

Exploring Behavioral Determinants of Flood Insurance Adoption with Explainable Machine Learning in the Continental US

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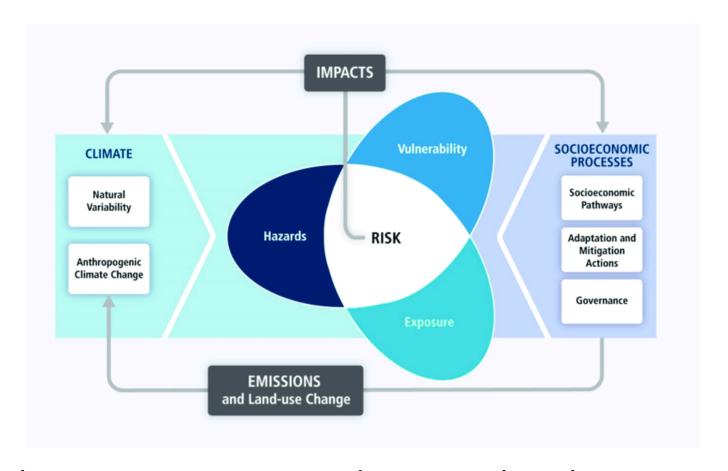
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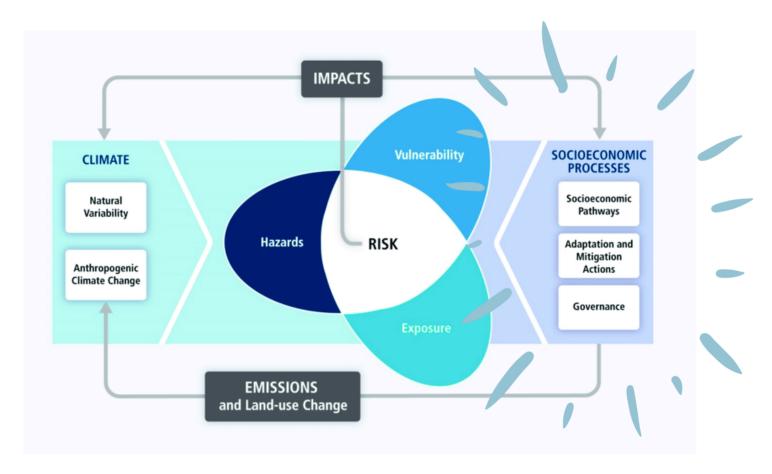
OVERARCHING RESEARCH QUESTION



How do heterogeneous socio-demographic characteristics and human behaviors influence flood resilience?

Source: IPCC, 2012

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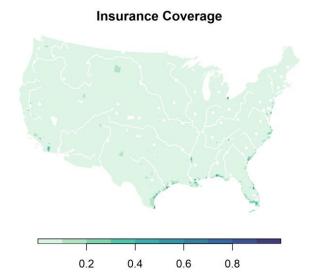


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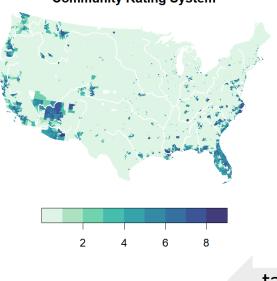
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Community Rating System



target

. Insurance data from 2009 to 2020:

. In 2017:

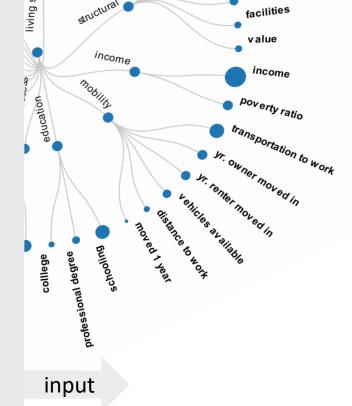
54.871.946 records

. Active insurance policies in 2020: 5.1 million households

22,200 communities

. only 6.5% of communities participate

. over 69% of flood insurance policies are in CRS communities



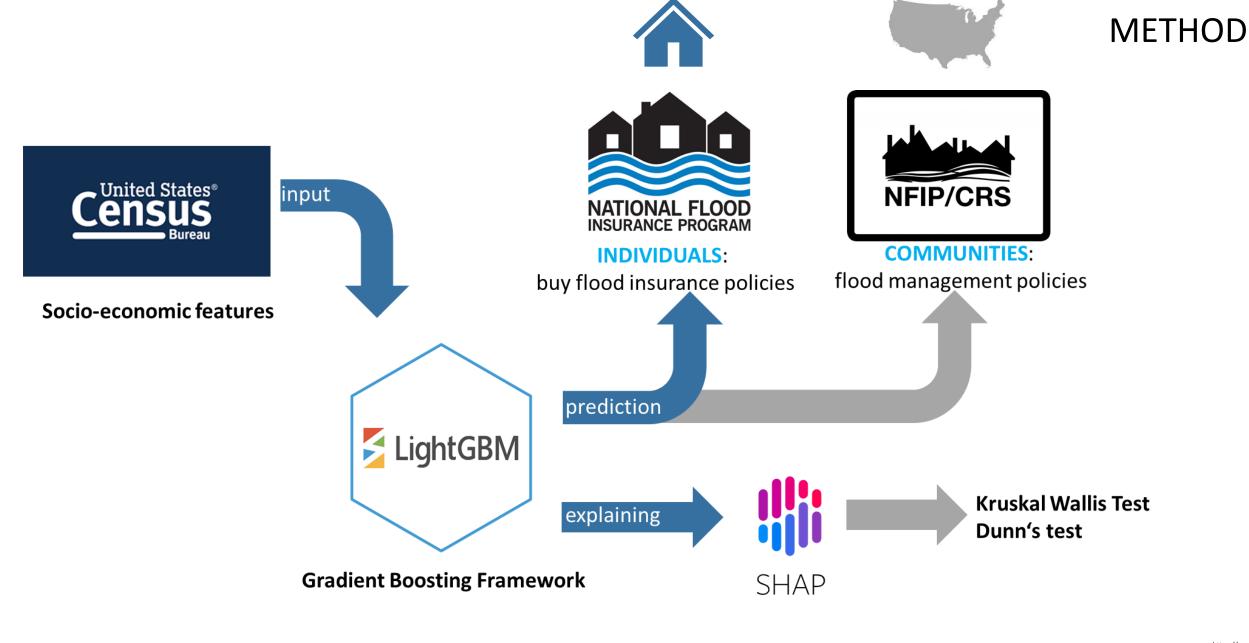
DATA

Data from the 2018 US community survey

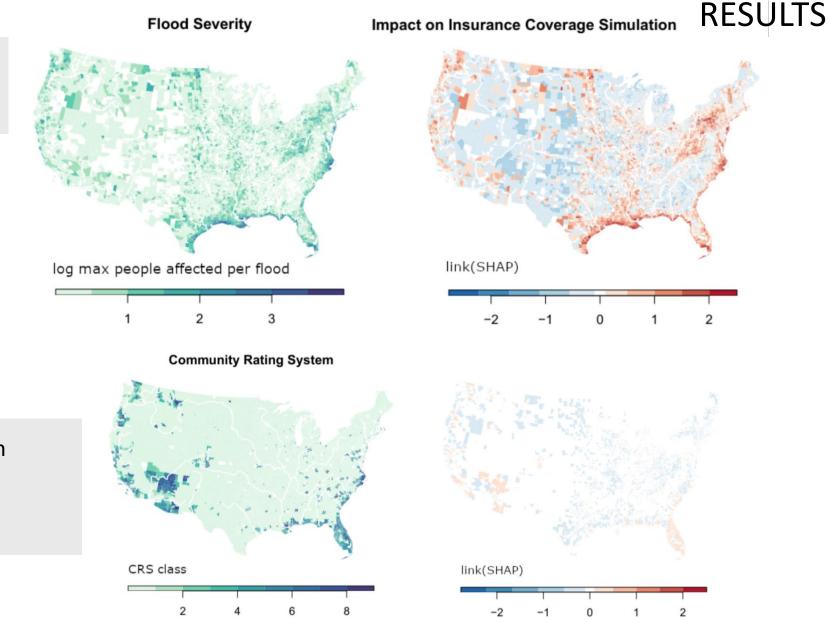
- . census tract scale
- . hierarchical system grouped with mix of expert-based and high-level hierarchy selection

Total number of variables after selection: 398

Source: https://www.fema.gov/openfema-data-page/openfema-dataset-fima-nfip-redacted-policies--v1



OWNERSHIP, FLOOD HISTORY, and CRS matter more than many sociodemographics variables.

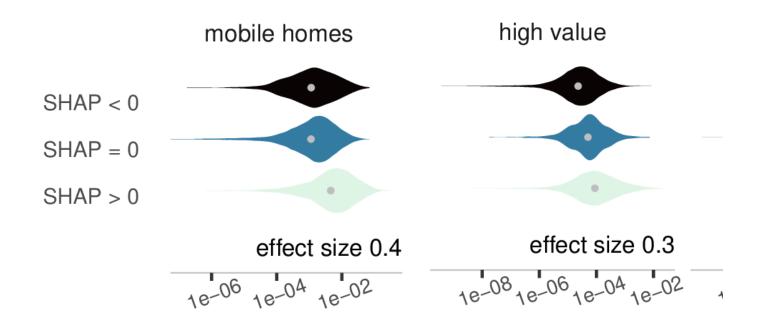


Analysis of the Community Rating System suggests that **POLICIES** were effective in promoting flood insurance purchase.

