ASSESSING FLOOD RESILIENCE IN WEST VIRGINIA COMMUNITIES

INTEGRATING PHYSICAL, INSTITUTIONAL, SOCIOECONOMIC, AND ENVIRONMENTAL DIMENSIONS

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Why This Subject

Passionate about city planning.

Like to work on the problems caused by natural disasters.

How can the cities get back to normal life? To work better?

Thinking about: “ Giving Life to the Devastated Cities”.

What about the Rural Communities?
What about the different damage they experience?

Why devastation?

How can we plan for flood-resilient communities?

Credit: https://www.istockphoto.com/vector/idea-concept-with-one-line-bulbs-innovation-idea-process-of-untangling-wire-to-gm1428194995-471781347

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Problem Statement

CHAPTER1

Flooding is one of the most frequent and damaging natural hazards in the United States.

Traditional approaches to flood risk assessment often focus on single dimensions of vulnerability or rely on binary floodplain maps.

In West Virginia, topography, development patterns, and socioeconomic disparities increase vulnerability.

Flood impacts vary significantly across communities.

The 12 Deadliest Flood Events in West Virginia History

Date of Event	Location Epicenter	Fatality Count	Flood Type
September 1870	Jefferson	42	Tropical Storm
July 1888	Ohio	20	Summer Thunderstorm
July 1889	Wood, Wirt, & Jackson	19	Summer Thunderstorm
June 1901	McDowell	44	Summer Thunderstorm
August 1916	Boone, Kanawha, & Raleigh	74	Summer Thunderstorm
July 1932	Kanawha & Fayette	18	Summer Thunderstorm
August 1943	Braxton, Gilmer, & Wirt	23	Summer Thunderstorm
June 1950	Doddridge, Harrison, & Ritchie	31	Summer Thunderstorm
July 1961	Greater Charleston Area	22	Summer Thunderstorm
February 1972	Logan	123	Dam Failure
November 1985	Eastern WV	49	Tropical Storm
June 2016	Central and Southern WV	[illegible]	Summer Thunderstorm
12 Disasters	------------------------------------	488	------------------------------

Research Gap

Limited integration of environmental processes and community-level characteristics in flood risk,

Lack of empirical analysis on how different vulnerability dimensions interact to create compounded risk,

Need for a community-scale approach to comprehensively assess flood resilience.

Literature Review

The concept of resilience originated in ecology, but it can be traced across various fields, from science to the human sciences (Alexander, 2013; Djalante et al., 2011)

The origins of resilience in the United States can be traced back several decades, primarily focusing on mitigating infrastructure damage caused by disasters (Fisher et al., 2018).

Resilience and vulnerability: two interconnected aspects, representing different sides of the same coin; however, resilience and vulnerability are relative (Cutter, 2016; Twigg, 2009).

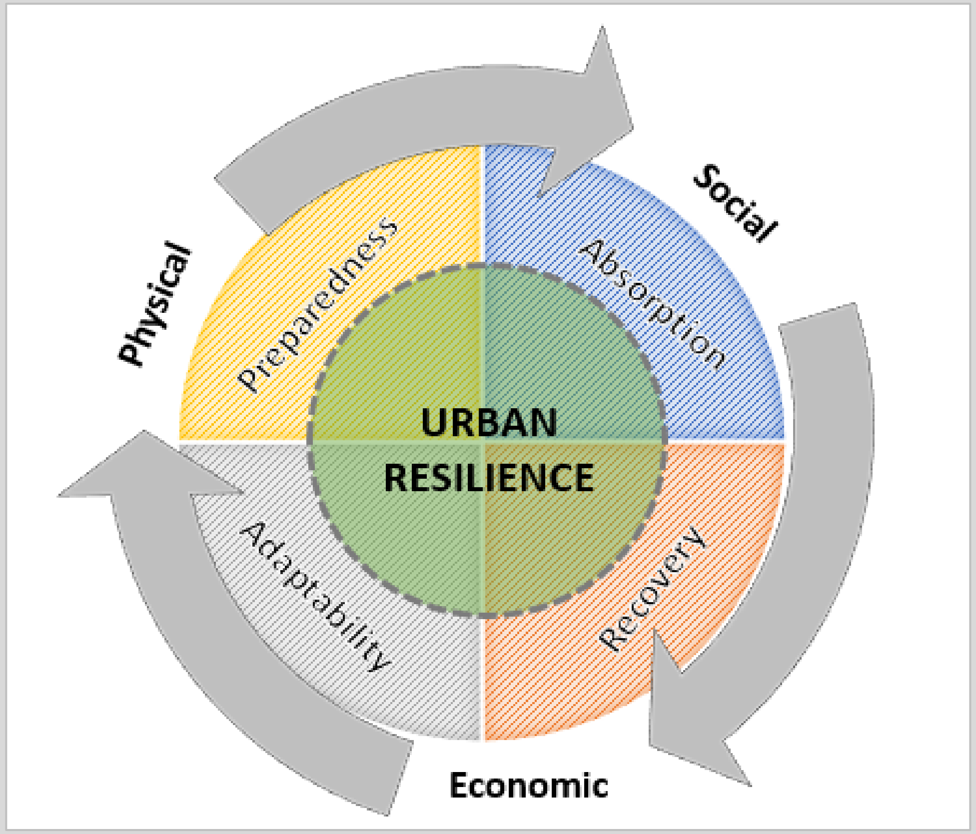
Incorporating them into a comprehensive model helps explain how society responds to potential impacts and uncertainties (Kelman et al., 2016; Smith, 1981).

Literature Review

Resilience measures a system's ability to absorb, withstand, and recover from hazardous events (Cutter et al., 2008; Xu et al., 2020).

Disaster resilience: systems designed to reduce the potential impacts of natural hazards (Patel & Nosal, 2016).

Disaster resilience frameworks should encompass social equity. Some individuals face disproportionate vulnerability due to social, economic, and political factors (Pelling, 2003).



Three Dimensions and Four Principles of Urban Resilience (Based on an image by Ferreira et al., 2021)

Literature Review

Shift in Flood Policies from Resistance to Resilience

Many frameworks in the context of resilience have similar disaster resilience concepts and focus on the factors that mitigate vulnerability and enhance resilience (Mayunga, 2007).

Enhancing resilience in a vulnerable community cannot be achieved solely by superficial policy or practice adjustments.

The foundation of disaster resilience hinges on the strength of every community aspect, including its physical infrastructure, socio-economic well-being, the health and education of its residents, and the integrity of its natural environment (National Research Council, 2012).

Literature Review

Floods become **disasters** when human **communities cannot** effectively **mitigate** and **manage** the **impacts of flood** hazards. The **level of vulnerability and resilience** of the affected communities **determines** the **severity of a flood** disaster (Kuang & Liao, 2020).

A more **comprehensive** range of **dimensions** will enable **a better understanding** and **assessment** of **community resilience** (Mayunga, 2007).

Credit: https://www.tuckerculture.com/the-great-flood-of-1985-finding-strength-in-community/

Research Design

This study adopts a multi-method approach to assess different dimensions of flood vulnerability.

- **Study One: Physical & Institutional**
  - *Indicator-based analysis*
  - *Spatial pattern identification*
- **Study 2: Environmental (Flood Susceptibility)**
  - *Machine learning (Random Forest)*
  - *Environmental variables*
- **Study 3: Socioeconomic**
  - *Composite index (SEVI)*
  - *Integration with physical exposure*

