Social Vulnerability Index Internal Validation for Scale-Centered Factors, Indicators, and Model Structures

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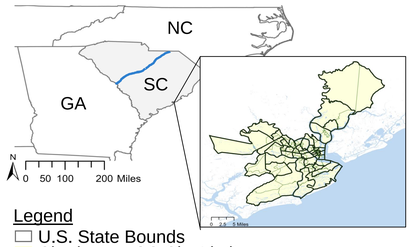
1 INTRODUCTION

- A Social Vulnerability Index (SVI) identifies vulnerabilities to help pinpoint communities with inherent social inequities for consideration in hazard planning and management [1]. However, its construction can introduce uncertainty.
- The spatial components (areal unit and geographic boundary) of SVIs remain understudied, and conflicting perspectives exist [2-5]. The importance of scale poses validation and construction challenges across structural designs [6].

This study examines the impact of scale properties and their interactions on model robustness and sensitivity across various SVI structures using Monte Carlo Simulation (MCS) and factorial Analysis of Variance (ANOVA) for Charleston, SC.

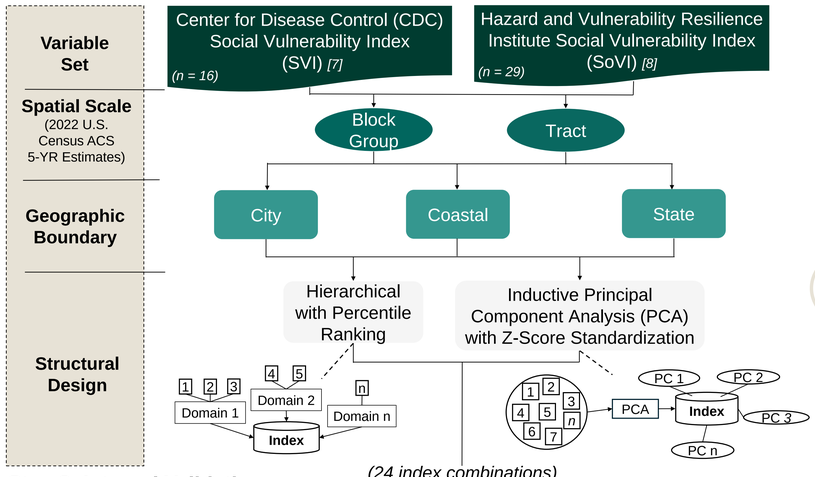


2 METHODS

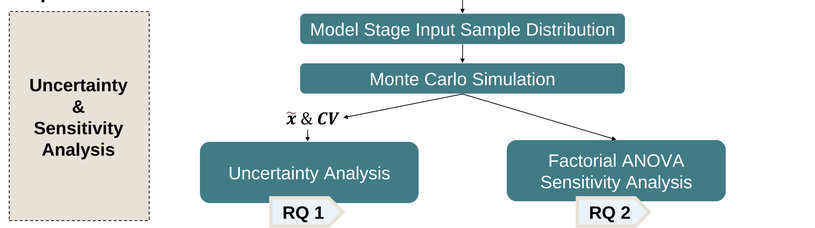
THIS STUDY ADDRESSES TWO QUESTIONS:

1. How do scalar components in SVI construction impact model **robustness** across structural designs?
2. Which spatial model stage and interaction in SVI construction contributes to the greatest **sensitivity** in model outcomes?

Step 1: Social Vulnerability Index Creation



Step 2: Internal Validation



3 RESULTS

RQ 1 **Uncertainty Analysis: Average Deviation from the Baseline Rank Distribution vs. the MCS Frequency Statistics**

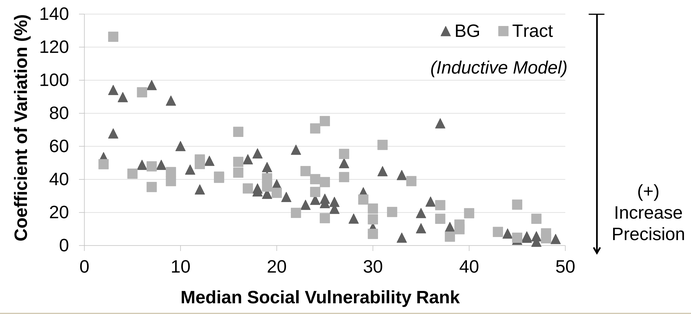
We found the inductive model (IM) less robust than the hierarchical model (HM) when altering scalar and indicator-based model stages.

