



Background

Hurricane Michael was the last **Category 5** hurricane to make landfall in Florida, resulting in catastrophic damage in the panhandle.

Before landfall, Hurricane Michael underwent **rapid intensification** and intensified from a Category 2 hurricane to a Category 5 major hurricane within 24 hours.

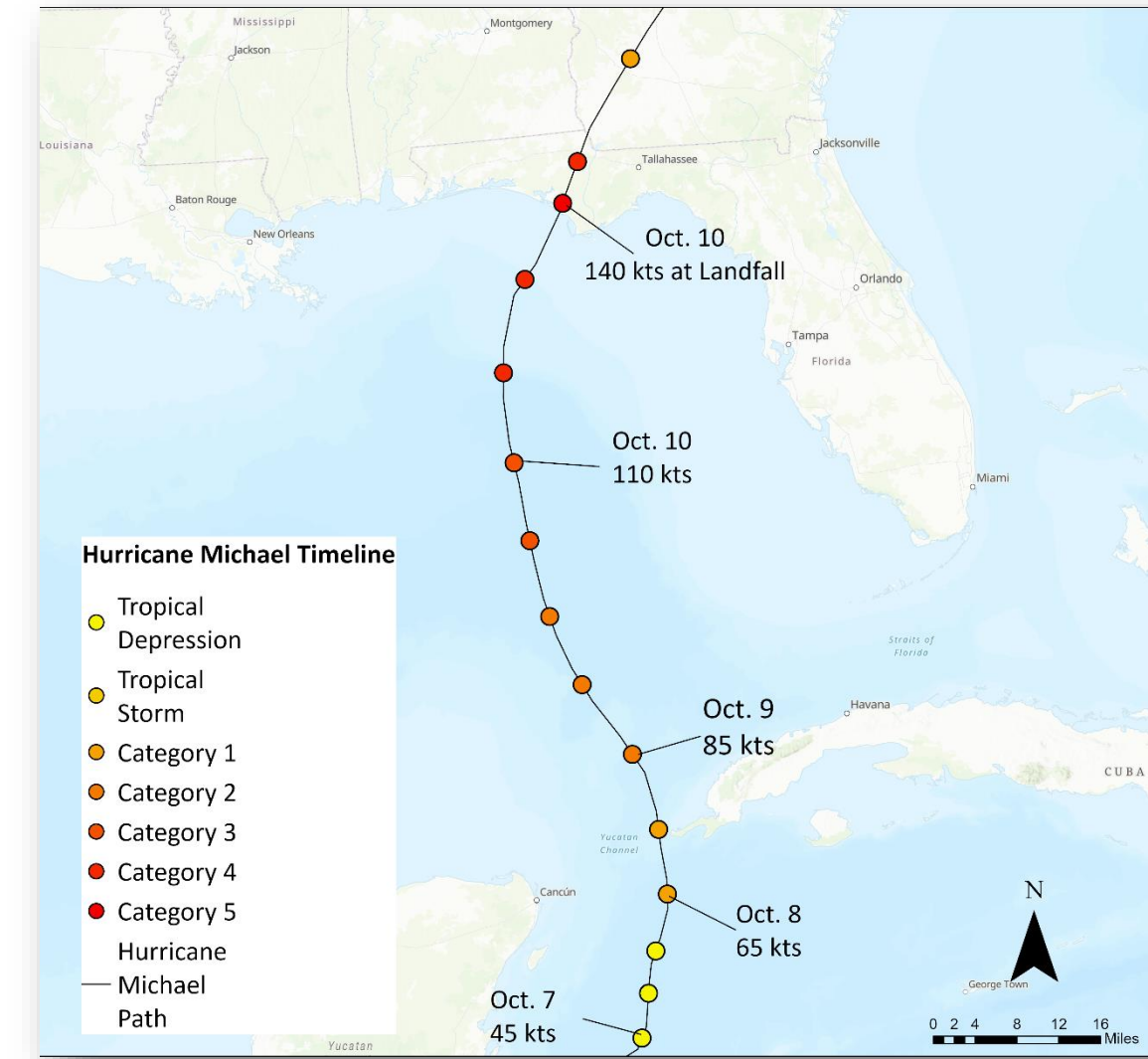


Figure 1: Hurricane Michael's track.