Research Objective

CHAPTER2

Assess flood resilience in West Virginia communities by examining the aspects of

- Physical
- Institutional
- Environmental
- Socioeconomic

Apply indicator-based and data-driven methods

Identify spatial patterns of vulnerability

Improve Community-level flood risk understanding

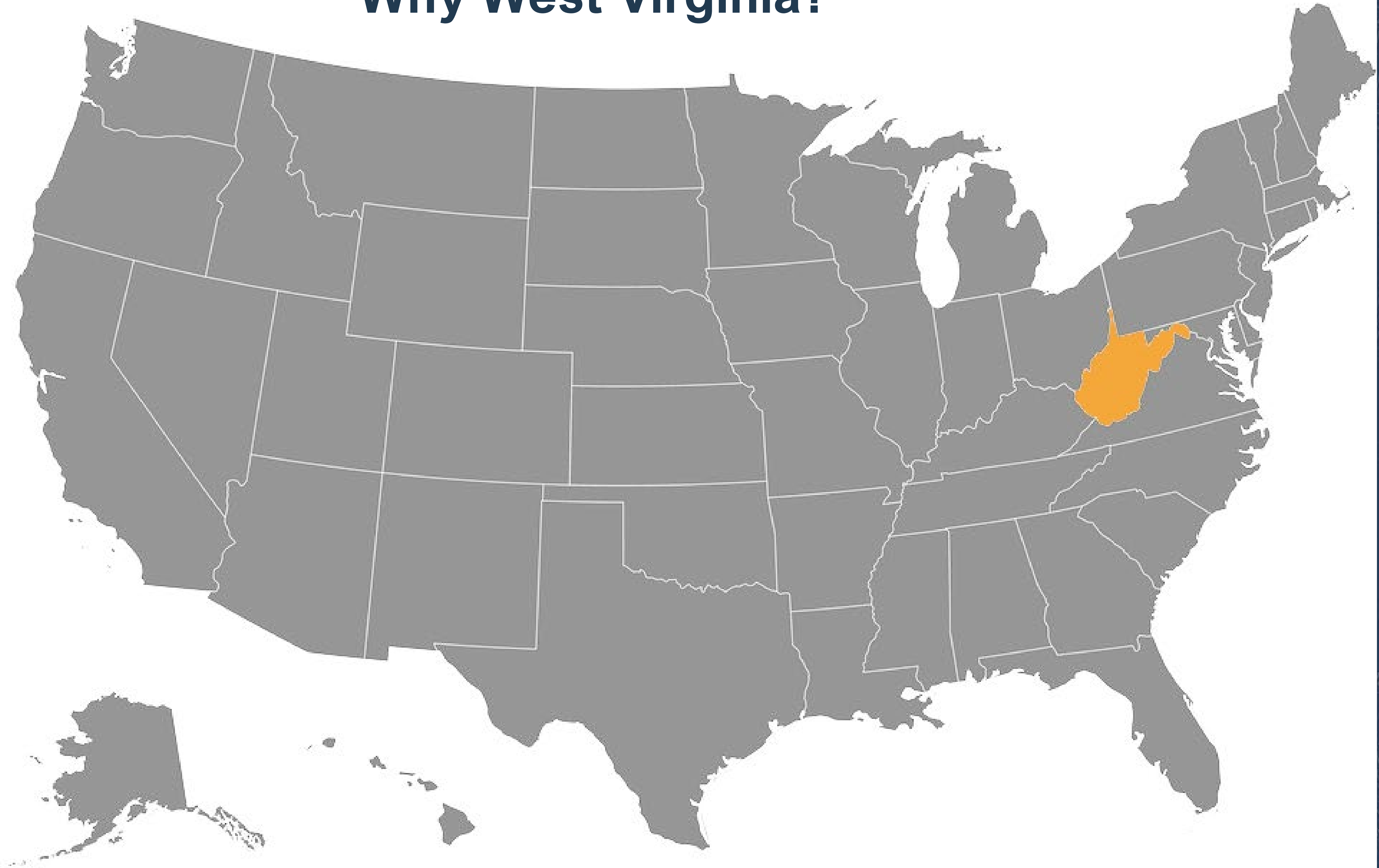
Research Questions

What indicators shape flood resilience?

How can they be measured?

How do vulnerabilities vary spatially?

Why West Virginia?



STUDY AREA

STATE'S TOPOGRAPHY

Communities have been located in steep, narrow valleys

Expansion of settlements and increasing population density in floodplain areas

Forest harvesting has increased due to rising demands for energy, water, sewage, and transportation networks.

A combination of expanding communities and resource development in densely populated floodplains

Excessive runoff that overwhelms river and stream capacity and causes flooding

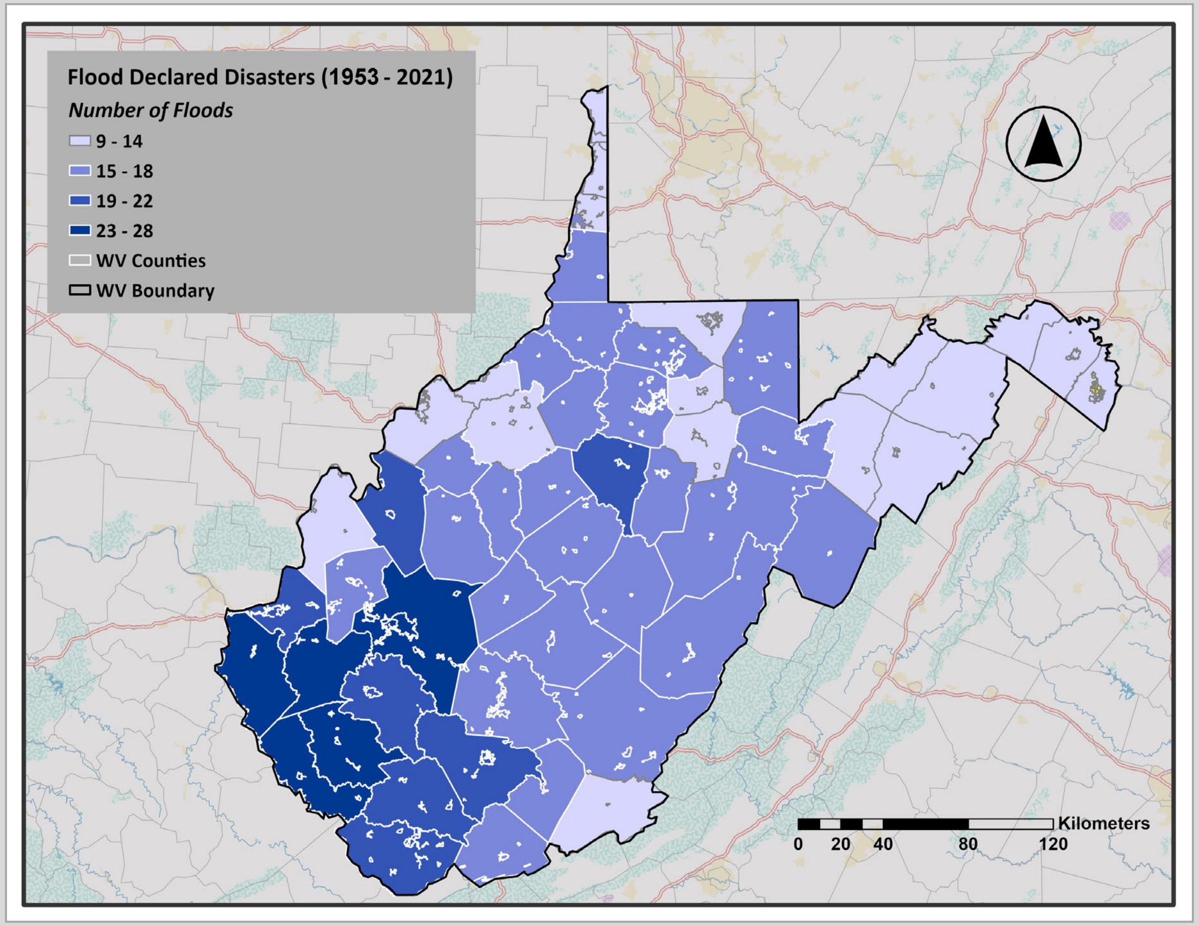
Credit: WVGIS TC, https://www.wvfrf.org/wvre/dashboard/?link=https://www.arcgis.com/apps/dashboards/817bb3791b0841898aa7edeec56a5788

STUDY AREA

West Virginia has experienced 64 declared flood disasters between 1953 and 2023 (FEMA, 2023).

More than 500,000 acres (more than 3 percent) are Special Flood Hazard Area (100-year floodplains) (WVGISTC, 2024).

Each county in the state experienced at least 14 flooding cases between 1991 and 2016.



