

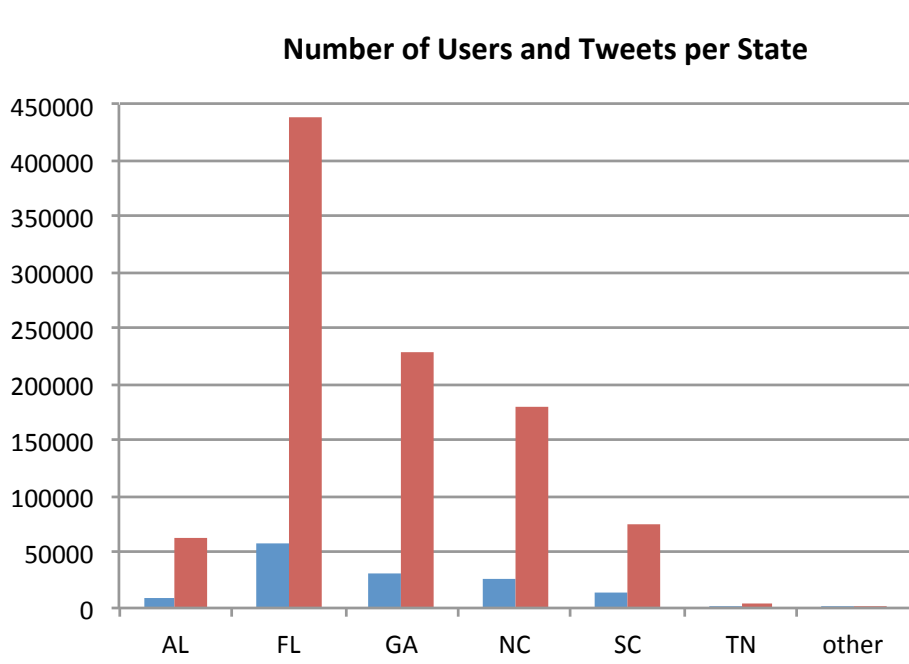
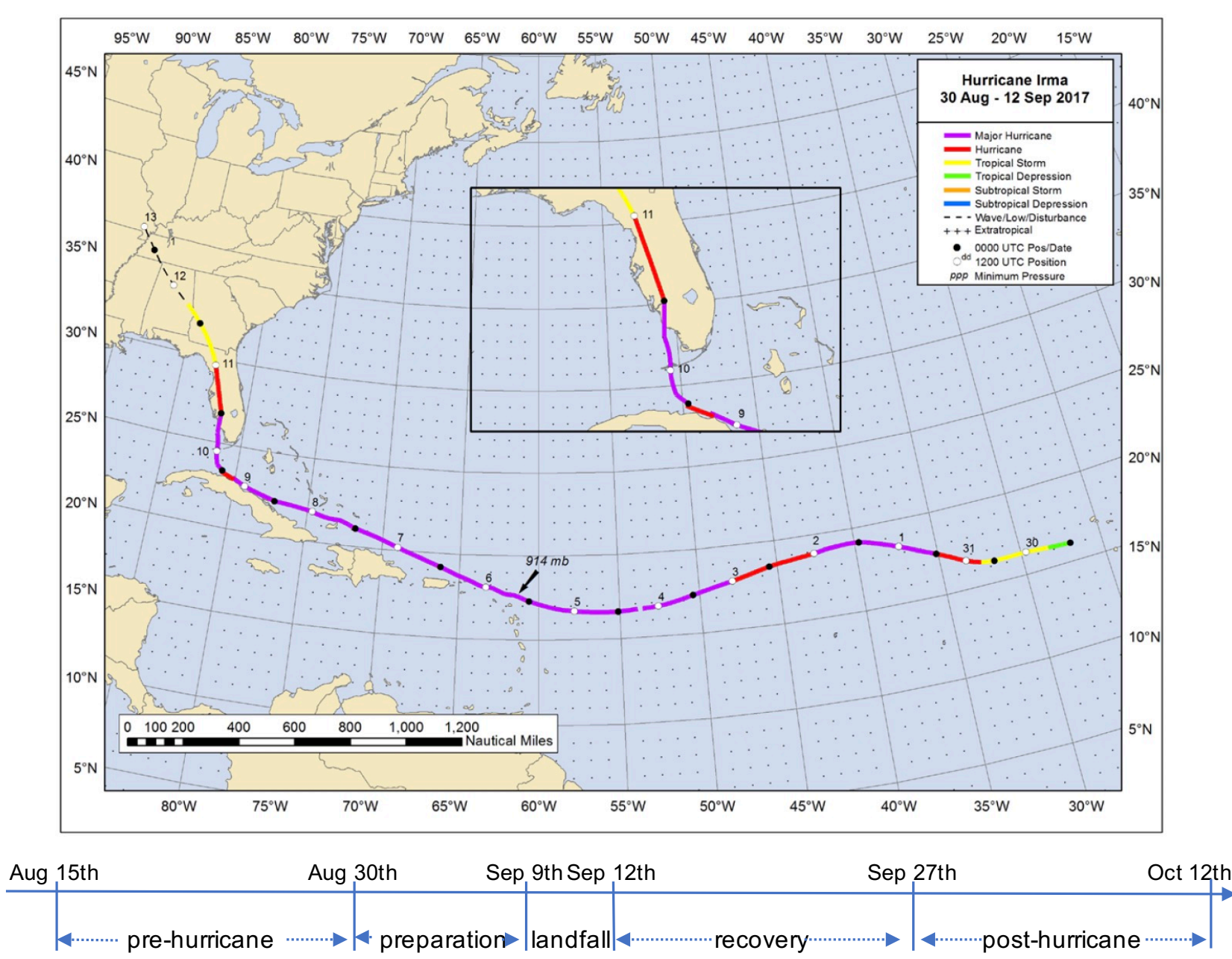
# CAREER:

