Assessing Disaster–Migration Relationships in the Contiguous U.S. from 2000 to 2020 Using Automated Machine Learning

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Introduction

- Migration under pressure: Disasters can make both immediate displacement and gradual migration due to cumulative impacts or degraded living conditions (Hermans et al., 2021).
- Different disasters, different effects: Disaster-related migration patterns vary considerably across geographic areas, time periods, and disaster types (Ton et al., 2024).
- Complex factors: migration patterns during and after disasters are influenced by a complex interplay of environmental, economic, and social factors (Czaika et al., 2022).
- Research Gaps: Many studies focus on individual disaster events or types, lacking quantitively cross-disaster comparisons.
 And studies usually struggle to isolate disasters' independent effects from other variables (Hirsch et al., 2020).
- This study: examines the impact of four major types of natural disasters (floods, hurricanes, wildfires, and tornadoes) on county-level human migration patterns across the contiguous United States (CONUS) from 2000 to 2020.

Research Questions

(1) How are the different types of natural disasters associated with human migration patterns across spatial and temporal dimensions? (2) How can we isolate the effects of disasters from socio-economic variables to quantify their independent impact on migration?

Materials and Methods

This study analyzes the relationship between four disasters and county-level migration in the CONUS from 2000–2020.

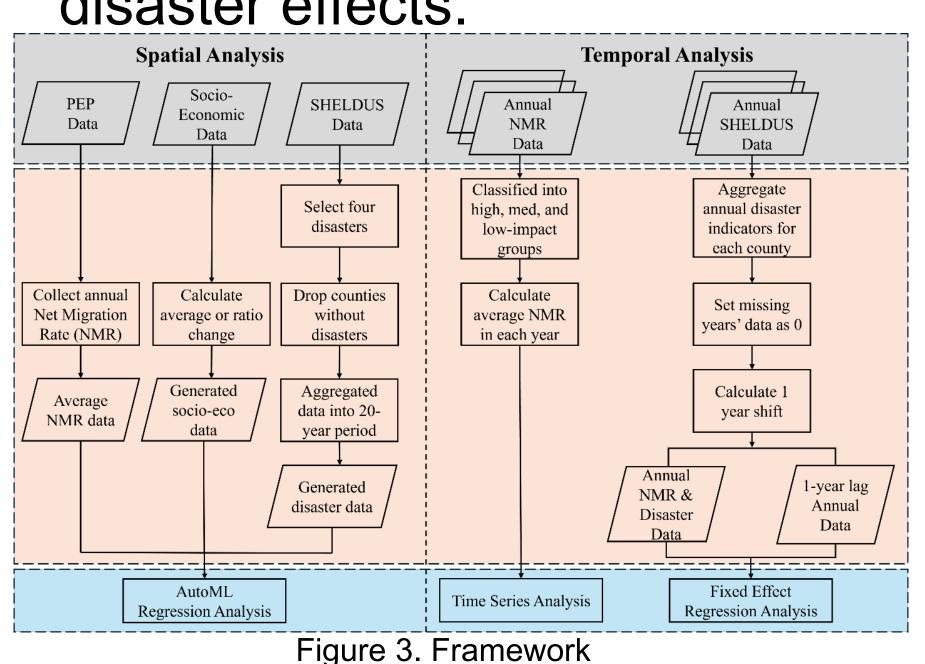
Data were derived from (Table 1):