STUDY ONE

CHAPTER3

Assessing Flood Resilience Using Physical and Institutional Vulnerability Indicators

Keywords: Flood resilience; Flood vulnerability; Built environment; Composite vulnerability index; West Virginia

OBJECTIVES

STUDY ONE

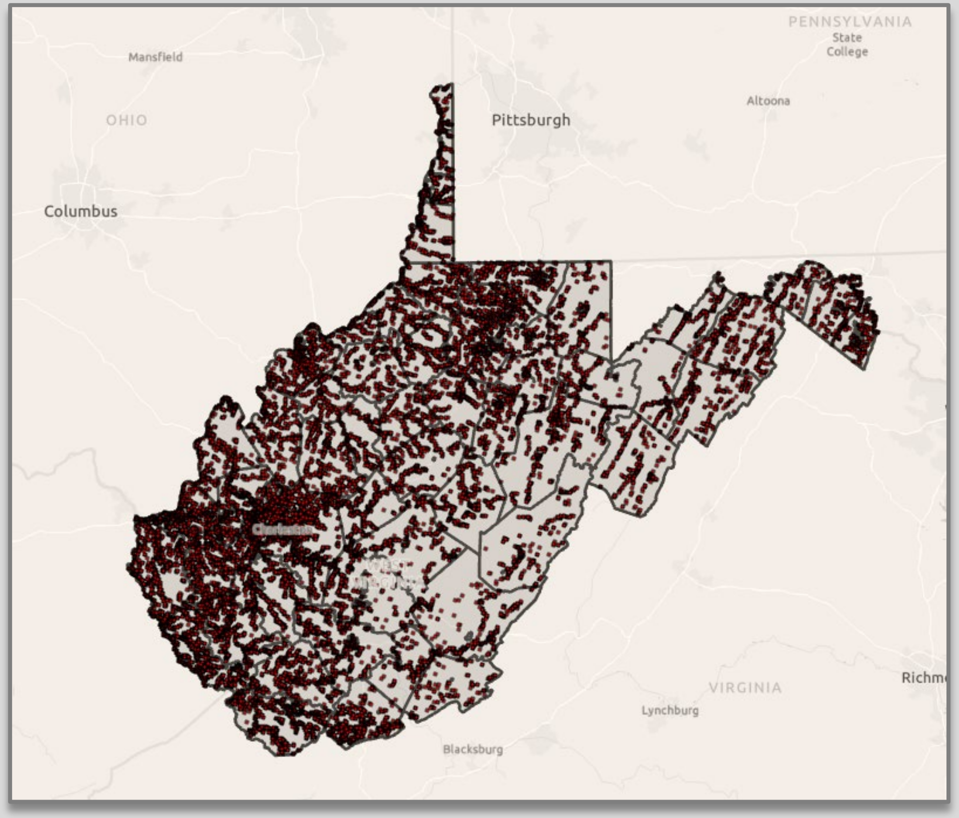
Identifying the Most Physically (Building & Infrastructures) and Institutionally Vulnerable Communities:

- ❑ Developing an indicator-based approach
- ❑ Evaluating physical and institutional dimensions of flood vulnerability
- ❑ Identifying spatial patterns of vulnerability
- ❑ Assessing community-level flood resilience in West Virginia

STUDY ONE

DATA

Identifying the Most Physically (Building & Infrastructures) and Institutionally Vulnerable Communities:



- **WV GIS Tech Center Data:** ***Using the data of more than 98,000 structures located in the flood zone (Tax data 2024)***
- **FEMA:** ***100-year and 500-year Flood Zones***

Building Type	Number of Buildings in the FEMA 100-year Flood Zone	Percentage
Residential	87,157	88.87%
Commercial	7,535	7.68%
Educational	299	0.3%
Governmental	776	0.79%
Religious	1,756	1.79%
Agricultural	39	0.04%
Industrial	500	0.51%

General_Occupancy_Code	Stories	Exterial_Wall_Type	Architectural_Style	Basement_Type	Foundation_Type	First_Floor_Height
Residential	1	Frame	Conventional	None	Slab-on-Grade	1.0

STUDY ONE

INDICATORS

Reviewing 31 disaster resilience studies that assess resilience at different scales, including county, community, and neighborhood levels

14 physical indicators and 13 institutional indicators selected

	Assessment Metric	Indicator Description
Physical (Buildings)	Buildings in Special Flood Hazard Area	Percentage of community buildings located within the 100-year flood zone.
	Buildings in Floodway	Percentage of flood-zone buildings that are located within the designated floodway.
	Residential buildings	Percentage of residential buildings in 100-year flood zone to total buildings in the flood zone
	Building density	Building density in 100-year flood zones (number of buildings in floodplain divided by floodplain area)
	Quality of Buildings	Percentage of Low-Quality Buildings in the Flood Zone to Total Buildings in the Flood Zone
	Having basements	Percentage of buildings with basements in the flood zone to total buildings in the flood zone
	Pre-FIRM* buildings	Percentage of buildings built or substantially improved on or before the effective date of the initial flood insurance rate map to total buildings in the flood zone
	Mobile homes	Percentage of manufactured buildings in 100-year flood zones to total buildings in the flood zone
	First-floor height	Percentage of buildings with first-floor height below water depth (height - water depth < 0) to total buildings in the flood zone
	One-Story Buildings	Percentage of One-Story Buildings in 100-year flood zones to Total Buildings in the Flood Zone
Physical (Infrastructure)	Number of community assets in the flood zone	Percentage of buildings used as government facilities (federal, state, local), religious institutions, utility infrastructures, or postsecondary educational institutions in 100-year flood zones, to the total number of community assets in the community
	Number of essential facilities in 100-year and 500-year flood zones	Percentage of buildings providing essential community services, including police and fire stations, e-911 emergency centers, schools (often serving as shelters), hospitals, and nursing homes in 100-year flood zones, to the total number of essential facilities in the community
	Length of roads in the flood zone	Percentage of length of Roads in 100-year Flood Zones to Total length of Roads in the Community
	Length of railroads in the flood zone	Percentage of length of Railroads in 100-year Flood Zones to Total length of Railroads in the Community

