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Influence of Community Characterization on the Output Uncertainty of the Florida Public Hurricane Loss Model

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ABSTRACT: The purpose of this paper is to quantify the effect of the uncertainty regarding building class assignments on the overall uncertainty of the projected losses in a hurricane wind risk model for residential infrastructure in Florida. The Florida Public Hurricane Loss Model is used as a case study, where the modelers have developed sets of exposure statistics that have become increasingly exhaustive and accurate over the years. The latest set of statistics covers the entire State of Florida, whereas the previous versions included a limited number of counties, and missing information was extrapolated from neighboring counties. The authors ran portfolio analyses using previous and the most recent statistics to demonstrate and quantify the range of uncertainty associated with inventory characterization. They did this for multiple scenario events in regions of Florida for which they have the associated claim data. The comparisons of the aggregated modeled losses against actual losses and their contrast with the spread among like-structures help quantify the uncertainty due to imperfect building characterization and should inform strategies to reduce that uncertainty.

1. INTRODUCTION

Catastrophe (cat) models for man-made infrastructure have four main components: a hazard component, which models the hazards, for example, hurricane or earthquake; an exposure component, which categorizes the exposure (e.g. buildings) into generic classes; a vulnerability component, which models the effects of the hazard on the exposure and defines vulnerability functions for each building class (or other type of exposure); and an actuarial component, which combines the vulnerability, the hazard, and the exposure, to quantify the risk in terms of physical damage, economic damage, or insured losses. Cat models address the needs of different user groups, including the insurance industry and insurance regulators (Dong 2002; Shah et al. 2018). In this case, insurance portfolios of exposure are input to the models, and the outputs are projected insured losses. Most of the cat models addressing the needs of the insurance industry are proprietary models from companies such as Risk Management Solutions (2019) and others. A notable exception is the Florida Public Hurricane Loss Model (FPHLM, 2019).

Significant epistemic uncertainties exist in cat models (Der Kiureghian and Ditlevsen, 2009), and the uncertainty in the output of a cat model is highly dependent on the quality of the data

(Roueche et al. 2018; Kaczmarska et al. 2018). Typically, in a hurricane risk model like the FPHLM, uncertainty is related to: the hazard characterization; the interaction between the structure and the wind and rain; the strength capacities of the external components of the building; the water absorption capacities of the interior and contents of the building; the cost of installation and repair of the different components; the actual replacement values of the exposure; the orientation of the building with respect to the storm; and the characterization of the exposure. The latter implies the matching of every building in the exposure set (e.g. insurance portfolio) with its proper building class (the quality of construction with respect to wind resistance) in the library of vulnerability models of the FPHLM.

The purpose of this paper is to quantify the effect of the uncertainty regarding the building class assignment on the overall uncertainty of the projected loss. The modelers of the FPHLM have developed sets of exposure statistics for the Florida inventory that have become increasingly exhaustive and accurate over the years. The statistics govern the matching of the policy to the most appropriate building class, even in cases where relevant information is missing in the portfolio. The latest set of statistics covers the entire State of Florida, whereas the previous versions included a limited number of counties. Missing information for any unaccounted-for county was extrapolated from neighboring counties, introducing uncertainty of unknown magnitude. The authors ran portfolio analyses using previous and the most recent statistics to demonstrate and quantify the range of uncertainty associated with characterization of community residential building inventory. They did this for multiple scenario events in Florida for which they have the associated claim data. The comparisons of the aggregated modeled losses against actual losses and their contrast with the spread among like-structures help quantify the uncertainty due to building characterization and should inform strategies to reduce that uncertainty.