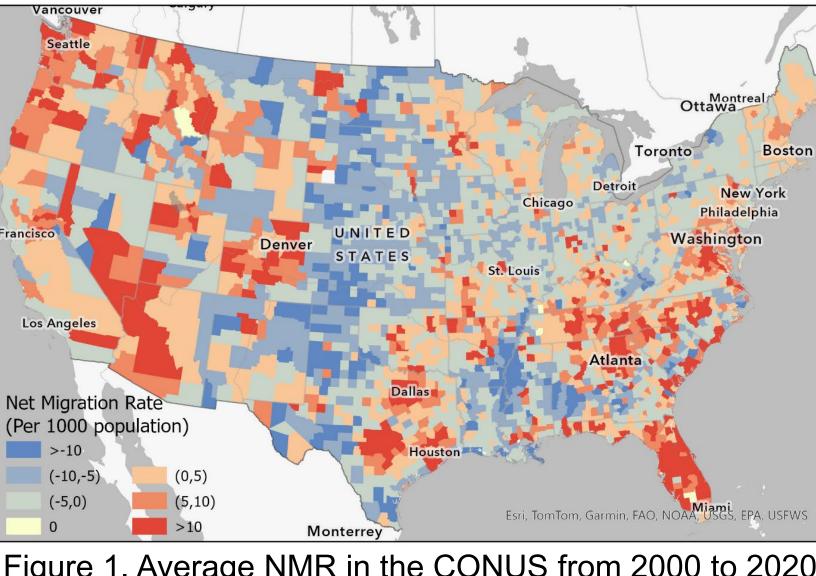
- Migration: Net Migration Rate (NMR) from U.S. Census PEP (Figure 1)
- Disasters: SHELDUS with disasters' counts, losses, fatalities, injuries (Figure 2)
- Socio-economic: U.S. Census, ACS, USDA, and HUD data

We conducted (Figure 3):

• Spatial analysis using 20-year averaged data to assess long-term associations by automated machine learning (AutoML) models.

• **Temporal analysis** using annual panel data and 1-year lag data to model yearly and delayed disaster effects.





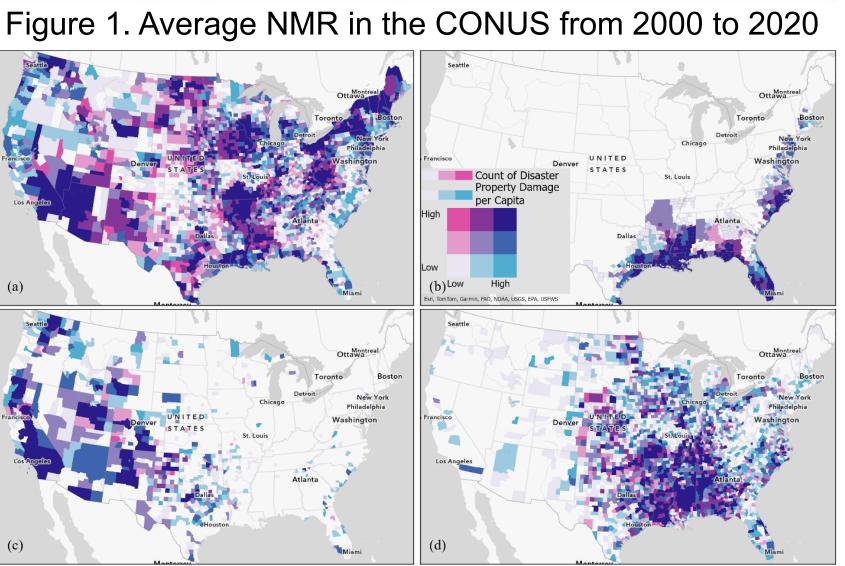


Figure 2. Disaster counts and property damage per capita for floods(a), hurricanes(b), wildfires(c), and tornadoes(d).

Table 1. Variables Table

| Categories | Variables | Datasets | |
|------------------------|-------------------------------------------------------------------------|----------|--|
| Disaster | Disaster Counts | CHELD. | |
| (Flood, | Disaster Induced Economic Loss | | |
| Hurricane, | Disaster Induced Fatalities | SHELD | |
| Wildfire, Tornado) | Disaster Induced Injuries | US | |
| House Affordability | Median Household Income / Median | Census | |
| | House Value | Bureau | |
| | % Change of Median Household Income / % Change of Median House value | ACS | |
| | House Affordability Index | HUD | |
| | % of Mobile Home | ACS | |
| | % of Multi-unit House | | |
| House Condition | % of Group Quarter | | |
| nouse Condition | % of House Population > Room | | |
| | % of Single-Parent Household | | |
| | % of No Vehicle Household | | |
| | Population Density | Census | |
| | Median Household Income | Bureau | |
| | % Change of Median Household Income | | |
| | % of Unemployment | | |
| Socio-Economic | Per Capita Income | | |
| | % Below Poverty | ACS | |
| | % of Adults without High School | | |
| | Diploma | | |
| | % of Age5+ with Limited English | | |
| Demographic | % of Elder than 65 | | |
| | % of Younger than 18 | ACS | |
| | % of Minority | | |
| Natural Amenities | Natural Amenity Scale | USDA | |