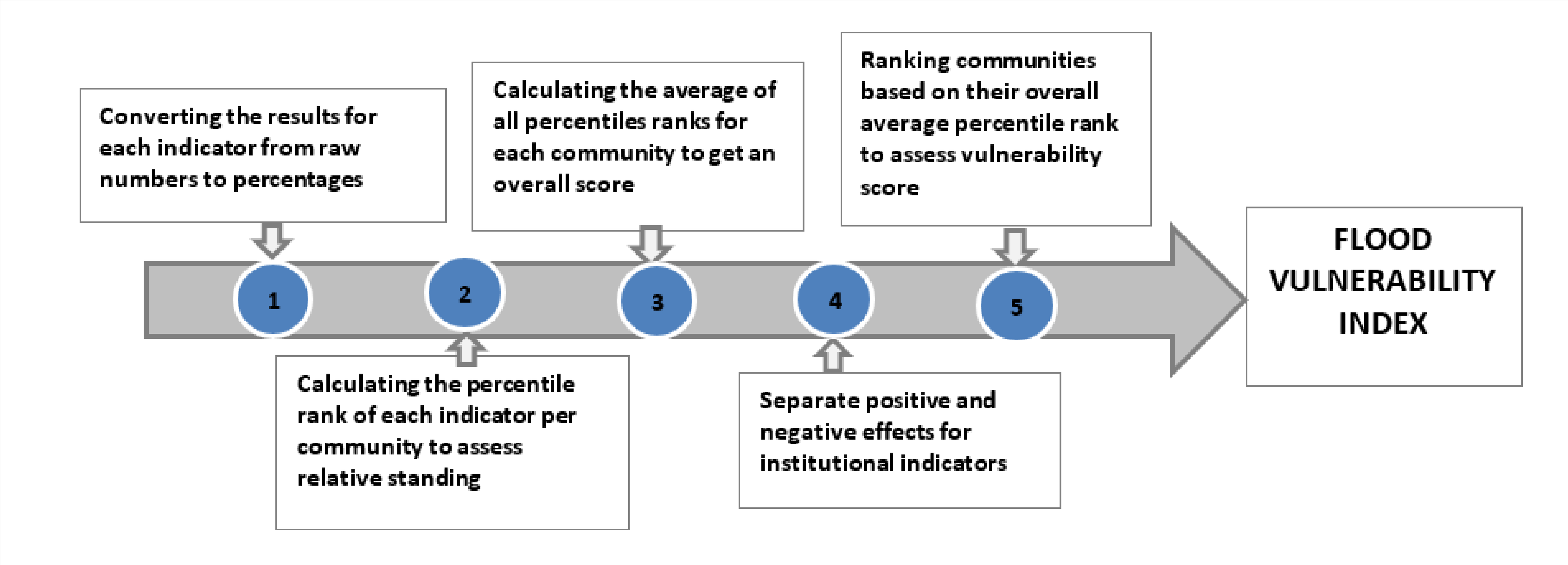
STUDY ONE

INDICATORS

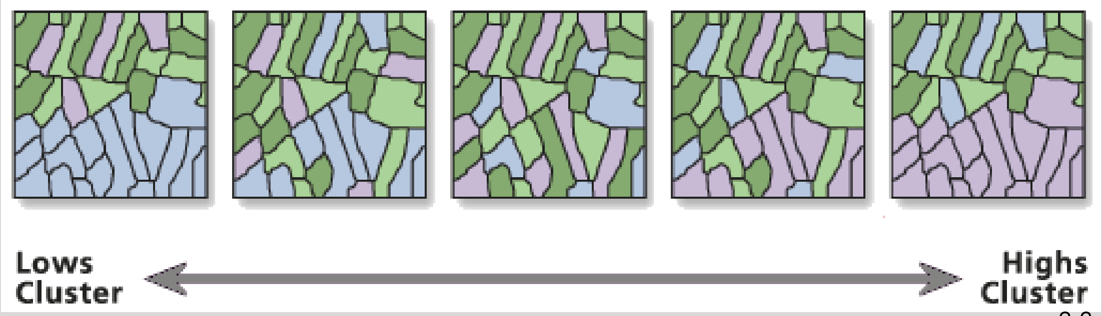
	Assessment Metric	Indicator Description
Institutional	Declared disasters	Number of declared disasters in the community
	Population living in the floodplain	Population residing in 100-year flood zones, calculated by multiplying residential units by average household size
	Number of displaced populations	Number of residential units located in the area with water depth >= 1 foot multiplied by average household size
	Previous damage claims	Number of claims received after past flood events
	Participating in NFIP	The community has attended the National Flood Insurance Program
	Entry in CRS	The community meets or exceeds NFIP minimum standards and is eligible to participate in the community rating system (CRS) (10, lowest – 1, Highest) rewards communities for going above minimum flood management requirements.
	Number of policies	Number of active flood policies in the community
	Claims outside of SFHA	Number of claims received from residents residing outside the Special Flood Hazard Area (SFHA)
	Higher standards	Any floodplain management regulations implemented by a state or community that are more restrictive than the criteria established by NFIP regulations.
	Availability of potential shelter buildings	Churches and schools. located outside 100-year flood zones and can be used as emergency shelters during floods.
	Percent of SFHA structures without flood insurance (County Level)	Percentage of buildings located in the 100-year flood zone without flood insurance
	Number of mitigated properties (County Level)	Percentage of buildings in the 100-year flood zone with flood mitigation actions (elevated or flood-proofed)
	Number of repetitive losses	Repetition of damage caused by floods in the community

STUDY ONE

METHODOLOGY



Understand the spatial distribution of flood vulnerability across West Virginia, a Hot Spot Analysis was performed using the Getis-Ord Gi* statistic in ArcGIS Pro.



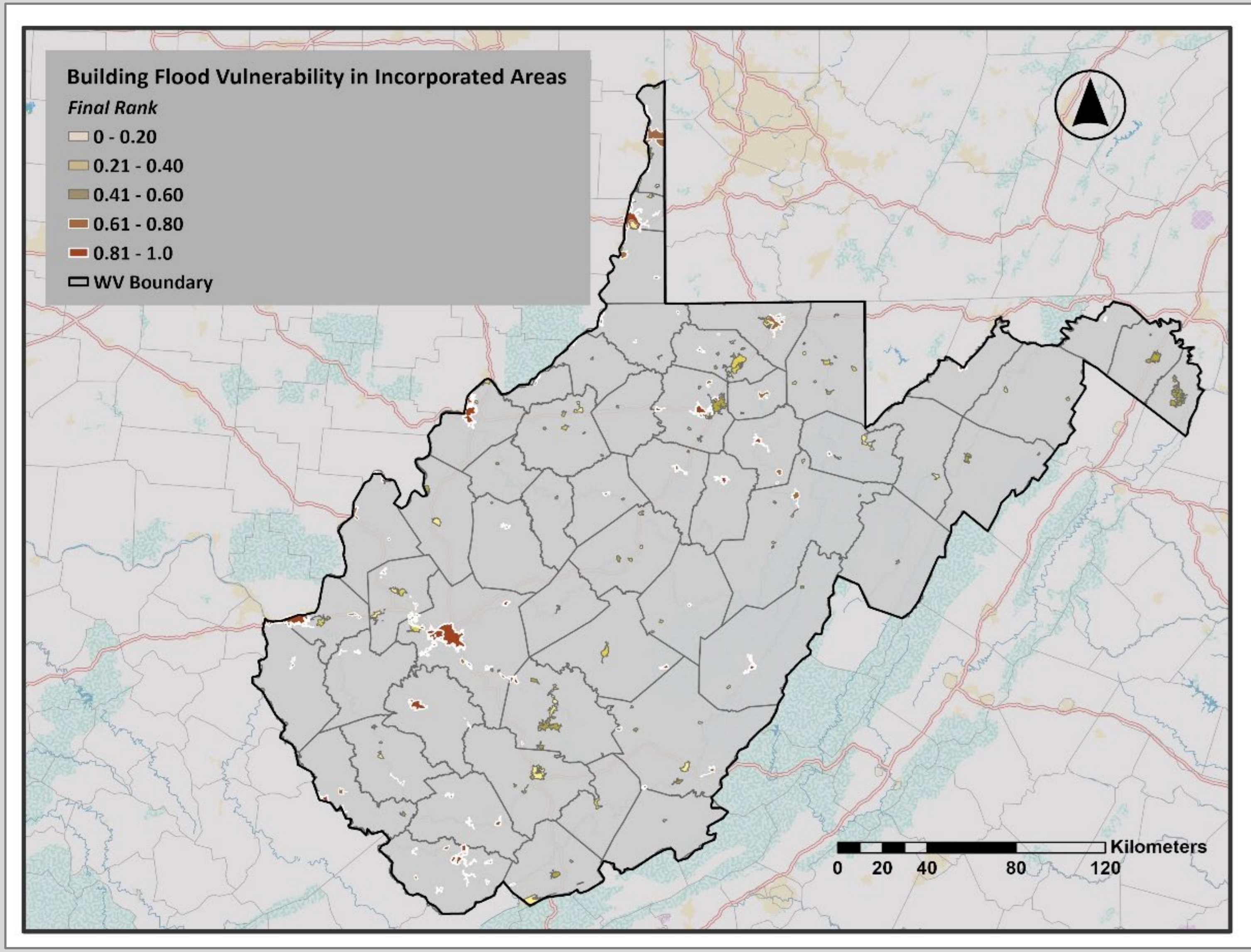
STUDY ONE

RESULT

Building Vulnerability

Incorporated Areas

Community Name	County	Average of Percentile Ranks	Final Rank of Vulnerability
Dunbar	Kanawha	74.2%	1.00
Wheeling	Marshall/Ohio	71.5%	0.995
Wellsburg	Brooke	70.6%	0.991
Richwood	Nicholas	70.0%	0.986
Gary	McDowell	69.8%	0.982
Philippi	Barbour	69.7%	0.978
Charleston	Kanawha	68.9%	0.973
Chesapeake	Kanawha	68.2%	0.969
New Martinsville	Wetzel	67.9%	0.964
Madison	Boone	67.5%	0.96