2. FLORIDA PUBLIC HURRICANE LOSS MODEL

2.1. Overview

The Florida Office of Insurance Regulation (FLOIR) sponsors the Florida Public Hurricane Loss Model (Hamid et al., 2011). Every two years, the model goes under the certification process of the Florida Commission on Hurricane Loss Projection Methodology (FCPHLM). The certified version at the time of this writing is version 8.1 (FPHLM, 2021). There are three distinct independent vulnerability models within the FPHLM framework: personal residential (PR) single-family homes, including manufactured homes (Pinelli et al., 2011), commercial residential low-rise buildings (CR-LR) (Pita et al., 2012; Johnson et al., 2018; Silva de Abreu et al., 2020), and commercial residential mid/high-rise buildings (MHR) (4 stories and higher) (Pita et al., 2016). The purpose of the FPHLM is to predict aggregated insured losses for insurance portfolios of residential properties in the form of annual expected losses (AEL) and probable maximum losses (PML). Insurance companies and state regulators use such loss estimates to define and evaluate rate filings and verify solvency (Nicholson et al. 2018). The model can also conduct scenario analyses to estimate losses for hypothetical and historical storms.

2.2. Vulnerability matrices

The output of the vulnerability model of the FPHLM are vulnerability matrices. The cells of a vulnerability matrix for a particular structural type represent the probability of a given damage ratio (defined as cost of repair over overall value of the building) occurring at a given wind speed. The columns of the matrix represent three-second gust wind speeds at 10 m, from 50 mph to 250 mph in 5 mph bands. The rows of the matrix correspond to damage ratios (DR) up to 100%. An important plot derived from the vulnerability matrix is the vulnerability curve. The vulnerability curve for any structural type is the plot of the mean damage ratio vs. wind speed.

2.3. Weighted vulnerability matrices.

Building vulnerability matrices were created for every combination of Florida region (Keys, South, Central, and North Florida), and subregion (inland, wind-borne debris region, or high velocity hurricane zone) for different building classes defined by a set of building parameters. These include year built, construction type (masonry, wood, or other), roof shape (gable or hip), roof cover (tile, shingle or metal), roof-to-wall connections, number of stories (one or two), and opening protection (e.g. with or without shutters).

Region, subregion, construction type, and year built are determined from the insurance files. The year the home was built is used to assist in defining the strength to be assigned to the home via building code era. For simplicity, consider wind resistance to be classified as weak, medium or strong, determined by year built and location. This leaves the roof shape, roof cover, number of stories, and shutter options undefined. From the exposure study of Florida counties (next section), the statistical distribution of construction type, number of stories, roof shapes, and roof cover by year built and region can be extrapolated. For a series of age groups, we define a weighted matrix for each construction type in each county belonging to a region and subregion. The weighted matrices are the sum of the corresponding vulnerability model matrices weighted based on their statistical distribution. For example, consider a masonry home built in the wind-borne debris region of central Florida in 1990. The exposure study indicates that 66% of such homes have gable roofs, 85% have shingle roof cover, and 20% have window shutters. Weight factors can be computed for each model matrix based on these statistics. The Central Florida, gable, tile, no shutters, masonry matrix would have a weight factor of 66% (masonry percent gable) x 15% (percent tile) x 80% (percent without shutters) = 7.9%; this is the percentage of that home type that would be expected in this region, for that year built. Each model matrix is multiplied by its weight factor, and the results are summed. The result is a weighted matrix that is a combination of all the model matrices and can be applied to an insurance policy if only the ZIP Code, year built, and Insurance Services Office (ISO) (Stanovich, 2015) classification are known. As a result, for each county in each subregion (inland, wind-borne debris region, and high velocity hurricane zone) of each region (Keys, South, Central, and North), there will be sets of weighted matrices (masonry, wood, and others) for weak, medium, and strong structures, for six different eras from pre-1960 to post-2002. If, in addition, the year built or year of last upgrade of a structure in a portfolio is not available, it becomes necessary to combine weak, medium, and strong weighted matrices into age-weighted matrices, based on the statistical distribution of ages in the county. The many possible combinations of all the building descriptors discussed so far (age, location, construction type, roof cover, etc.), lead to a library of 4356 building classes, each with their own un-weighted vulnerability matrix. Their weighted combinations result in a total of 5517 FPHLM model variations in each of the 67 counties, meant to represent the vast majority of residential construction in Florida.