Are there inequalities? Is the CRS "favoring" specific socio-demographic categories?

CRS COVERS HETEROGENEOUS SOCIO-ECONOMIC BACKGROUNDS

example: housing value

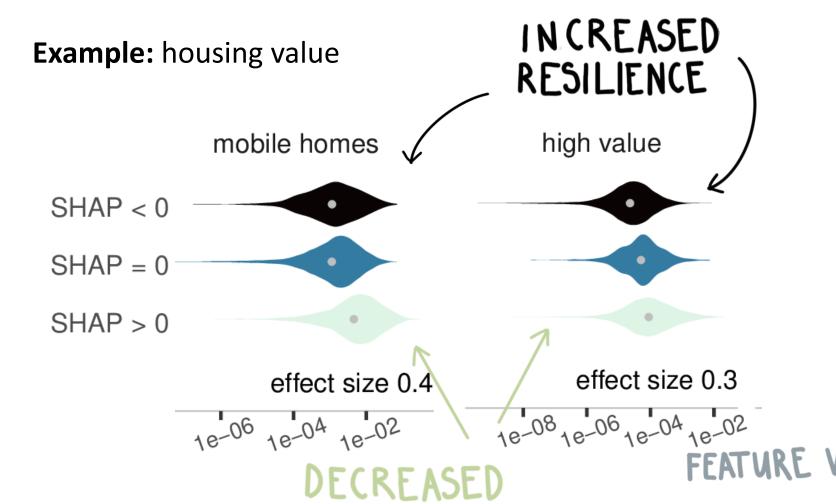


21 features showed differences with a medium to strong effect size corrected for exposure. The CRS apparently supports a wide spectrum of population **segments**, including those that might be vulnerable (structural deficits, mobile homes, etc.)

none



CRS COVERS HETEROGENEOUS SOCIO-ECONOMICS



RESILIENCE

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none

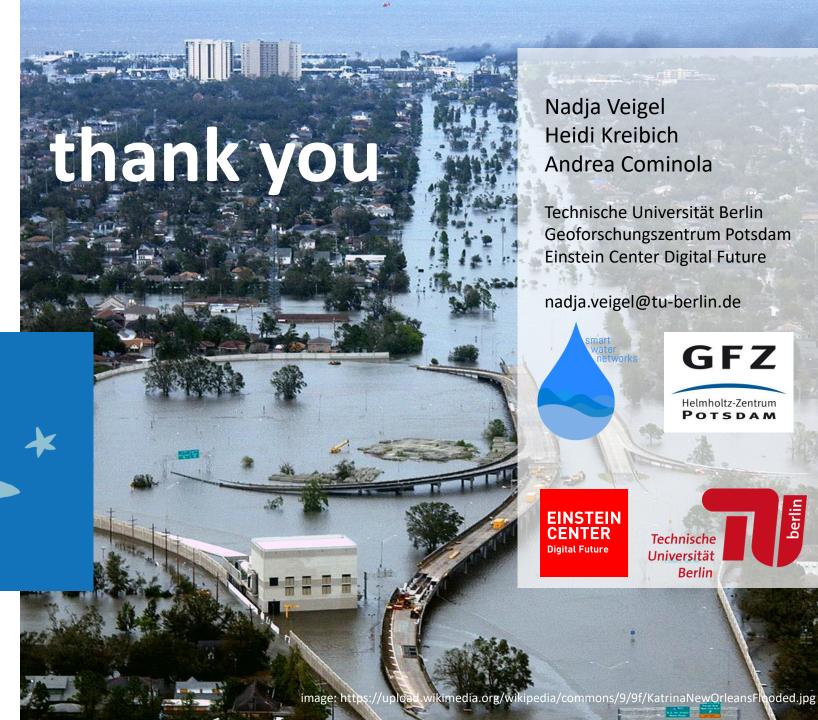
TAKE-HOME MESSAGES

. HOUSEHOLD FLOOD INSURANCE PURCHASE

ownership, experience, exposure, and policies matter more than socio-demographics. Reactive behaviors following severe events.

. CURRENT POLICIES (Community Rating System)

CRS (community measure) encourages resilience measures at the individual level (insurance purchase) in an inclusive and non-discriminatory way. Hence, public policies seem to effectively support private initiatives.





PLEASE ENTER
YOUR FEEDBACK
IN THE
OSPP PORTAL

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