

Stakeholder mapping for targeted policy implementation to increase resilience in post-hurricane Louisiana community

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1 INTRODUCTION & SCOPE OF WORK

Climate change is intensifying hurricane losses, while gaps in building codes leave many homes vulnerable, making voluntary structural retrofits an important yet underutilized adaptation strategy. This study asks whether, and why, homeowners independently adapt their properties in response to increasing risk. While prior research has examined individual drivers of adaptation using conventional statistical methods implemented to test a priori hypotheses, understanding what motivates action more broadly requires evaluating many interacting factors simultaneously, a challenge for traditional methods. However, recent advances in machine learning (ML) enable the analysis of high-dimensional behavioral data without a priori hypotheses. We propose an ML-based methodology to identify combinations of predictors most strongly associated with homeowner structural adaptation decisions and demonstrate it using survey data from 373 homeowners in Calcasieu Parish, Louisiana, collected after Hurricane Laura. Note that this study does not consider non-structural adaptations (e.g., insurance purchase). The predictor combinations are used to develop stakeholder profiles across three decision periods: post-purchase investments, post-storm reconstruction, and future planned retrofits, revealing the three homeowner personas most likely to engage in structural protective action uptake: the *Concerned Preparer*, the *True Believer*, and the *Engaged Planner*.

2 METHODOLOGY

We developed a modular survey instrument with sophisticated skip logic that inventories each home's unique components, damage scenarios and associated protective actions, appropriately adapting the question sequence for each component based on reported damage level and, if applicable, reconstruction progress (Kijewski-Correa et al, 2023). Our survey was deployed from April 7 to June 6, 2023 in Calcasieu Parish, Louisiana, adopting Hurricane Laura as the reference hazard, which landfell on August 27, 2020, as a Category 4 storm (Hamburger et al, 2024).

Using survey data from 373 respondents, we construct 45 explanatory variables (or simply "variables"), which are used as the independent inputs to each model. Informed by the literature, the selected variables encompass prior disaster experience (including novel measures of damage experiences of friends and neighbors), risk perception, home characteristics, retrofit-related attitudes, incentives, resources, environmental cues, and sociocultural, demographic, and identity-related factors. Response variables (or "responses") denote the dependent target for each model. Responses capture homeowner actions taken to strengthen their homes at three points in time: (1) after purchasing the home, represented by the post-purchase action variable (PPA); (2) in the recovery following Hurricane Laura, represented by the post-disaster action variable (PDA); and (3) future intentions to retrofit, represented by the intended action variable (IA) – particularly critical for those experiencing delays in recovery assistance. We evaluate four regression ML models: Decision Tree (DTR), Random Forest (RFR), Support Vector (SVR), and Multilayer Perceptron (MLP). Each ML model has distinct hyperparameters that describe configuration settings which must be tuned before training; separate models are trained for each response, yielding 12 final models. Hyperparameter tuning and variable selection for each model are performed simultaneously within a robust cross-validation framework using a hybrid genetic algorithm–particle swarm optimization (GA–PSO) approach (Divasón et al, 2023).

We examine variable importance from each optimized model using SHAP (SHapley Additive exPlanations) values, which represent each variable’s average marginal contribution. We use a Monte Carlo-based approximation of SHAP, which estimates values by iterating over randomly sampled permutations of variables. To identify variables with interpretable and consistent effects on the response, we introduce a *separation factor* that quantifies the normalized distance between the expected SHAP values for high and low realizations of the variable. Larger separation factors indicate a clearer and more distinguishable influence on the model outcome.

3 RESEARCH OUTCOMES

To ensure reliability, the optimization is repeated five times for each model. Each run identifies the most influential combination of variables for a given ML–response pair. A variable is retained for final training if it is selected in at least four of the optimization runs for that specific ML–response pair. The results thus represent near-optimal variable sets. Because each optimization run yields a potentially different set of optimal hyperparameters, the final hyperparameter set is chosen from the run that produces a model most consistent with the final reduced variable set derived across all five iterations of the optimization. In total, 60 optimization processes are performed (12 ML–response pairs $\times$ 5 iterations). Final model performance is shown in Table 1, which describes the number of variables retained for each configuration and the final root mean squared error (RMSE) when deployed over the dataset.