2.4. Portfolio analyses

The first step in a portfolio analysis is to match every building in the insurance portfolio with the proper building class within the library of FPHLM vulnerability models. Typically, most of the building parameters are missing from insurance portfolios, except construction type and year built, and the modelers rely on statistical studies of the regional exposure to make-up for missing information, based on location and year-built if available. The missing information for any given property is assigned based on statistics, and the appropriate weighted vulnerability matrix is subsequently assigned to the property. Any incorrect assignment shall affect the accuracy of the projected insured loss. The actuarial component assigns a maximum wind speed from the hazard model to each property location, which combined with the vulnerability assignment leads to a projected loss.

3. EXPOSURE STATISTICAL STUDIES

The FPHLM engineers used several sources of information for getting up-to-date building structural type information in Florida. One important source is the Florida counties property tax appraisers' databases. Property appraisers' databases (CPTA) are the most comprehensive and accurate information of building structural characteristics accessible at the present time. Although the databases' contents and format vary county to county, many of them contain the critical structural information to define the most common structural types in each county

Since the inception of the FPHLM, its developers have conducted studies that produced an initial and then three revisions of the exposure of Florida residential inventory based on the CPTA's. Each revision incorporated additional counties as that data become available, and if possible updated the data of counties previously available, progressively increasing the coverage of the exposure study. As the coverage of the exposure study increased, so did the accuracy of the statistics from the study. The four studies are summarized below.

Tax appraiser databases contain large quantities of building information, and it was necessary to extract those characteristics related to the vulnerability of the buildings to wind. First, all the buildings in each county database were divided into three major categories: single family personal residential (PR) buildings, commercial residential buildings (apartment and condominium buildings), and manufactured homes. Under each category, the authors chose to extract information on 6 critical building characteristics for analysis and statistical distribution. They are roof cover, roof shape, exterior wall material, number of stories, year built and building area. This paper focuses on the statistics for PR buildings.

3.1. Exposure study of 9 Florida counties (2003)

The aim of the original survey was to generate a manageable number of building classes or models to cover the majority of the Florida building stock (Zhang, 2003). The team divided Florida into four regions: North, Central, South, and the Keys. Geography and the statistics from the Florida Hurricane Catastrophe Fund (FHCF) (Pacini & Marlett, 2001) guided them in defining regions that would have a similar building mix throughout their counties (Hamid et al., 2011). For example, the FHCF shows that northern Florida has a preponderance of frame houses.

Databases from nine counties were processed (Fig.1 a). Escambia, Walton, and Leon counties in the Northern region; Brevard, Pinellas, and Hillsborough in the Central region; Palm Beach, and Broward in the Southeast region. Monroe County fully covers the Keys region.

To define the structural types, the modelers chose a combination of 4 characteristics: number of stories (1 or 2), roof cover (shingle/tile), roof type (gable or hip) and structural material (concrete blocks or timber). Based on the information contained in the databases, the team computed the statistics for each structural type in every sample county and then used weighted average techniques to extrapolate the results to each region. These statistics were used in the initial certified versions of the FPHLM up to v3.1.

3.2. Exposure study of 33 Florida counties (2011)

The 52 most populous counties were contacted to acquire their tax appraiser database, producing information from 33 counties (Torkian et al., 2011). These 33 counties account for more than 90% of Florida's population. Fig. 1 b) shows the regions, with each county for which data were available marked with a star and shaded.

The available building characteristics vary from county to county and include some combination of the following: exterior wall material, interior wall material, roof shape, roof cover, floor covering, foundation, opening protection, year built, number of stories, area per floor, area per unit, and geometry of the building. The parameters important for modeling are roof cover, roof shape, exterior wall material, number of stories, year built, and building area. For each of these categories, the authors extracted statistical information. The dependency between critical building characteristics was also investigated. For example, it was found that roof shape and area of the building are strongly dependent on the year built. The survey statistics were calculated for different eras to account for the correlation between various factors and year built.

These statistics were used in the certified versions of the FPHLM v4.1 to v6.1. The significant increase in number of counties (from 9 to 33), changes in the year built eras, and a better understanding of dependency between different building's characteristics resulted in a new weighting scheme, which takes into account the dependencies mentioned above. In addition, the matrices were now weighted county by county instead than region by region.

3.3. Exposure study of 51 Florida counties (2016)

In this new round, an additional 18 counties were added to the database which yielded a total of 51 counties. These 51 counties account for approximately 97% of Florida's population. Fig. 1 c) shows the regions, with each county for which data were available shaded. Databases representing the 2014 tax roll are shaded in green. Databases collected prior to 2014 are shaded in yellow (Michalski, 2016).