# Data-Driven Models of Human Mobility and Resilience for Decision Making

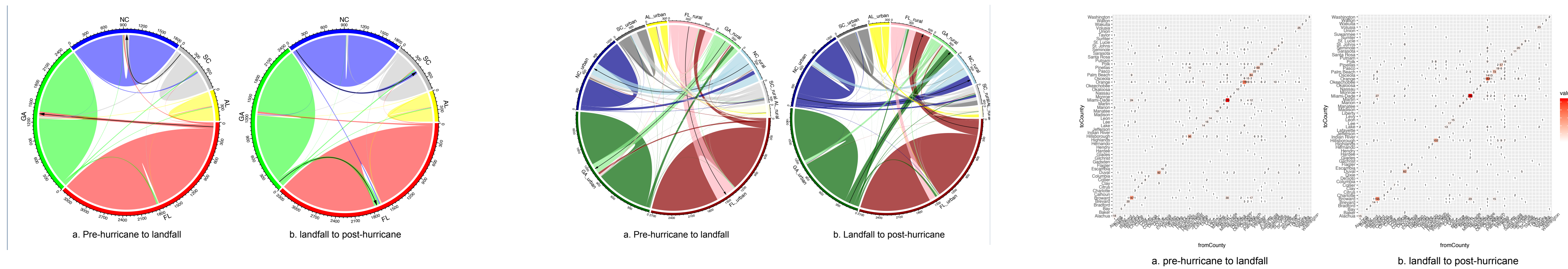
Vanessa Frias-Martinez  
University of Maryland, College Park

## USING TWITTER DATA TO MODEL AND PREDICT EVACUATION BEHAVIORS DURING HURRICANES: THE CASE FOR IRMA

### 1. HURRICANE PHASES AND TWITTER POPULATION



### 2. EVACUATION FLOWS AT STATE AND COUNTY LEVEL



- Most people stay in state
- Rural to urban migrations to seek refuge
- In-county displacements are predominant