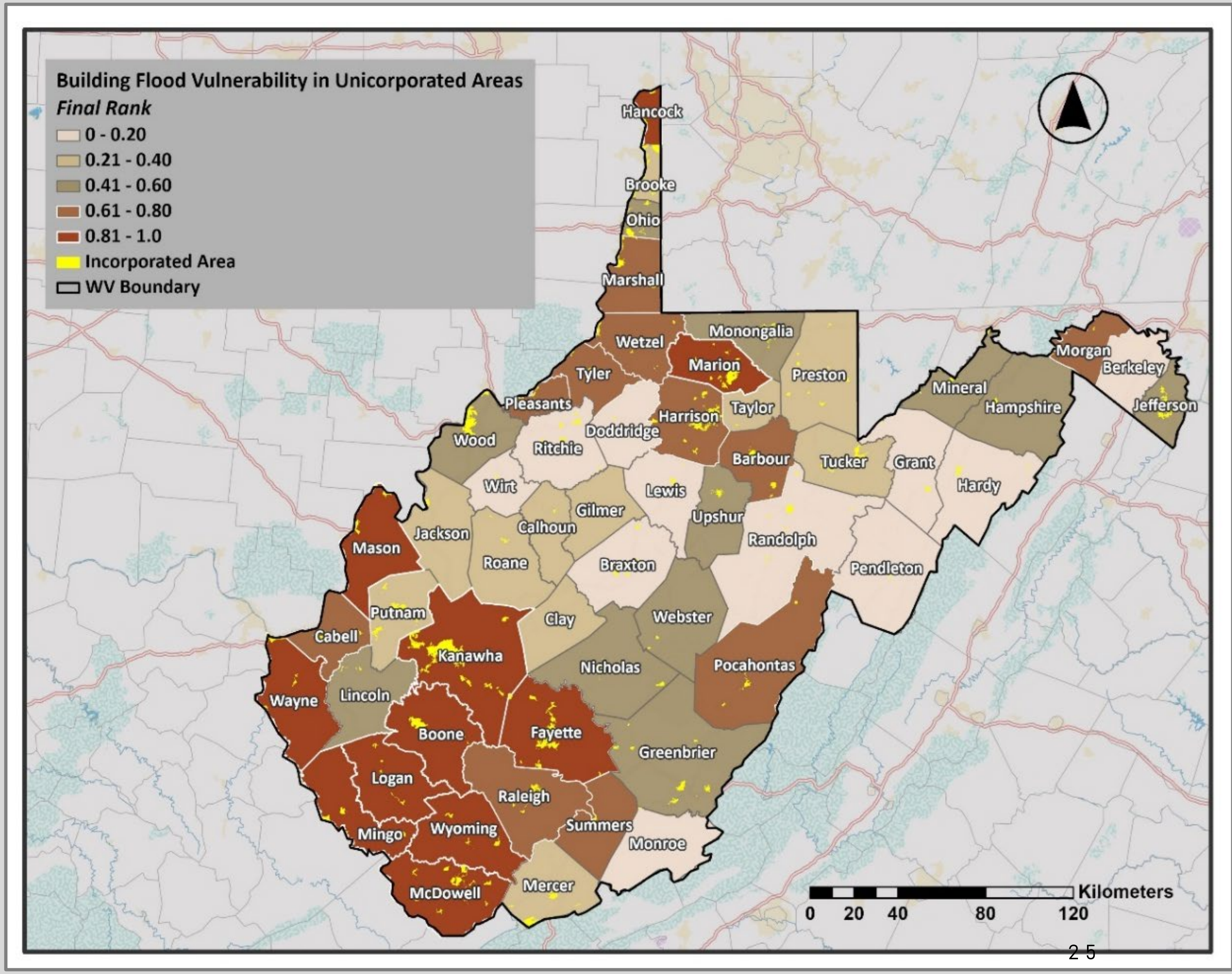
STUDY ONE

RESULT

Building Vulnerability

Unincorporated Areas

Community Name	Average of Percentile Ranks	Final Rank of Vulnerability
Kanawha	76.7%	1.00
Boone	73.2%	0.981
McDowell	65.7%	0.962
Wyoming	63.5%	0.944
Mingo	62.5%	0.925
Mason	60.6%	0.907
Logan	59.9%	0.888
Wayne	59.8%	0.87
Hancock	59.2%	0.851
Marion	57.1%	0.833

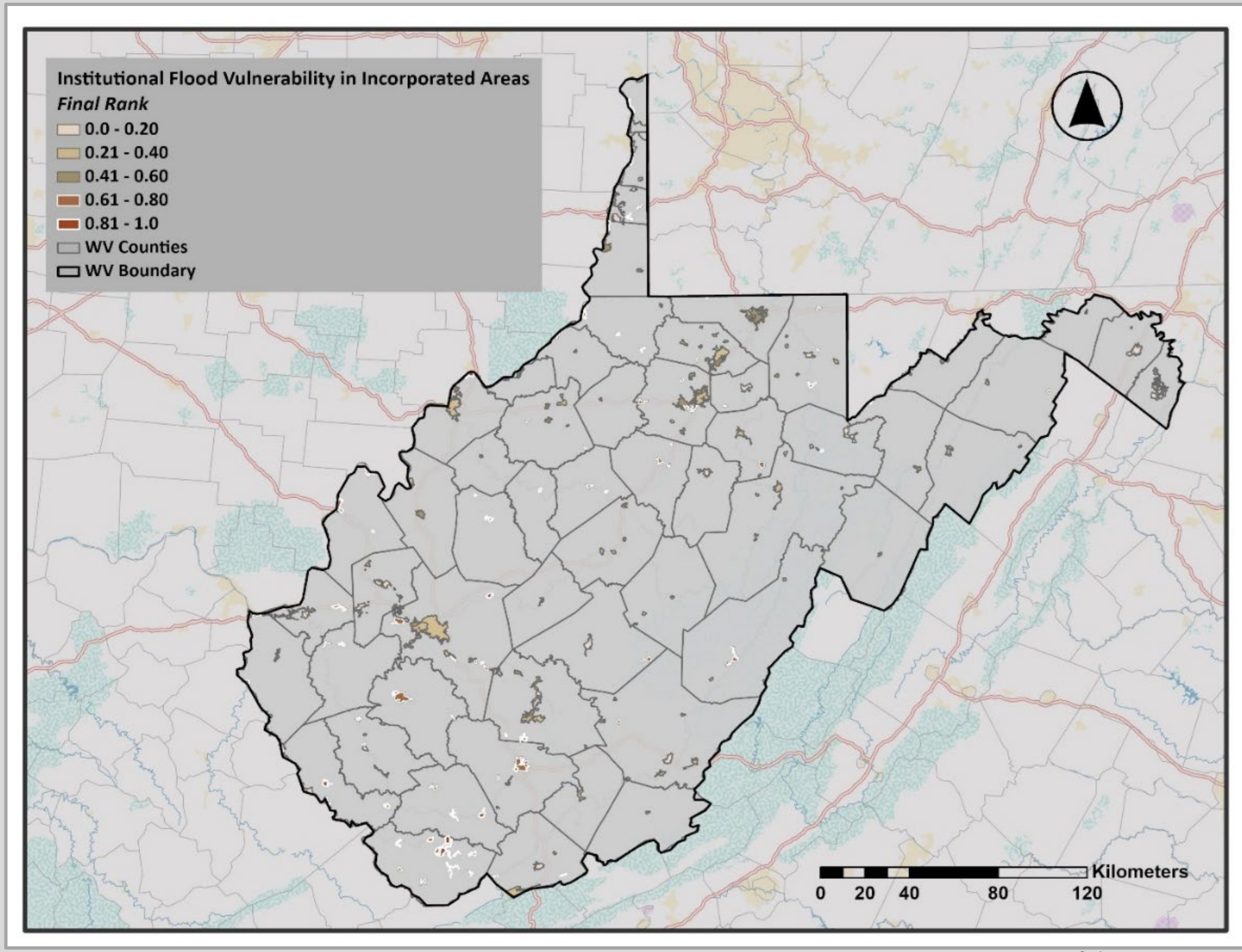


RESULT

Institutional Vulnerability

Incorporated Areas

Community Name	County	subtracting the average of negative-effect indicators from the average of positive-effect indicators	Final Rank of Vulnerability
Rowlesburg	Preston	43.5%	1
Benwood	Marshall	41.9%	0.995
Danville	Boone	37.1%	0.991
Kimball	McDowell	35.4%	0.986
Fort Gay	Wayne	33.8%	0.982
Spencer	Roane	33.6%	0.978
Keystone	McDowell	33.2%	0.973
Northfork	McDowell	32.7%	0.969
Davy	McDowell	30.2%	0.964
Smithfield	Wetzel	30.1%	0.96



