Predicting Hurricane Evacuation Decisions with Interpretable Machine Learning Models

Yuran Sun[1], Shih-Kai Huang[2], and Xilei Zhao[1]
[1]Department of Civil and Coastal Engineering, University of Florida, Gainesville, FL
[2]Department of Emergency Management and Public Administration, Jacksonville State University, Jacksonville, AL

Introduction

Research Contexts and Gaps

Existing studies
- Primarily relied on linear-based causality analyses.
- Focused on psychological factors (e.g., risk perception), the main cause of evacuation decisions, and the mediator of other influencing factors.

Limitations
- Linear-based models: mainly designed for causal analysis, often lacking prediction accuracy.
- Prediction models based on psychological frameworks: lacking data availability and sensitivity to diverse demographics and social contexts.
- Machine learning models can address these issues, but many are uninterpretable black-box models.

➢ **This study proposes the development of an interpretable machine learning model based only on social context data.**

Research Goals

- Examine the non-linear mechanism of social contexts and resource requirements on evacuation decisions.
- Develop an interpretable-machine-learning model for more accurate prediction of evacuation decisions.

Research Objectives

Nonlinearity detection: Low-depth decision trees
- Identify critical thresholds
- Build transparent model structure
- Ensure robustness

Methodology practicability examination
- An empirical dataset collected after Hurricanes Katrina and Rita