Statistics were computed for each structural type in every sampled county. Weighted average techniques were used to extrapolate the results to the remaining counties in each region. The statistics from this new study were used in the certified versions of the FPHLM v6.2 up to the current v8.2.

3.4. Exposure study of 62 Florida counties (2021)

In this last study, the FPHLM team collected tax appraiser (TA) datasets for 62 out of 67 Florida counties comprising approximately 99% of the state's population. Only 5 small rural counties did not provide databases: Highlands, Holmes, Lafayette, Suwannee and Union. The TA databases vary in size from 457,492 properties for large urban counties like Broward, to 4584 properties for small rural counties like Madison. Fig. 1 d) shows each county for which data were available as shaded. In addition, the team processed two other main sources of data: National Flood Insurance Protection (NFIP) portfolios, and wind insurance portfolios. The data from these different sources were reformatted and processed, and the insurance databases were separately cross-referenced at the county level with tax appraiser databases. The results are augmented CPTA databases (Pinelli et al., 2020; Otarola Farah, 2021).

The outcome are more accurate building population statistics, which results in a better weighting of the vulnerability functions and a more accurate random assignment of missing parameters in the insurance portfolios. The five missing counties were assigned the same stats than neighboring rural counties. These statistics have not been implemented yet in a certified version of the FPHLM. They have been tested in a beta version.

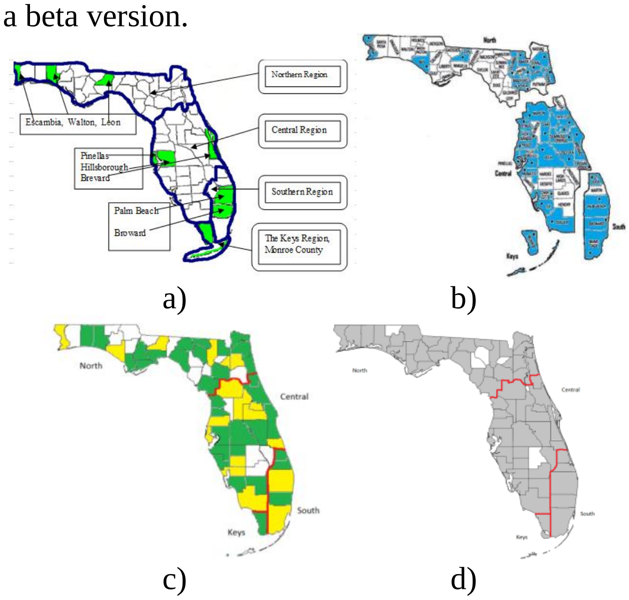

Figure 1: Regional classification of Florida with surveyed counties(shaded): a) Zhang, 2003; b) Torkian, 2011; c) Michalski; 2016; d) Otarola, 2021

4. IMPACTS OF THE DIFFERENT EXPOSURE STUDIES

The FPHLM processes insurance portfolios from many different insurance companies. In many cases most of the building structural information in a portfolio is unknown since, in general, detailed records of building characteristics are not recorded. In a minority of cases, parameters are known, but they do not match any value in the library of the FPHLM. In this case these parameters are classified as “other.” For example, the FPHLM models only timber or masonry residential single-family homes. A steel structure would be classified as other. The “other” matrices are an average of timber and masonry matrices.

This lack of knowledge of important structural characteristics within insurance portfolios makes the mapping of existing portfolio policies to available vulnerability matrices challenging. The FPHLM team designed a mapping tool to read a policy and assign building characteristics, if unknown or other, based on the building population statistics and year built, where year built serves as a proxy for the strength of the building. Table 1 summarizes the process.

Table 1: Assignment of vulnerability matrix depending on data availability in insurance portfolios.