Table 1. Number of features retained and RMSE of final ML model configurations

Model	Post-Purchase Action (PPA)		Post-Disaster Action (PDA)		Intended Action (IA)	
	N_F	RMSE	N_F	RMSE	N_F	RMSE
DTR	3	0.149	3	0.106	3	0.100
RFR	5	0.121	9	0.079	5	0.099
SVR	9	0.152	5	0.100	8	0.087
MLP	7	0.167	7	0.165	4	0.104

Note: Best performing model for each response variable bolded.

Application of SHAP analysis to each reduced-order model reveals both the magnitude and direction of influence for the retained variables to quantify which correlate most strongly with homeowner actions. Figure 1 provides an example of these results in the form of beeswarm plots for the optimal random forest regressor (RFR) model of post-purchase action (PPA). This figure vertically stacks the plots for the different retained variables plotted alongside their calculated separation factor, revealing the strength (magnitude) and direction (sign) of each variable’s influence. Points along each plot represent SHAP values, with colors reflecting the variable’s values (blue for low values and red for high).

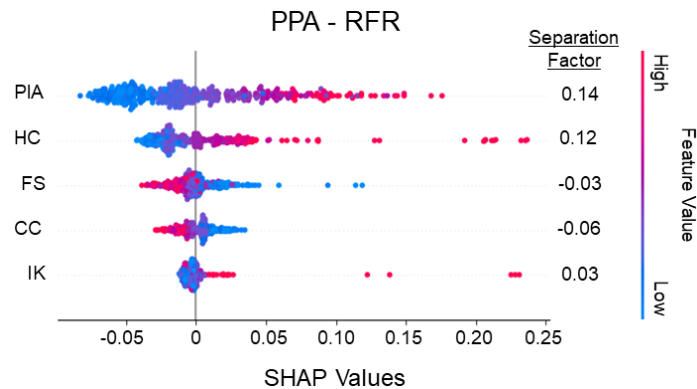


Figure 1. Stacked beeswarm plots of SHAP values for the optimal random forest regressor (RFR) model of post-purchase action (PPA) with separation factors for selected variables: place attachment (PIA), hurricane concern (HC), financial support (FS), code cycle of home (CC), and knowledge of incentive programs (IK).

Results from the SHAP analyses were used to identify and characterize three distinct homeowner personas, defined as composite profiles of the variables most strongly associated with homeowner responses across the four ML models. Results show a high degree of agreement among the variables retained across ML models for each response, indicating convergence to the same underlying personas. Accordingly, the personas described below represent composite profiles synthesized from the optimized DTR, RFR, SVR, and MLP models for each of the three homeowner action responses:

- **Concerned preparer:** Homeowners who reported higher levels of hurricane concern (**HC**) prior to Hurricane Laura were more likely to invest in retrofits before the event. These individuals also exhibited stronger place attachment (**PIA**), reflected in longer tenure within their communities and higher community engagement. Additionally, these homeowners were more likely to invest in retrofits for homes constructed under earlier code cycles (**CC**), indicating an awareness of their older homes' vulnerability.
- **True believer:** Homeowners who reported high levels of hurricane concern prior to Hurricane Laura (**HC**) and who sustained lower damage to their home in that hurricane (**DS**) tended to invest more in retrofits after the storm. This lower level of damage may have been due to prior investments in the home (**HI**). They may continue to invest thanks to the proven benefits of such retrofit investments coupled with high perceived affordability of such measures (**MA**).
- **Engaged planner:** Homeowners who experienced high levels of property damage (**DS**) in Hurricane Laura reported stronger intentions to retrofit their homes to improve future protection. These individuals demonstrate higher engagement with retrofit incentive programs (**RI**), potentially helping to finance their decisions to build back better in the future.

4 CONCLUSIONS

Results from this study demonstrate the potential of machine learning to extract insights into homeowner decisions to invest in voluntary structural retrofits, overcoming the dimensionality constraints of traditional statistical models and the need for a priori hypotheses on the drivers of risk reducing behaviors. By integrating hybrid GA-PSO-based variable selection with SHAP-driven variables importance analysis, we develop parsimonious, interpretable models of homeowner responses at different stages of a home's life cycle (post-purchase, post-disaster, and intended future actions). We further show how these models enable persona development, which can be leveraged for future targeted messaging and policy interventions to promote homeowners' proactive investments that reduce a home's structural vulnerabilities to hurricanes.

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