### 3. PREDICTION OF EVACUATION FLOWS

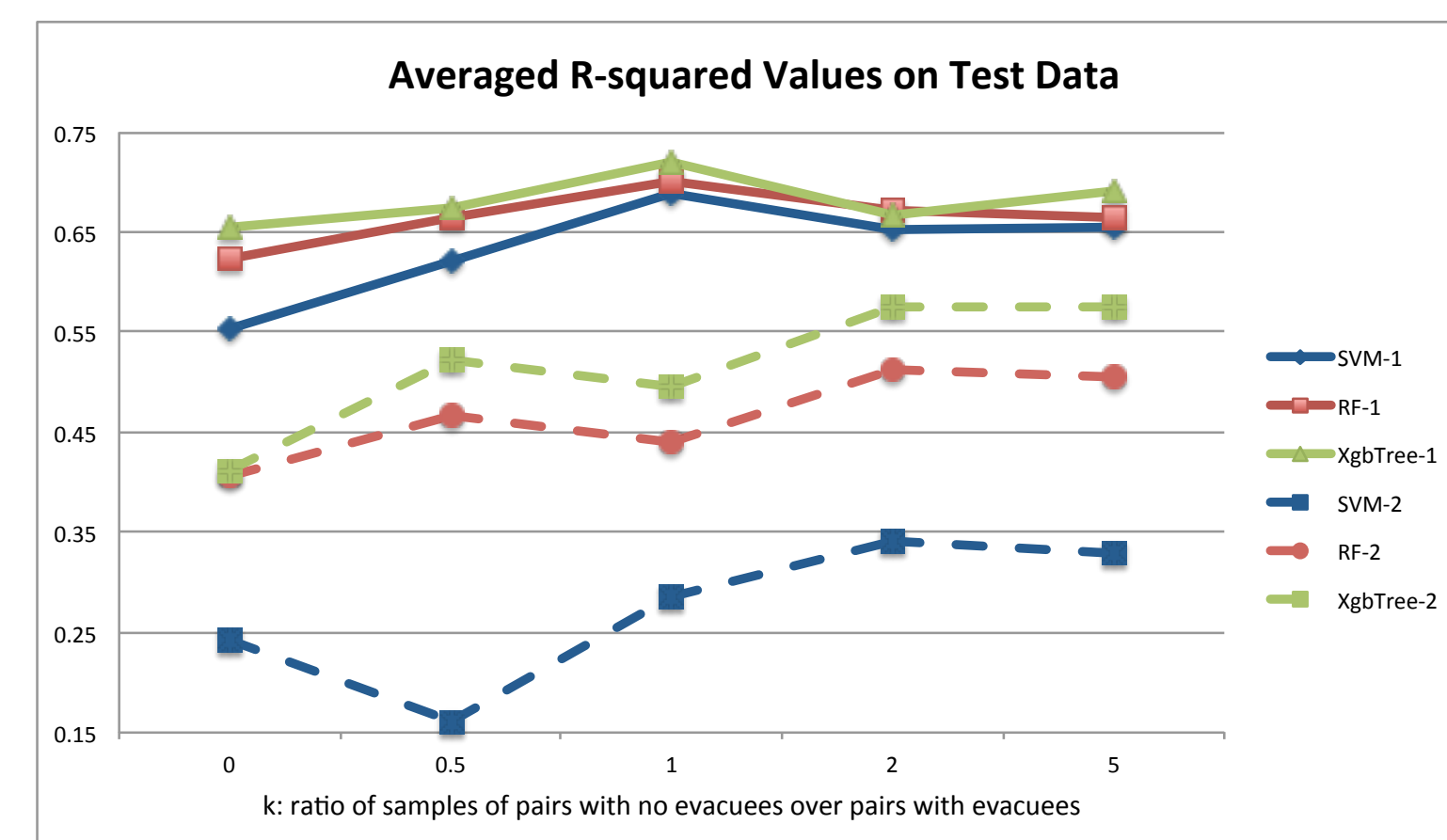
#### 3.1 FEATURES (U<sub>i</sub>):