Hurricane Michael caused \$25 billion in damage in the U.S.

Rapid intensification is expected to increase with **climate change** due to warmer sea surface temperatures (SSTs), particularly in the Gulf of Mexico.

This increase in intense storms, coupled with continued population growth, can result in **more damage and losses for vulnerable populations** in the future.

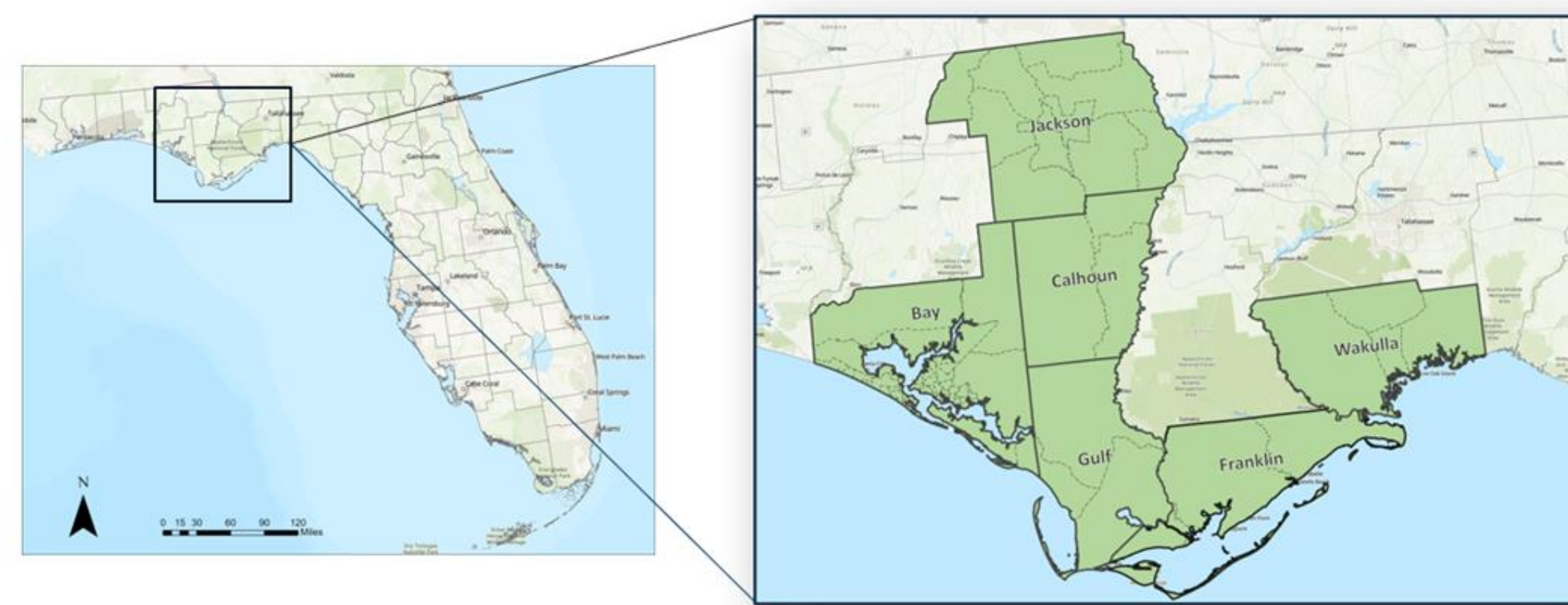


Figure 2: Map of the six counties and census tracts declared as disaster areas post-Hurricane Michael.

Research Question

Is there a spatial relationship between social vulnerability indicators and homeowners' property losses from Hurricane Michael?