Data in Insurance Portfolio	Year Built	Exterior Wall	No. of Story	Roof Shape	Roof Cover	Opening Protection	Vulnerability Matrix
Case 1	known	known	known	known	known	known	Use unweighted vulnerability matrix
Case 2	known	known or unknown	Any combination of the four parameters is either unknown or other				Use weighted matrix or replace all unknown and others based on stats and use unweighted vulnerability matrix
Case 3	known	other	Any combination of the four parameters is either unknown or other				Use the “other” weighted matrix
Case 4	unknown	known	Any combination of the four parameters is either unknown or other				Use age weighted matrix or replace all unknown and others based on stats and use unweighted vulnerability matrix
Case 5	unknown	other	Any combination of the four parameters is either unknown or other				Use age weighted matrices for “other”

Once all the unknown parameters in the policy have been identified, an unweighted vulnerability matrix based on the corresponding combination of parameters is assigned. If the number of unknown parameters exceeds a certain threshold defined by actuarial considerations, a weighted matrix or age-weighted matrix is used instead. Because building statistics govern the assignment of missing parameters, and the make-up of the weighted matrices, they have a direct influence on the vulnerability and actuarial outputs of the FPHLM.

4.1. Weighted vulnerability curves

This section compares the changes in weighted vulnerability curves due to changes in exposure statistics, all other things being equal. For example, the only change between the PR vulnerabilities of FPHLM v3.1 and 4.1 were the statistics: PR v3.1 uses the (Zhang, 2003) stats while PR v4.1 uses the (Torkian, 2011) stats. This is true also of changes between FPHLM v6.1 and v6.2. The only change between these versions were that PR v6.1 used the (Torkian, 2011) stats while PR v6.2 uses (Michalski, 2016) stats. Finally, while v8.2 uses (Michalski, 2016) stats, the team also produced alternative weighted PR vulnerabilities for v8.2 using the (Otarola, 2021) stats (the beta version). Fig. 2 illustrates the changes in weighted vulnerabilities for the case of masonry buildings in Martin county. Within each county, for different eras, the magnitude of the changes in vulnerabilities depend on the magnitude of the changes in the building stats.

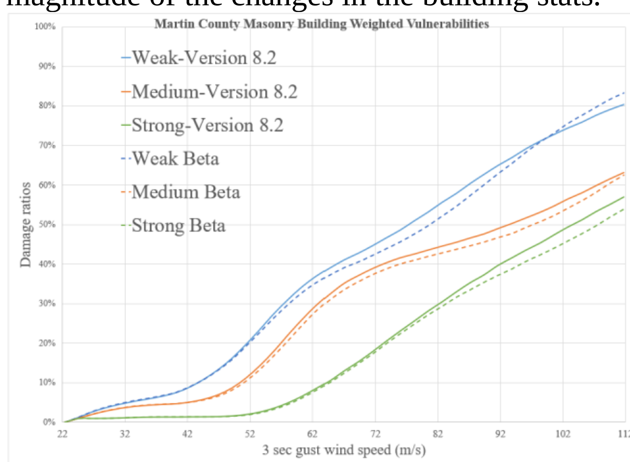

Figure 2: Comparisons for weighted vulnerabilities between v8.2 with (Michalski, 2016) stats and v beta with (Otarola, 2021) stats (dashed lines)

4.2. Portfolio analyses

This section compares the changes in insured losses due to changes in statistics, all other things being equal. For this purpose, it was necessary to run the same version of the FPHLM model, v8.2, with the 4 different sets of building statistics. Figure 2 shows a comparison of the modeled losses for v8.2 with both the (Michalski, 2016) stats (red squares) and the (Otarola, 2021) stats (blue triangles), vs. the actual claims for 66 portfolios from different insurance companies, for different hurricanes, including Andrew and the 2004 and 2005 storms.