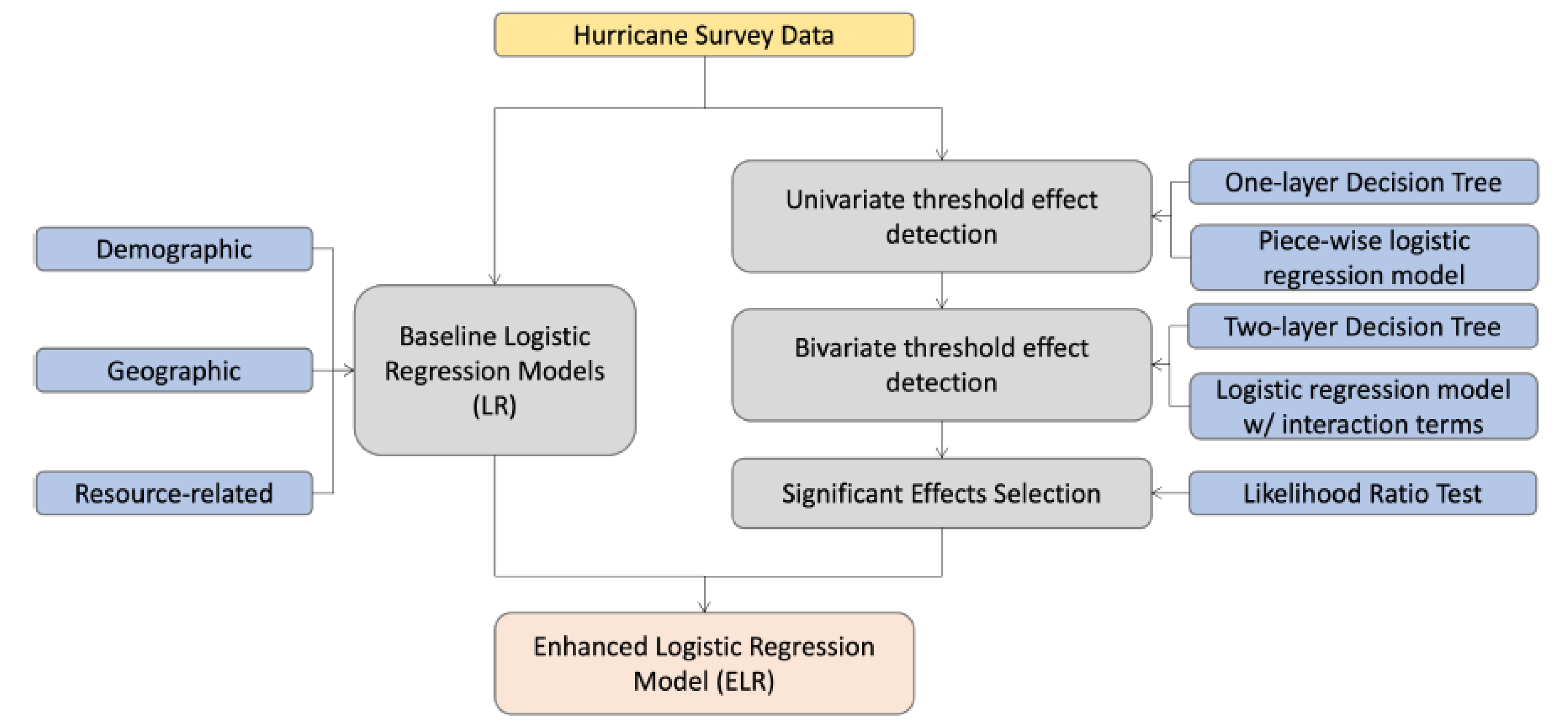
Significant Threshold Effects

Predictor1	Threshold1	Predictor2	Threshold2	p-value (LRT)
HHSize	> 2.39	/	/	< 0.01
RegVeh	> 2.01	/	/	< 0.01
EvaVeh	> 1.00	/	/	< 0.01
EvaCost	> 704.03	/	/	< 0.01
RiskArea	> 3.45	EvaCost	> 704.03	< 0.01
HHSize	≤ 15.00	RegVeh	> 2.99	< 0.01
HHSize	≤ 13.50	EvaVeh	> 2.00	< 0.01
Edu	> 10.33	EvaCost	≤ 511.22	< 0.01

Model Comparisons

	In-Sample Performance		Out-of-Sample Performance				
Model	R^2	Adj R^2	Accuracy	Precision	Recall	F1 Score	AUC
Baseline LR	0.1141	0.1032	0.7734	0.7734	0.9904	0.8722	0.5000
Baseline LR w/ Psychological Variables	0.3025	0.2882	0.8516	0.8571	0.9697	0.9100	0.7090
ELR w/ Significant Univariate Threshold Effects	0.5363	0.5293	0.8750	0.8878	0.9596	0.9223	0.7729
ELR w/ All Significant Threshold Effects	**0.8316**	**0.8285**	**0.9375**	**0.9333**	**0.9899**	**0.9608**	**0.8743**

Research Flow



➢ **Development of ELR based on low-depth decision trees**
- Explore threshold effects of demographic, geographic, and resource-related variables on evacuation decisions

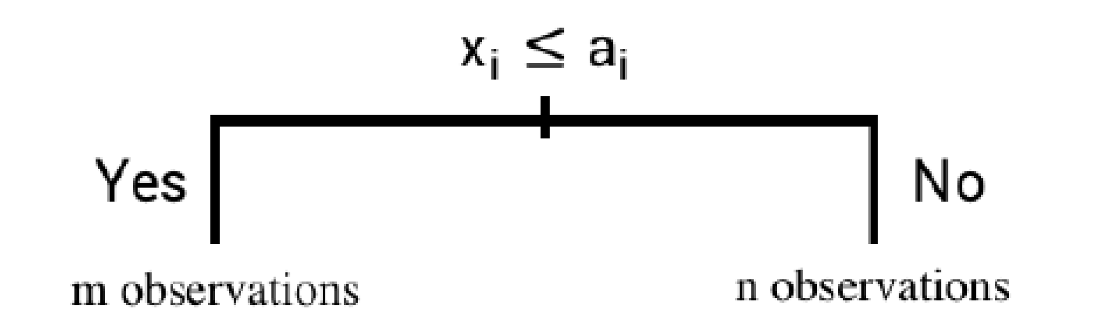
➢ **Examination of interpretability of detected thresholds**

➢ **Model performance comparison**
- Proposed ELR model
- Baseline logistic regression model
- Traditional psychological model