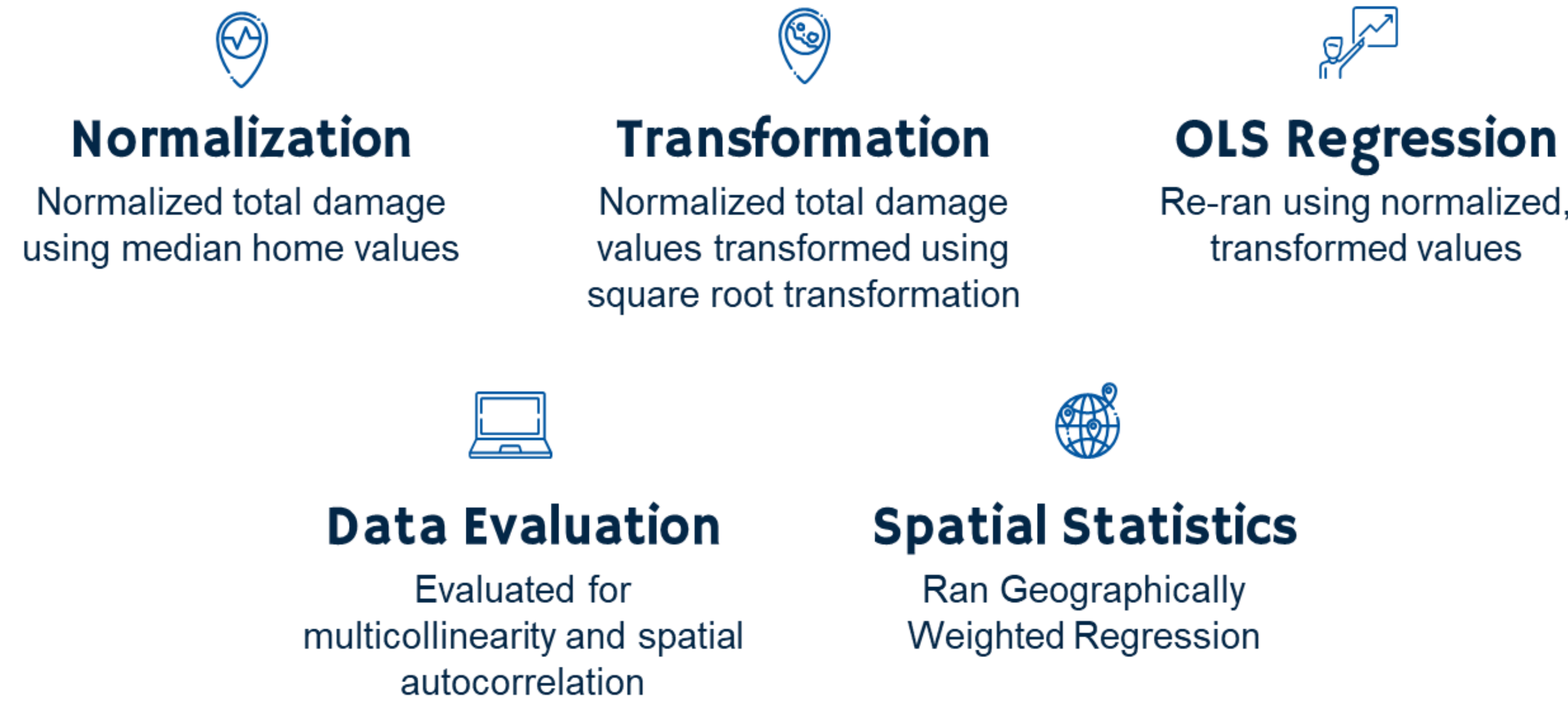
Methods

- We used the **CDC's Social Vulnerability Index (SVI)** data and **Housing Assistance Program Data for owners from the Federal Emergency Management Agency (FEMA)** from 2018 at the census tract level.
- This paper employs **Ordinary Least Squares (OLS)** and **Geographically Weighted Regression (GWR)** models, following the methodology of Rifat et al. (2021), to assess the impact of natural hazards, in this case a landfalling hurricane, on populations and the built environment.

