts on risk modeling expect a range of possible curves [31].

Table 4. PML (% exposed value) for different return periods for the four models available and the severity and frequency blending with equal and different weights

Return period	PML (% Exposed value)							
	CIGIDEN	GAR	IDB	ASLAC	Frequency blending		Severity blending	
					Equal weights	Different weights	Equal weights	Different weights
10	0.4	0.4	1.2	0.42	0.59	0.56	0.60	0.56
25	1.1	0.8	2.7	0.99	1.43	1.39	1.42	1.35
50	2.4	1.4	5.2	1.82	2.66	2.63	2.69	2.56
100	5.0	2.3	7.9	3.12	5.00	5.00	4.57	4.36
250	9.8	4.6	12.0	6.30	9.06	9.21	8.18	7.97
500	14.0	6.8	15.8	10.13	12.52	12.95	11.67	11.69
1000	18.3	9.7	18.8	17.28	17.09	17.79	16.02	17.03
1500	20.3	11.2	20.1	22.29	19.28	20.06	18.47	20.34
2000	21.6	12.3	20.9	26.62	20.67	21.67	20.36	23.04
5000	26.4	17.3	23.9	38.49	27.13	28.82	26.52	31.03
10000	29.0	20.3	27.2	47.28	32.80	35.37	30.97	36.92

Another approach is to use intervals, using two LECs setting an upper and a lower limit, as shown in Figure 7 and Figure 8. The way how the upper and lower limit curves are obtained is by choosing the highest and the lowest values of the four models available resulting in envelope-curves. This can be interpreted as an "imprecise loss exceedance curve" [19] and the probability distribution within this interval is not known. This approach becomes useful to define the characteristics of future conditions which are usually non-probabilistic and exhibit deep uncertainty. This interval gives a less precise picture of CAT modeling results but a more realistic one.

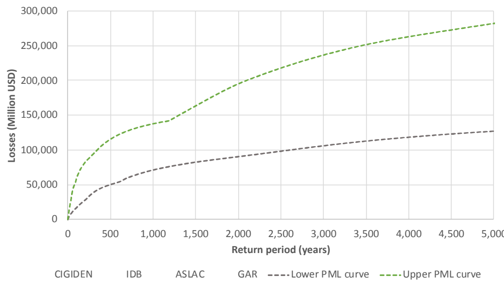

Figure 7. Probable Maximum Loss interval including PML curves from original models

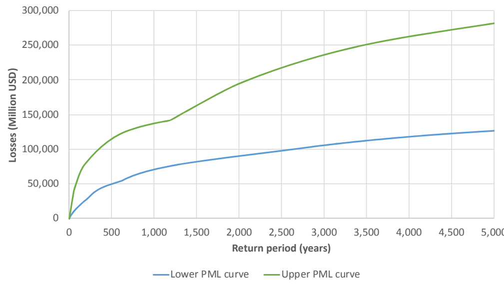

Figure 8. Probable Maximum Loss interval. Lower and upper limits

5. Conclusions

PRA has several sources of random and epistemic uncertainty, due to inherent randomness, lack of data, and knowledge to understand the different phenomena. Therefore, probabilistic risk models that account for these uncertainties are necessary to account for them and to understand their propagation. Despite significant differences in specific risk results for the same area of analysis, especially at more localized geographical levels, models tend to converge in terms of global trends. While uncertainty in models can be considerable, they are valuable tools to represent reality though not reality itself. The uncertainty is not a defect but a characteristic, and the challenge is to deal with it. These models are a powerful tool for communication and decision making. Since results from these models can set a risk benchmark useful to make decisions according to that risk.

Probabilistic risk models are composed of hazard, exposure, and vulnerability. This fact allows for modification or module replacement, and the analysis of uncertainties can be separated in these modules. With the existing four hazard models available for the Chilean seismic setting, it was possible to compare and observe the effects on risk results of using different hazard models. Using multiple models, however, will not overcome uncertainties coming from limitations of historical data, data errors and oversimplify assumptions.

This paper presented three different ways of using risk results arising from multiple models, and no approach is superior to the other. The approach to adopt depends mainly on the criteria of the experts. Since no single model can predict the real risk, multiple models may diversify and reduce models bias and eccentricities.

As observed, the estimated losses of the frequency and severity blending are similar. However, considering the philosophy of the concepts, the frequency blending is preferred because it preserves the consistency of CAT modeling. The curve resulting from the frequency blending approach can be obtained from the weighted average of the frequencies of loss thresholds or by combining all the scenarios from the original models available. On the other hand, blending on the results, which is the only way to do the severity blending, can be preferable because users can explicitly factor based on their own experience of the loss, at lower return periods, but it affects modeled loss integrity. Because it is not possible to look at the drivers of the loss because a blended curve cannot be decomposed into factor contributions. Severity blending focuses on the level of losses and not on the probabilities of exceeding thresholds of losses, which is the nature of CAT modeling. Therefore, any model blending will involve trade-offs between ease of implementation, mathematical correctness, and functionality.

The latter approach was selected in this paper since it preserves the original model, which enables to deconvolve to understand and analyse the model contributions. Moreover, adopting a loss exceedance interval has different advantages. First, all models are considered and maintain their integrity. Second, the user has a wider spectrum of possible values that can give more flexibility on the selection for establishing alternatives of risk management according to the user risk aversion.

Blending is a very common approach in the insurance market, but it is not very widely known or used in other fields of the CAT modelling world. There are quite a few points of view available and easily accessible. The motivation for this research was to provide a discussion on the use of multiple risk models, since they are more and more common in current practice. The good is to reduce implementation uncertainty with the aim of reaching better disaster risk management decision making.

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