Results

- Average NMR is usually lower in high-impact disaster areas (Figure 4).
 Counties with high disaster impact often exhibit the lowest NMR compared to moderate- or high-impact counties, especially for floods and tornadoes.
 Additionally, average NMR appears to respond to disaster-related property damage in specific years.
- Annual floods and hurricanes conditions have significantly current and lag effects on NMR (Table 2). However, Wildfire and tornado impacts aren't significant.
- Socio-economic factors still dominate migration predictions across all four disasters (Figure 5). Population density, housing affordability, and income are the most important variables of NMR. Disaster variables make only minor contributions.

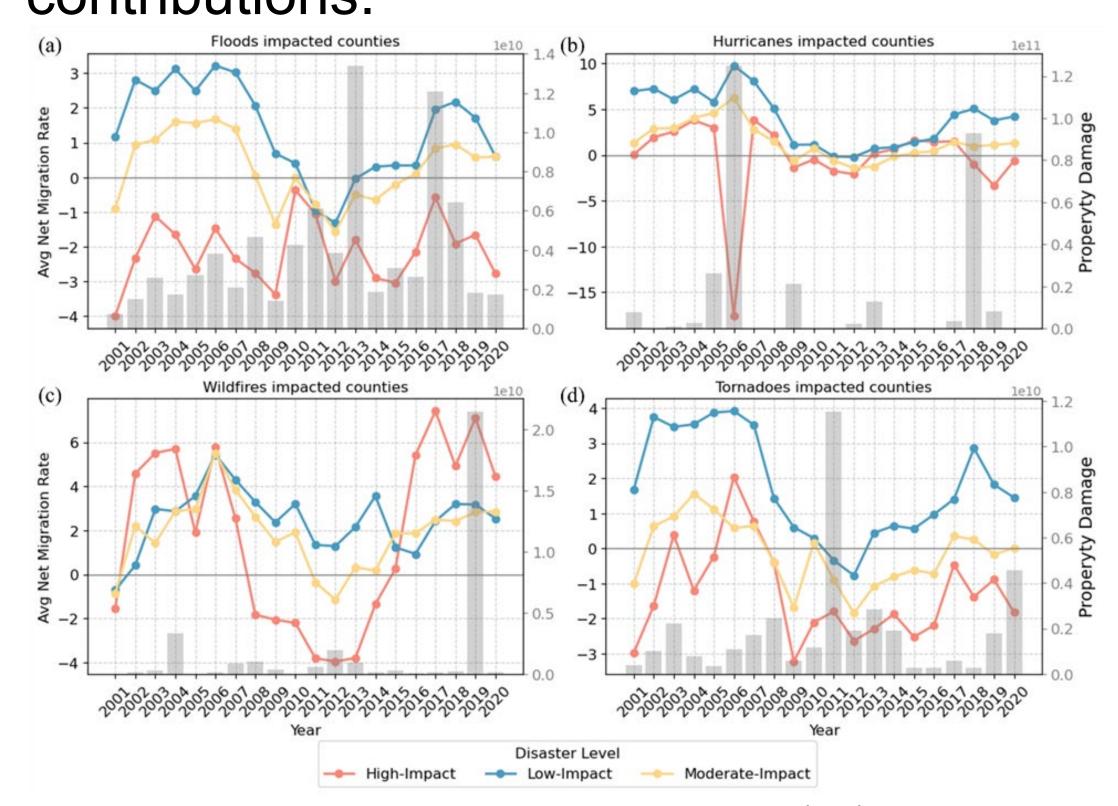


Figure 4. Time series analysis plots in high-impact counties (red), moderate-impact counties (yellow), and low-impact counties (blue) for flood (a), hurricanes (b), wildfires (c), and tornadoes (d).