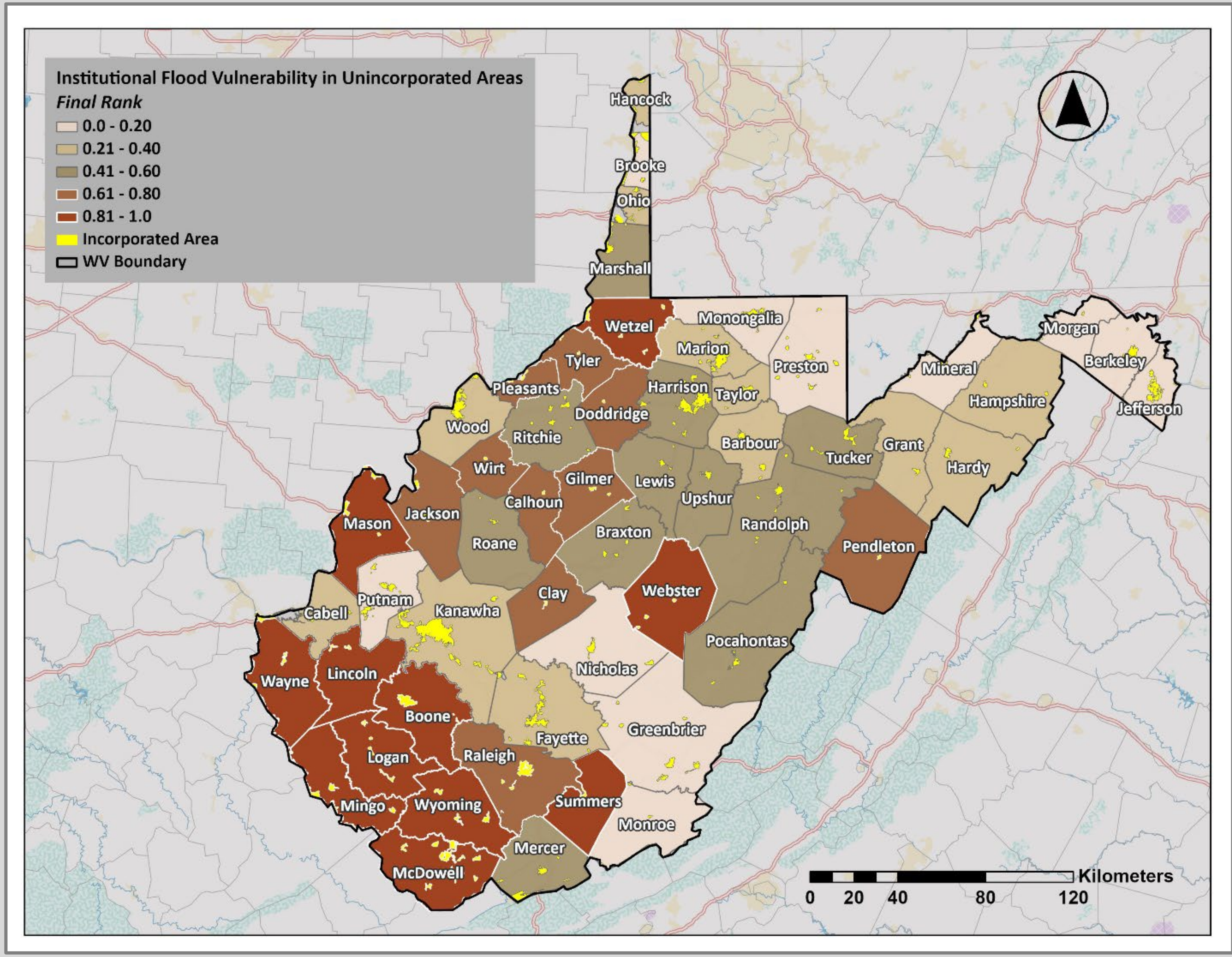
STUDY ONE

RESULT

Institutional Vulnerability

Unincorporated Areas

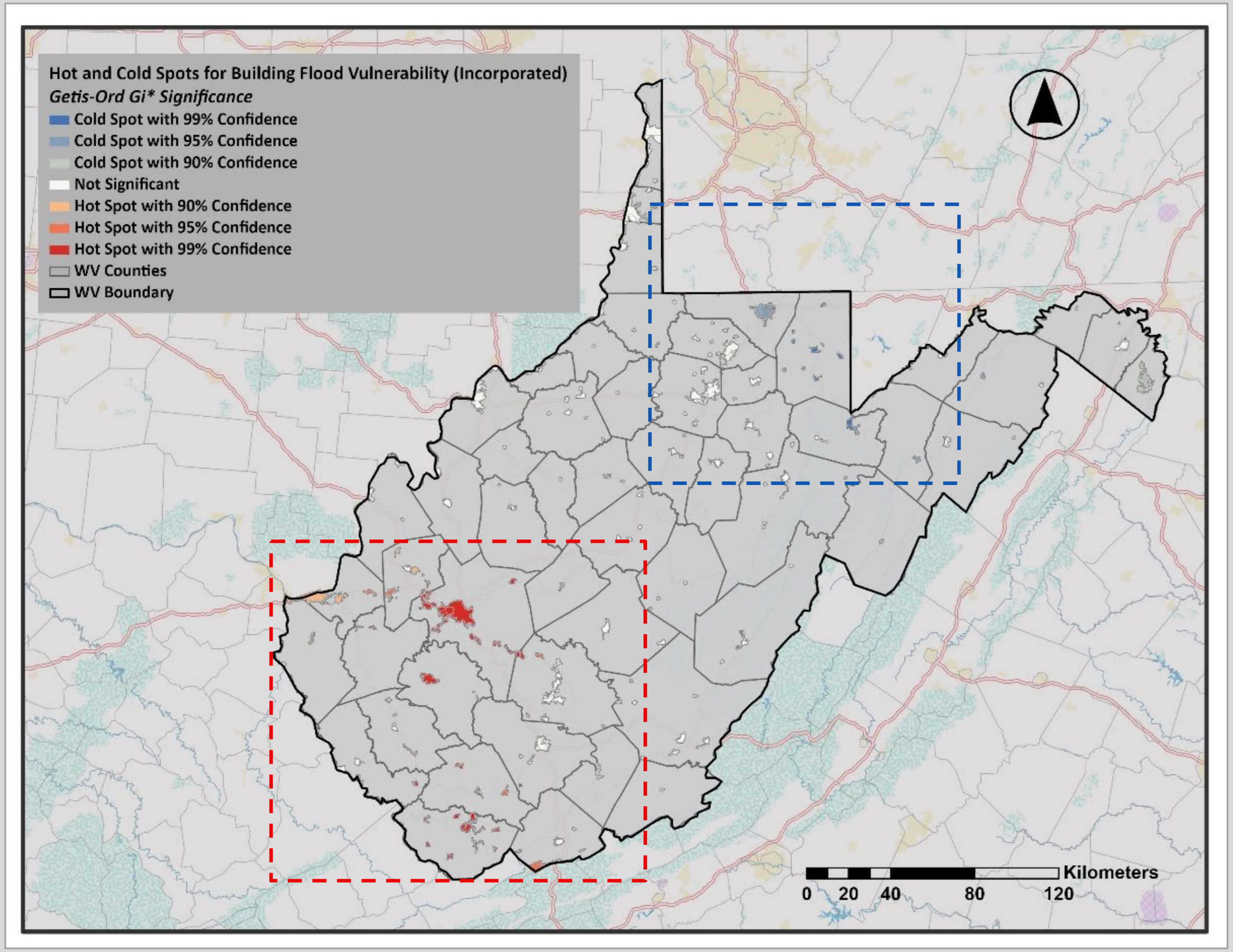
Community Name	subtracting the average of negative-effect indicators from the average of positive-effect indicators	Final Rank of Vulnerability
Wyoming	26.1%	0.992
McDowell	22.6%	0.981
Summers	21.6%	0.962
Wetzel	18.7%	0.943
Lincoln	18.5%	0.924
Webster	17.3%	0.905
Boone	16.7%	0.886
Logan	14.7%	0.867
Wayne	13.4%	0.849
Wyoming	26.1%	0.992

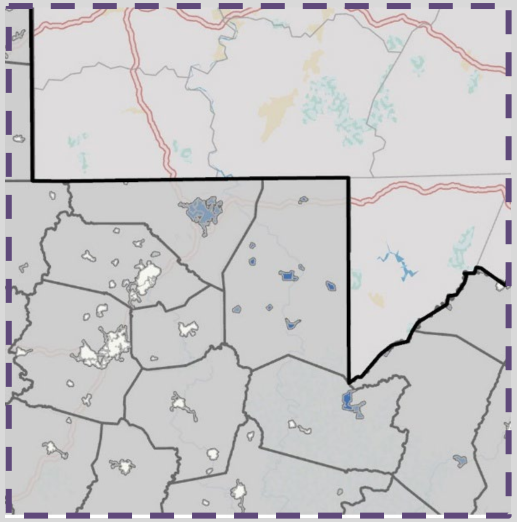


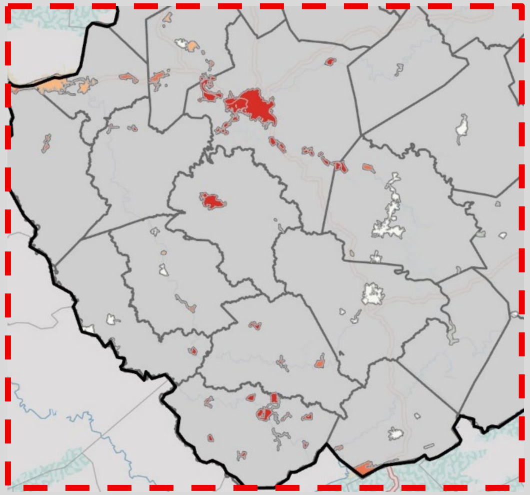
RESULT

Spatial Patterns of Flood Vulnerability in Communities (Physical, Incorporated Areas)

(Distance was calculated based on *Incremental Auto Correlation* in ArcGIS, distance method: Euclidean)