- A. Meteorological Factors
- B. Flooding Information
- C. Census (population, poverty)
- D. Evacuation Policy
- E. FEMA Assistance Data

$$U_i = \{u_{i,1}, u_{i,2}, \dots, u_{i,N}\}$$

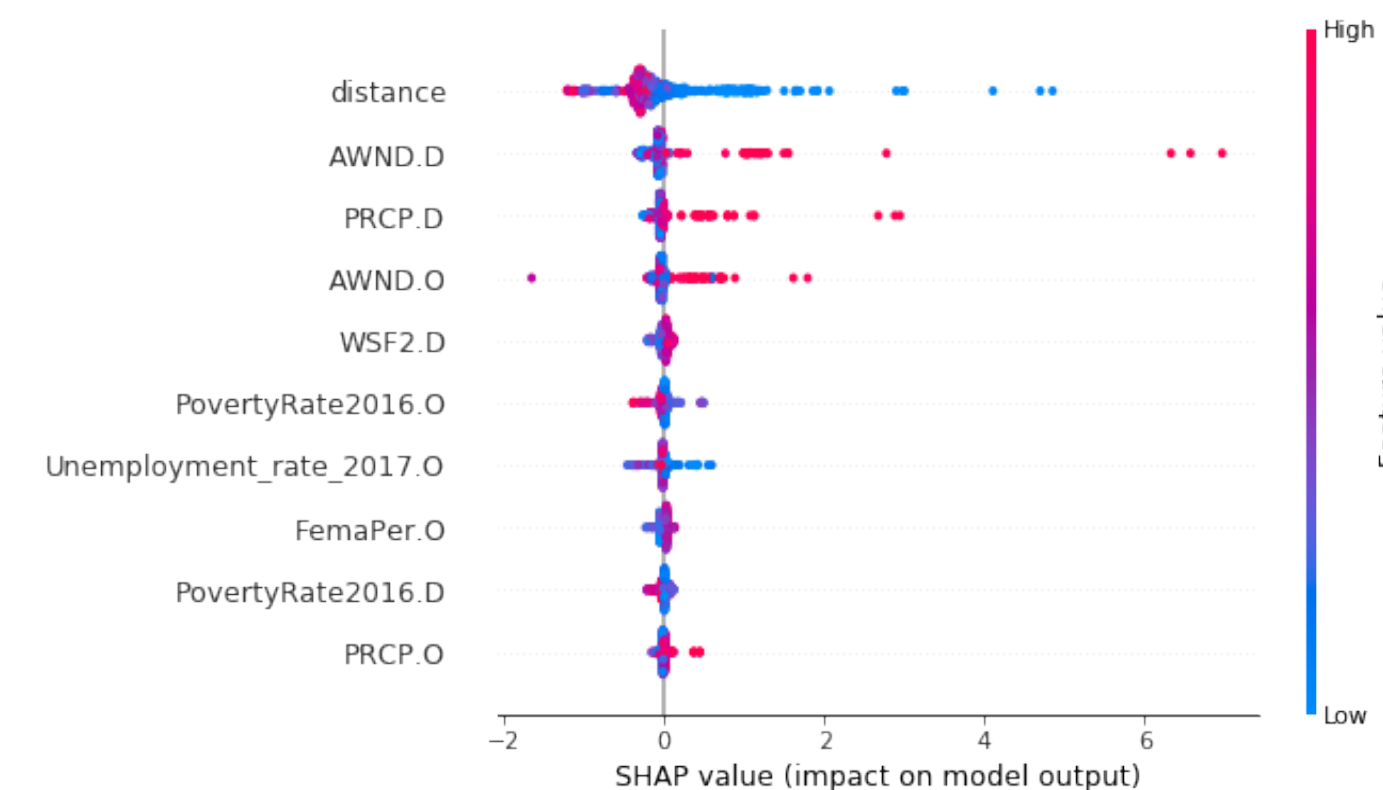
#### 3.2 MACHINE LEARNING MODEL:

-ML models are used to predict evacuation flows from origin to destination county using U<sub>i</sub> features  
- Features are modeled joint for each O-D pair (W<sub>i</sub>)

$$w_k = \frac{U_{i,k} \cdot U_{j,k}}{dist^2(i, j)}$$


#### 3.3 RESULTS:

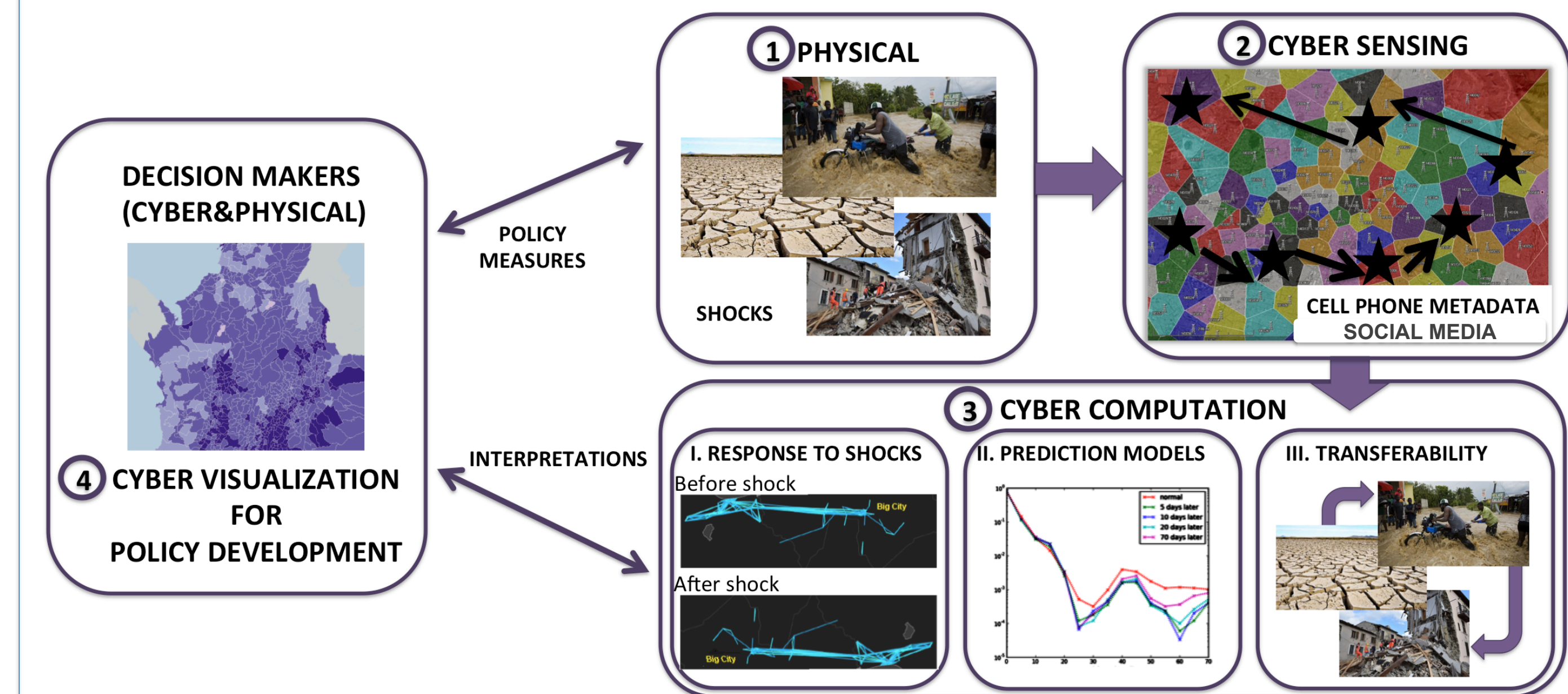
- Filtering out zero-flow pairs does not improve results in unnormalized approach
- XGBoost offers best results (72%)
- Best predictors: distance, socioeconomic features and damage rates (FEMA)



### 4. BROADER IMPACTS

- Workshop with UN partners on the use of social media to model and predict evacuation flows

### AWARD FRAMEWORK



### AWARD OBJECTIVES

- I. Context-aware Human Response to Shocks:
  - Mobility Patterns and Resilience
- II. Prediction of Human Behaviors during Shocks:
  - Human Mobility and Resilience Prediction
- III. Transferability of Behavioral Patterns:
  - Across types of shocks, data, space, time