Model Structure	Baseline Index*	Scalar Property	Median (Accuracy)	Variance (Precision)	Robustness
Inductive	CDC SVI	City	▲ 9.6	▲ 2.9	HA - HP
		Coastal	▲ 7.6	▬ 12.9	HA - MP
		State	▲ 5.2	▼ 28.1	HA - LP
		BG	▲ 7.6	▲ 7.3	HA - HP
		Tract	▲ 9.6	▼ 23.2	HA - LP
		Collective	▲ 9.6	▬ 15.9	HA - MP
	HVRI SoVI	City	▬ 11.6	▲ 4.1	MA - HP
		Coastal	▬ 11.6	▲ 4.5	MA - HP
		State	▬ 11.4	▼ 26.6	MA - LP
		BG	▬ 11.4	▲ 6.1	MA - HP
		Tract	▬ 10.4	▬ 18.2	MA - MP
		Collective	▬ 10.4	▬ 12.3	MA - MP
Hierarchical	CDC SVI	City	▲ 5	▲ 1.1	HA - HP
		Coastal	▲ 2.4	▲ 4	HA - HP
		State	▲ 2.6	▲ 4.8	HA - HP
		BG	▲ 5	▲ 1.6	HA - HP
		Tract	▲ 2.6	▲ 4.7	HA - HP
		Collective	▲ 3.5	▲ 3.5	HA - HP
	HVRI SoVI	City	▲ 3.9	▲ 1.3	HA - HP
		Coastal	▲ 5.3	▲ 3.4	HA - HP
		State	▲ 5.1	▲ 4.9	HA - HP
		BG	▲ 3.9	▲ 1.6	HA - HP
		Tract	▲ 5.1	▲ 4.7	HA - HP
		Collective	▲ 5.1	▲ 3.5	HA - HP

*Baseline index combination is calculated at the tract scale and state boundary

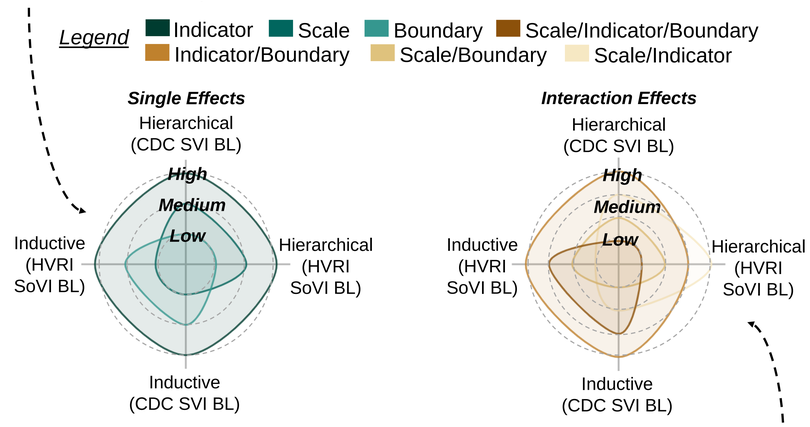
How does SVI rank vary across vulnerability classes?

Precision increased with higher social vulnerability rank across all model structures and areal units (BG and tract), contrary to trends found in the literature [5] [9].



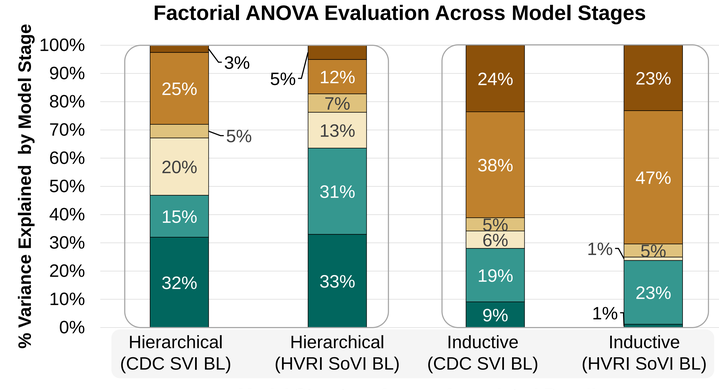
RQ 2 **Sensitivity Analysis: Variability Ranking Contribution of Scalar Components**

Indicator selection presents the greatest variability in SVI rankings across models. Spatially, the IM had increased variability in boundary selection, while the HM was more sensitive to spatial scale.



Significant interaction effects were observed between scalar model stages and indicator selection. The IM was most sensitive to boundary and indicator selection, while the HM had similar sensitivity to both scalar and indicator stages.

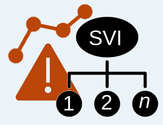
Factorial ANOVA Evaluation Across Model Stages



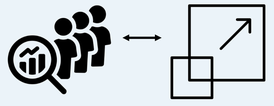
(Note indicator set as a model stage was not included above)

4 CONCLUSION

The inductive model is less robust and more sensitive to scalar and indicator-based model changes compared to the hierarchical model structure.

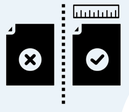


A significant relationship was found between scalar model stages and indicator selection across two widely used SVIs.



As spatial scale and boundary selection became more refined, the precision of SVI rankings increased.

The choice of baseline index can significantly impact validation results when comparing alternative SVI configurations.



SCAN ME

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Acknowledgments

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