| Table 2. Coefficients of Fixed Effect Regression | | | | | | | | | | |
|------------------------------------------------------|---------|--------|-----------|------------|----------|--------|---------|--------|--|--|
| | Flood | | Hurricane | | Wildfire | | Tornado | | | |
| | Current | 1 Year | Current | 1 Year Lag | Current | 1 Year | Current | 1 Year | | |
| | Year | Lag | Year | | Year | Lag | Year | Lag | | |
| Damage | -0.46** | 0.17** | -0.69** | 0.22 | 0.01 | 0.29 | -0.02 | 0.07 | | |
| Fatality | -0.30 | -0.44 | -57.95** | 11.55** | -2.43** | -1.69 | -0.67 | -1.19* | | |
| Injury | -0.23 | -0.39 | 6.32** | -0.22 | 0.08 | 0.35 | 0.23 | 0.26 | | |
| Count | -0.63* | -0.88* | 1.03 | -24.99** | -1.28 | -1.67 | 0.53 | -0.53 | | |
| Presence | 1.16** | 0.47 | 3.95* | 17.28** | 0.52 | 0.35 | -0.64 | 0.01 | | |
| * means p value < 0.05, and ** means p value < 0.01. | | | | | | | | | | |

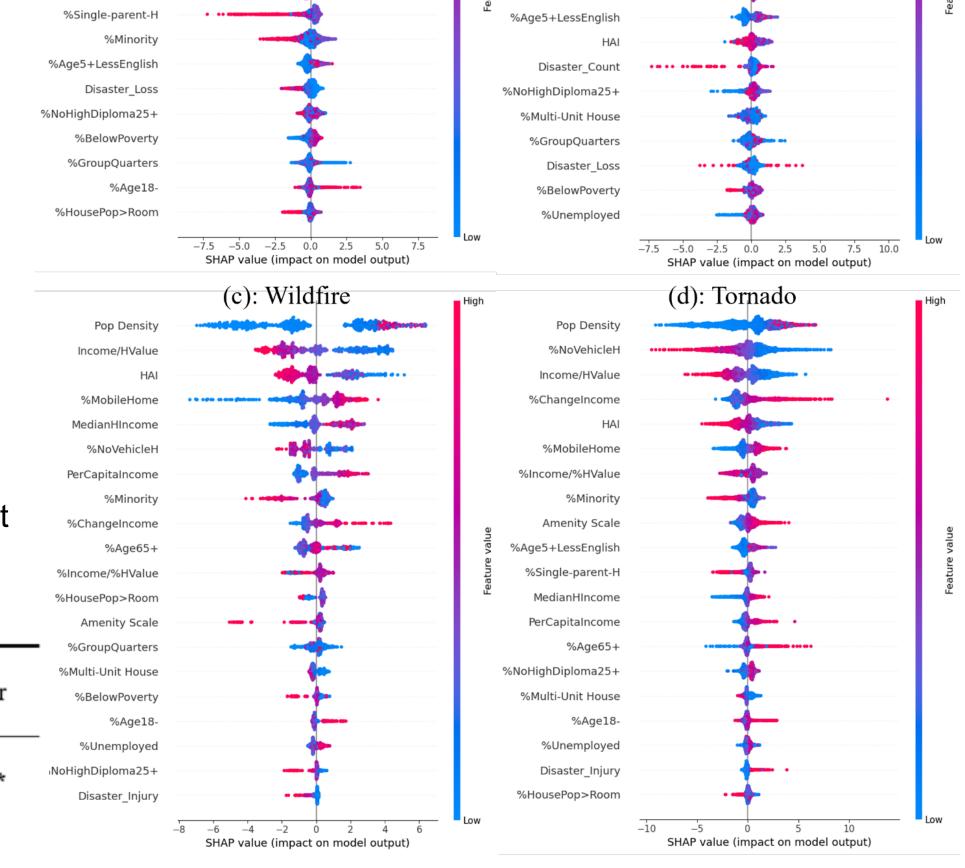


Figure 5. SHAP summary plots for feature contributions to NMR by disaster type.

Conclusion

- This study examines how four major natural disasters affect county-level migration across the CONUS from 2000 to 2020.
- Floods and hurricanes have the strongest negative impacts on NMR, with both current-year and lagged effects. In contrast, wildfires and tornadoes show weaker and inconsistent associations with migration.
- Using AutoML modeling, we demonstrate that socio-economic factors are still the dominant drivers of migration. Disaster variables act more as stress multipliers than primary motivators.
- This study demonstrates the value of explainable AI in capturing the complex dynamics between disasters and human migration and offers insights into the varying impacts of different disaster types on migration patterns.

Literature cited

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Hazards, 1-21.