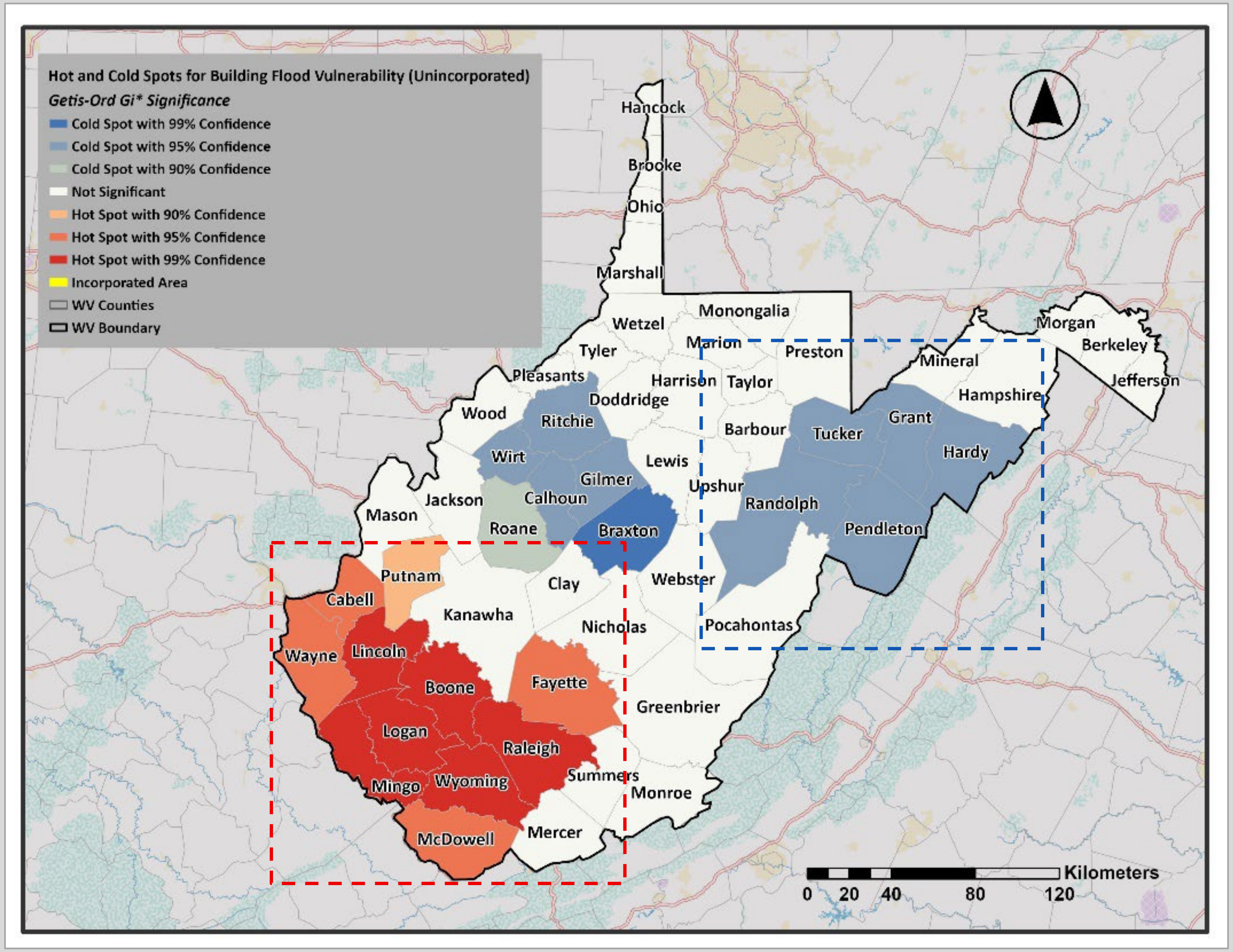


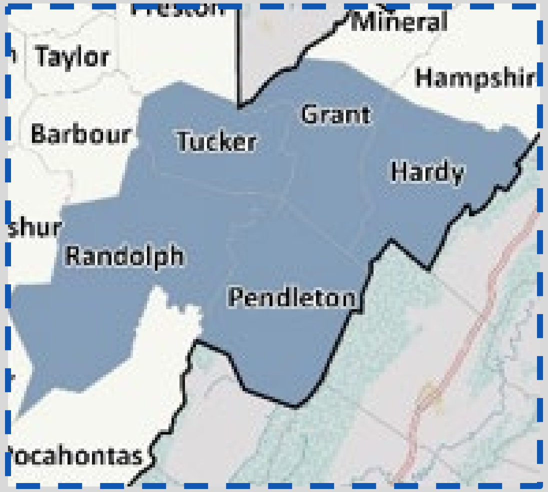


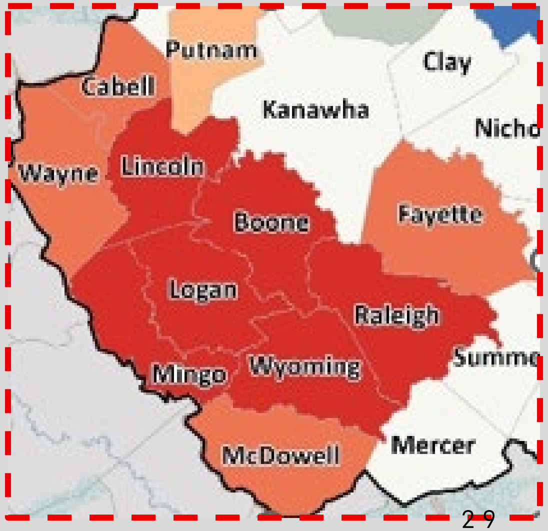


RESULT

Spatial Patterns of Flood Vulnerability in Communities (Physical, Unincorporated Areas)