The OLS regression model for this analysis is the following:

$$Total\ damage = \beta_0 + \beta_1(below\ poverty) + \beta_2(unemployed) + \beta_3(income) + \beta_4(no\ high\ school\ diploma) + \beta_5(aged\ 65\ or\ older) + \beta_6(aged\ 17\ or\ younger) + \beta_7(civilian\ with\ a\ disability) + \beta_8(single\ parent\ household) + \beta_9(minority) + \beta_{10}(English\ proficiency) + \beta_{11}(multi\ unit\ structures) + \beta_{12}(mobile\ homes) + \beta_{13}(crowding) + \beta_{14}(no\ vehicle) + \beta_{15}(group\ quarters) + \epsilon$$

Methods



Results

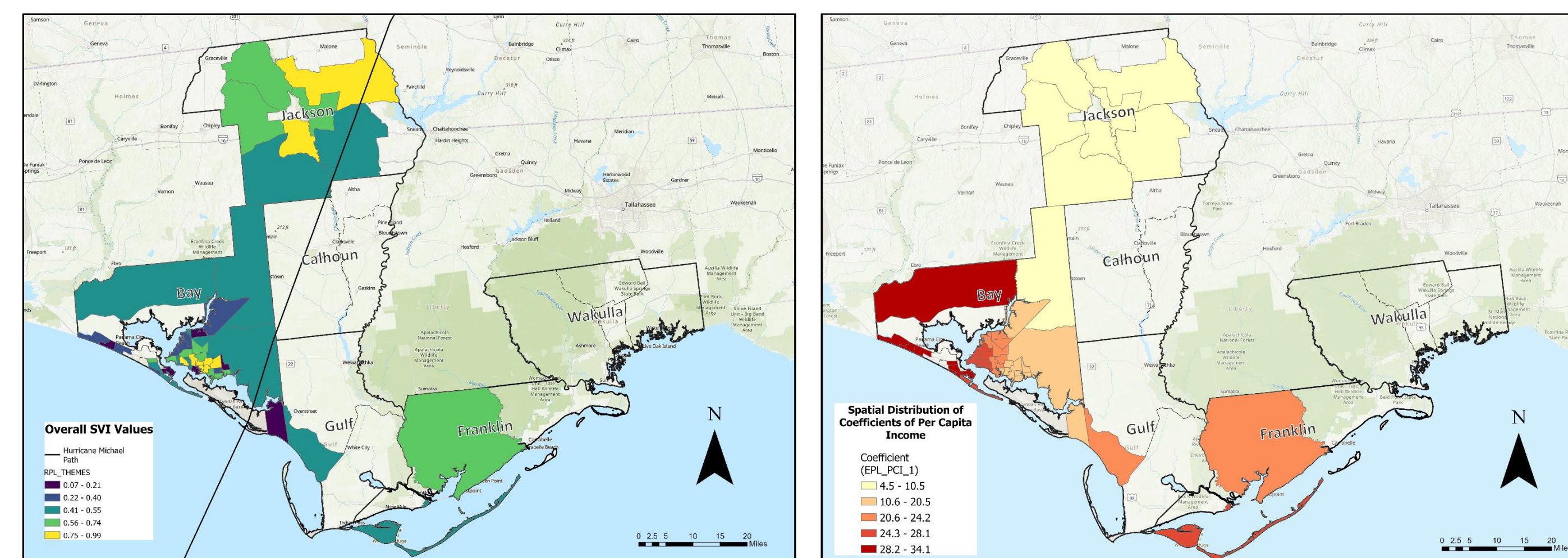


Figure 3: Map of the overall SVI values for census tracts impacted by Hurricane Michael.