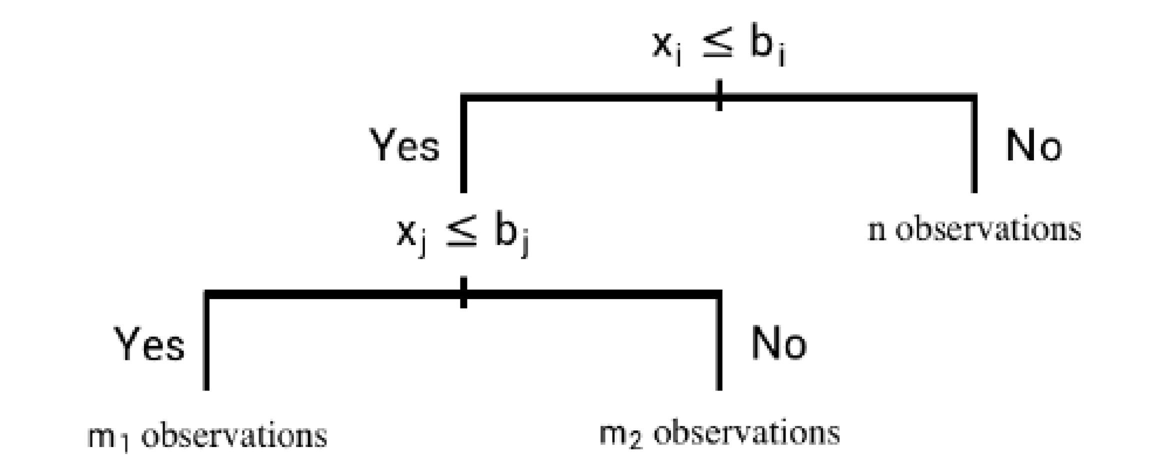
Enhanced Logistic Regression Model

	β	SE	Z-Value
Age	-0.009	0.012	-0.707
Female	1.535***	0.356	4.306
White	-0.190	0.367	-0.517
Married	1.480***	0.428	3.454
Household Size	-0.984**	0.366	-2.685
Education	0.045	0.073	0.614
Income	0.000	0.000	-1.053
Home Ownership	-0.312	0.198	-0.638
Risk Area	-0.329	0.515	-1.576
Reg Vehicle	0.681	0.360	1.919
Eva Vehicle	3.121***	0.547	5.710
Eva Trail	0.229	0.607	0.377
Eva Cost	0.003**	0.001	3.036
Univariate Effect			
Household Size (>2.39)	0.238	0.226	1.055
Reg Vehicle (>2.01)	-0.626**	0.231	-2.713
Eva Vehicle (>1.00)	-4.815***	0.468	-10.288
Eva Cost (>704.03)	-0.003**	0.001	-2.756
Interaction			
Risk Area (>3.45)·Eva Cost (>704.03)	0.000	0.000	-1.409
Household Size (≤15.00)·Reg Vehicle (>2.99)	0.157*	0.077	2.031
Household Size (≤13.50)·Eva Vehicle (>2.00)	0.969***	0.120	3.131
Intercept	1.383	1.642	0.842

Decision Tree for Threshold Effect Detection



(a) Univariate Threshold Effect Detection



(b) Bivariate Threshold Effect Detection

Takeaways

Significant nonlinear effects

➢ **Household size and resource-related variables**
- Identification of vulnerable groups with specific contextual and socioeconomic factors indicating the importance of considering diverse backgrounds of individuals.
- Practical implications: Integrating vulnerable group identification in prediction models can enhance risk communication and emergency response efforts.

➢ **Resource requirements and expenses**
- Diminishing marginal effect of resource requirements indicating an optimal level of resource support for evacuation.
- Practical implications: Providing adequate resources without excess during evacuations.
- Inflection point for expenses suggesting a ceiling on the expected evacuation costs households are willing to incur.
- Practical implications: Considering cost limitations and ensuring financial feasibility of evacuation measures.

➢ **Route effects**
- Household size serving as a reliable predictor in reflecting households' vulnerability regarding resource demands during hurricane evacuation.

Model performance results
- Enhanced logistic regression (ELR) model outperforms previous linear models in terms of model fit and prediction.
- Practical implications: The proposed methodology serving as a new tool and framework for emergency management authorities to improve timely and accurate estimation of evacuation traffic demands.

Future work
- Developing a more sophisticated framework for decision trees.
- Validating the results and models by collecting data from a variety of hurricanes and geographical areas.

National Science Foundation
WHERE DISCOVERIES BEGIN

This work was supported by the National Science Foundation under Grant SES-0527699, SES-0838654, IIS-1212790, SES-2303578, and SES-2303579.
None of the conclusions expressed here necessarily reflects views other than those of the authors.