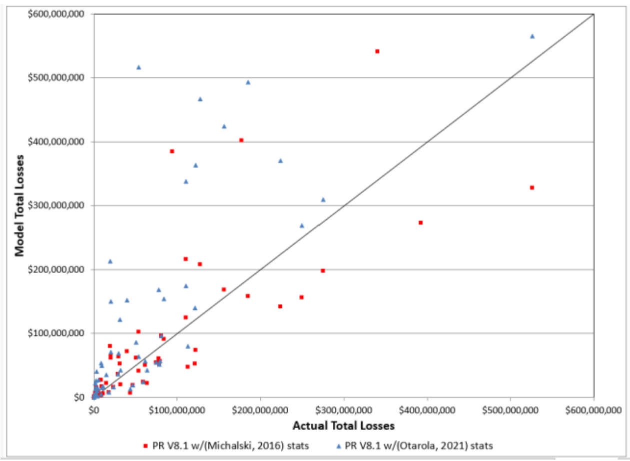

Figure 2: Modeled losses with (Michalski, 2016) stats (red squares) and the (Otarola, 2021) stats (blue triangles), vs. actual losses

Fig. 2 shows that the FPHLM v8.2 with the (Otarola, 2021) stats produces higher losses. The increases in model losses with the new stats for the different portfolios range from 445% to 11%. The differences are explained by the use of different statistics to randomly assign missing building parameters to the policies, or the use of weighted matrices derived from different stats. The percentage differences are not uniform because the differences in stats between the old and the new sets differ greatly from county to county, and era to era.

Table 2 lists several metrics that quantify the differences between modeled losses and actual losses. The better the agreement between the modeled and actual losses, the better and more accurate the model should be. Fig. 2 and Table 2 indicate a reasonable agreement between the actual and modeled losses for v8.2 with the (Michalski, 2016) stats. The correlation between actual and modeled losses is found to be 0.970, which shows a strong positive linear relationship between actual and modeled losses. We tested whether the difference in paired mean values equals zero using the paired t test (t = 1.43, df = 65, p-value = 0.158) and Wilcoxon signed rank test (V= 1249, p-value = 0.364). Based on these tests, we fail to reject the null hypothesis of equality of paired means and conclude that there is insufficient evidence to suggest a difference between actual and modeled losses. Table 2 also shows that about 52% of the actual losses are less than the corresponding modeled losses, and 48% is the inverse. This shows that the modeling process is not biased. Following Lin (1989), the bias correction factor (measure of accuracy) is obtained as 0.944, and the sample concordance correlation coefficient is found to be 0.916, which again shows a strong agreement between actual and modeled losses.

By contrast, Table 2 shows that there is a clear degradation of the accuracy of the loss prediction when the same model uses the (Otarola, 2021) stats (referred to as the beta model). The results of the paired t test and the Wilcoxon signed rank test show that there is no agreement between actual and modeled losses. Table 2 shows that about 73% of the actual losses are less than the corresponding modeled losses. This shows that the modeling process tends to overpredict the losses.

The results highlight how the inaccuracy and incompleteness of the exposure characterization can produce a bias in the results, and how this bias can hide or cancel an existing bias in the model itself.

Table 2: Metrics evaluating modeled losses with v8.2 and vBeta (Otarola, 2021) vs. actual losses

version	v8.2	Beta
correlation	0.97	0.88
wilcox.test(Actual, Model, paired=T)		
V	1248	419
p-value	0.364	0.000
t.test(Actual, Model, paired=T)		
t	1.430	-3.781
df	65	65
p-value	0.158	0.000
95% confidence interval	$ (10,154,848)	$ (180,159,091)
	$ 61,334,736	$ (55,616,273)
mean of the differences	$ 25,589,944	$ (117,887,682)
length(pp[pp>-1])/length(dd)	0.515	0.273
correction factor	0.944	0.941
concordance correlation	0.916	0.832
% of model > actual	52%	73%
% of model < actual	48%	27%

5. CONCLUSIONS

This paper shows that the loss projections of the FPHLM are highly dependent on the quality of the building statistics used to either assign missing parameters to insurance exposure data, or to weight vulnerability matrices to be assigned to properties with incomplete or missing data in a portfolio. The resulting uncertainty is highly dependent on the quality of the insurance data, and on the accuracy of the community characterization through its statistical descriptors. If the insurance data were complete and accurate, there would be no need for the statistics. If the statistics were 100% accurate, for a sufficiently large number of properties, the effect on the loss projections would be minimal.

It is difficult to quantify the external contribution of community characterization to the overall model uncertainty. This is a work in progress, but the preliminary results clearly show that an incomplete community characterization can hide a substantial bias in the model, and modelers should pay attention to this issue.

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