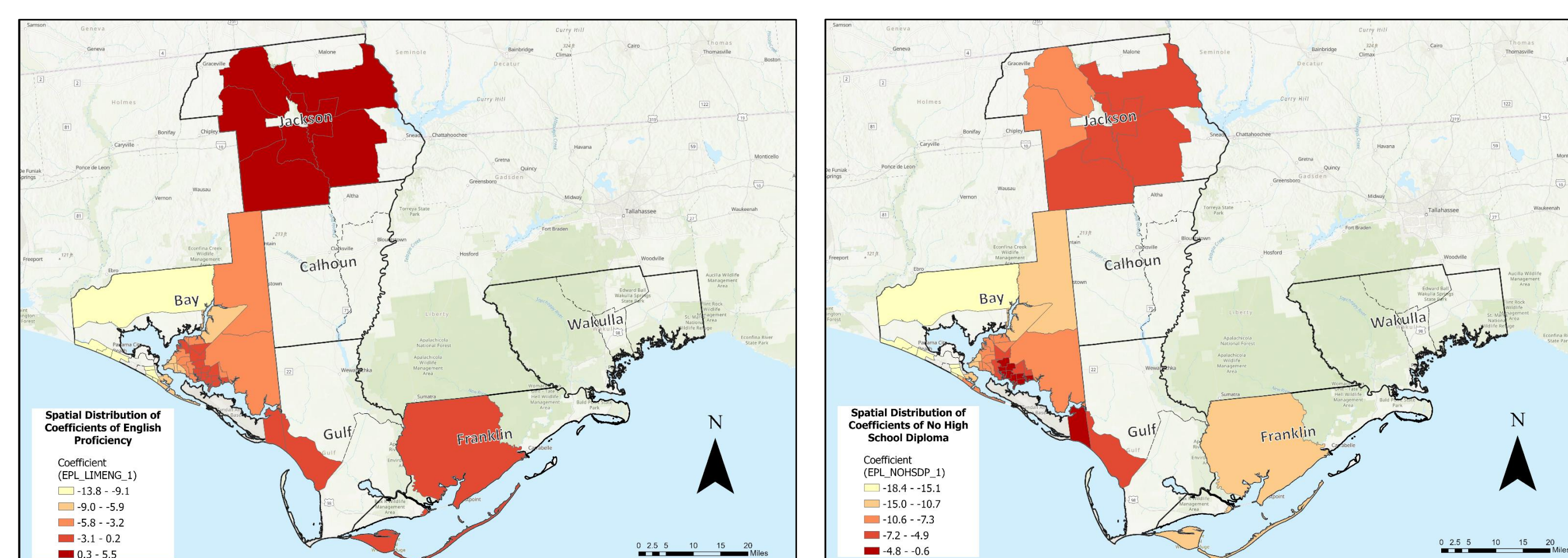
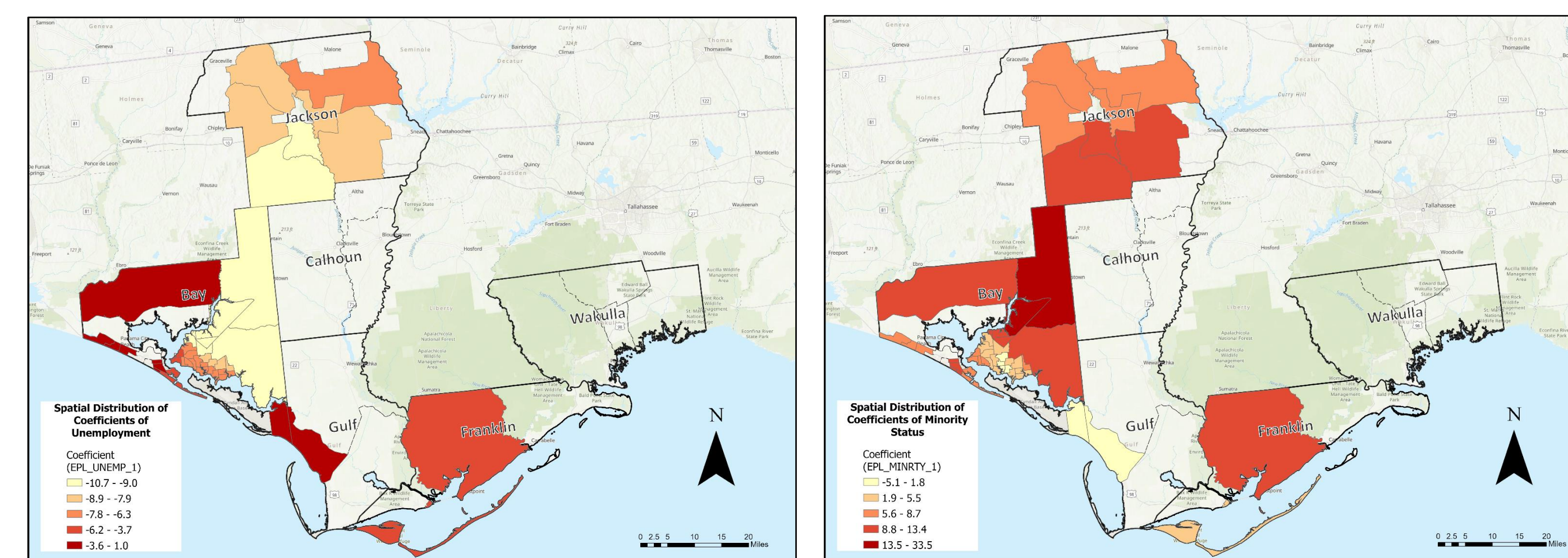


Figure 4: Spatial Distribution of Coefficients of a. Per Capita Income, b. Unemployment, c. Minority Status, d. English Proficiency, and e. No High School Diploma based on Geographically Weighted Regression (GWR) model results.

Results

Per capita income had the greatest influence on the total damage losses for homeowners.

Two of the four SVI themes were most salient for this study: **socioeconomic status and minority status/language.**

OLS Models	Adjusted R-squared (R ²)	Akaike Information Criterion (AIC)	Variables
Model 1	0.46	302.9	All 15 variables included
Model 2	0.47	301.9	Removed Poverty (EPL_POV) variable
Model 3	0.45	302.6	Removed Poverty (EPL_POV) and Disability Status (EPL_DISABL) variable
Model 4	0.48	294.3	Included only significant variables: Unemployment (EPL_UNEMP), Per Capita Income (EPL_PCI), No High School Diploma (EPL_NOHSDP), English Proficiency (EPL_LIMENG), Minority Status (EPL_MINRTY)
GWR Model			
Model 1	0.74	300.4	Included only significant variables: Unemployment (EPL_UNEMP), Per Capita Income (EPL_PCI), No High School Diploma (EPL_NOHSDP), English Proficiency (EPL_LIMENG), Minority Status (EPL_MINRTY)

The following model may be better suited for illustrating the spatial heterogeneity of total property damage losses for homeowners:

$$Total\ damage = \beta_0 + \beta_1(unemployment) + \beta_2(per\ capita\ income) + \beta_3(no\ high\ school\ diploma) + \beta_4(English\ proficiency) + \beta_5(minority\ status) + \epsilon$$

Conclusions

- For every **decrease** in the unemployment rate, the number of individuals with no high school diploma, or the number of individuals with limited English proficiency, the expected total damage **increases**.
- For every **increase** in per capita income or in the population of individuals who identify as minorities, the expected total damages **increase**.
- The **spatial variability** observed from the coefficients overlaps with the spatial distribution of overall SVI values, particularly for Bay County.
- SVI indicators can be useful for understanding the **impacts of natural hazards on vulnerable populations**, even when the overall index is not a significant predictor.
- Further research is necessary to **uncover the causes** of the spatial variability between SVI indicators and total damage losses.
- Future research will focus on incorporating **exposure data** such as wind and rainfall.

References

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Contact Information

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