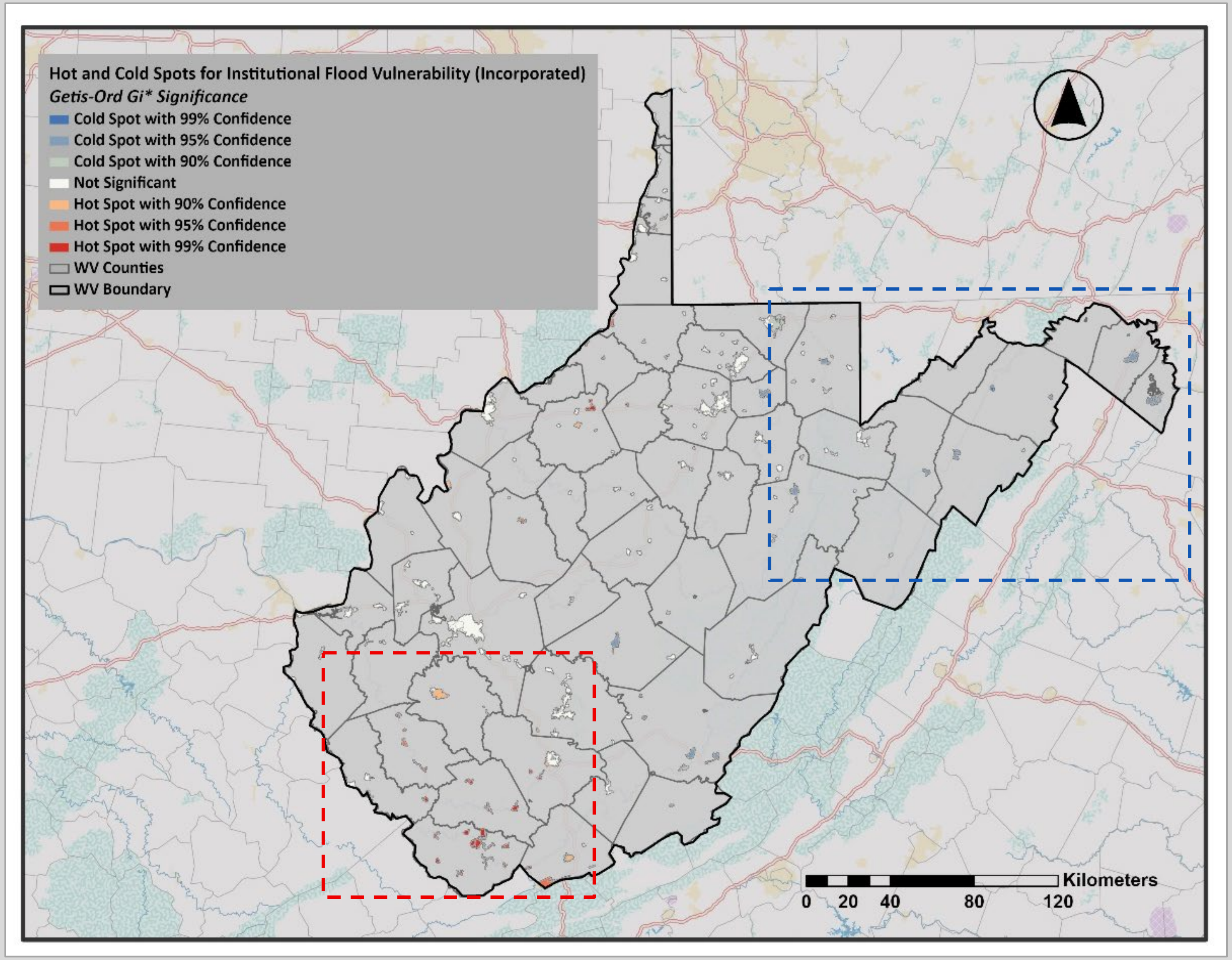


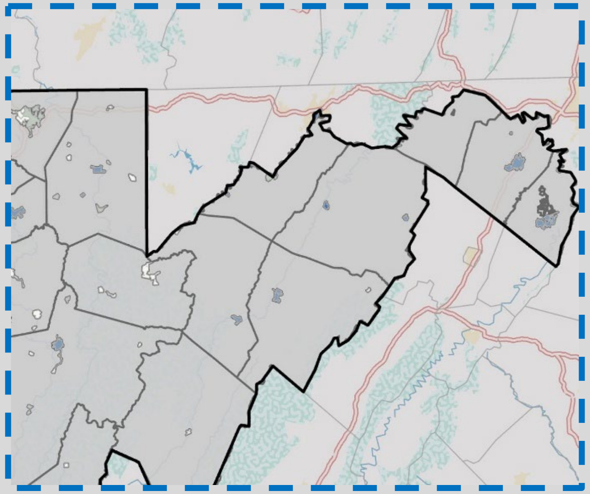


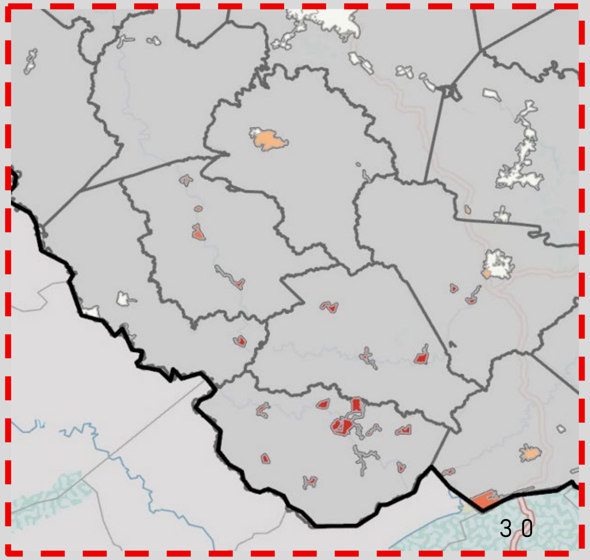
STUDY ONE

RESULT

Spatial Patterns of Flood Vulnerability in Communities (Institutional, Incorporated Areas)





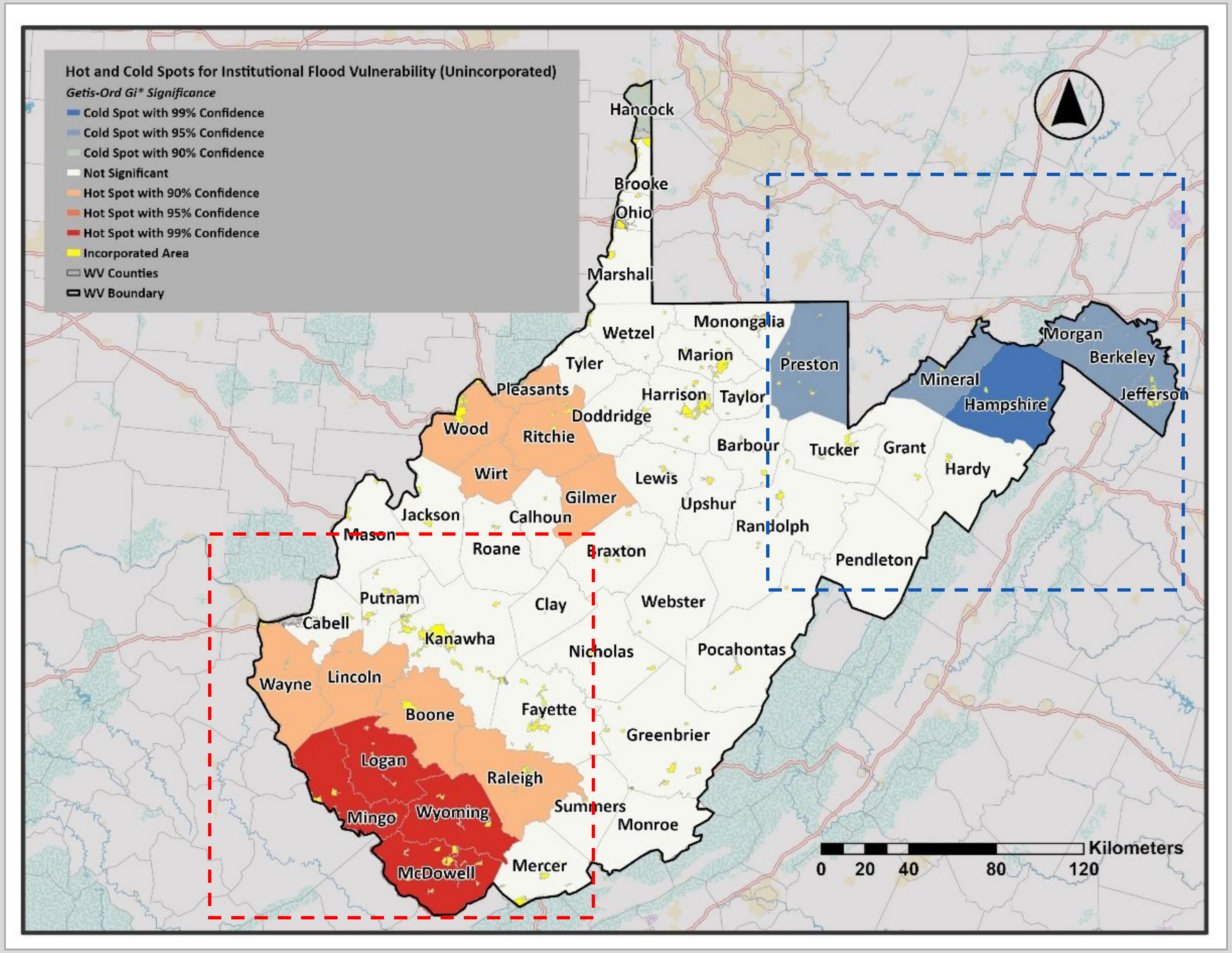


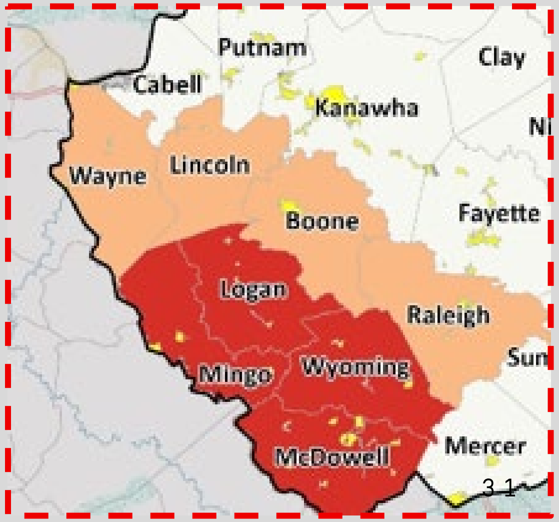
STUDY ONE

STUDY ONE

RESULT

Spatial Patterns of Flood Vulnerability in Communities (Institutional, Unincorporated Areas)





STUDY ONE

KEY FINDINGS

Incorporated

- The results show statistically significant hotspots of building flood vulnerability at the 99% confidence level. Indicating strong spatial clustering of high values.
- Institutional vulnerability exhibits statistically significant clustering at the 99% confidence level, indicating non-random spatial concentration.

Unincorporated

- A clear cluster of high building flood vulnerability, particularly in southern counties. The 99% confidence level indicates that this pattern is statistically significant.
- Institutional vulnerability is significantly concentrated in the southern parts, with hotspots identified at the 99% confidence level.

STUDY ONE

KEY FINDINGS

Incorporated

- ❑ Fifteen percent of incorporated communities fall within statistically significant hotspots of building flood vulnerability at the 99% confidence level.
- ❑ Among these communities, 32% also fall within statistically significant hotspots of institutional vulnerability at the 99% confidence level.

Unincorporated

- ❑ Six out of 55 (11%) unincorporated communities fall within statistically significant hotspots of building flood vulnerability at the 99% confidence level.
- ❑ Among these six communities, three (50%) also fall within statistically significant hotspots of institutional vulnerability at the 99% confidence level.

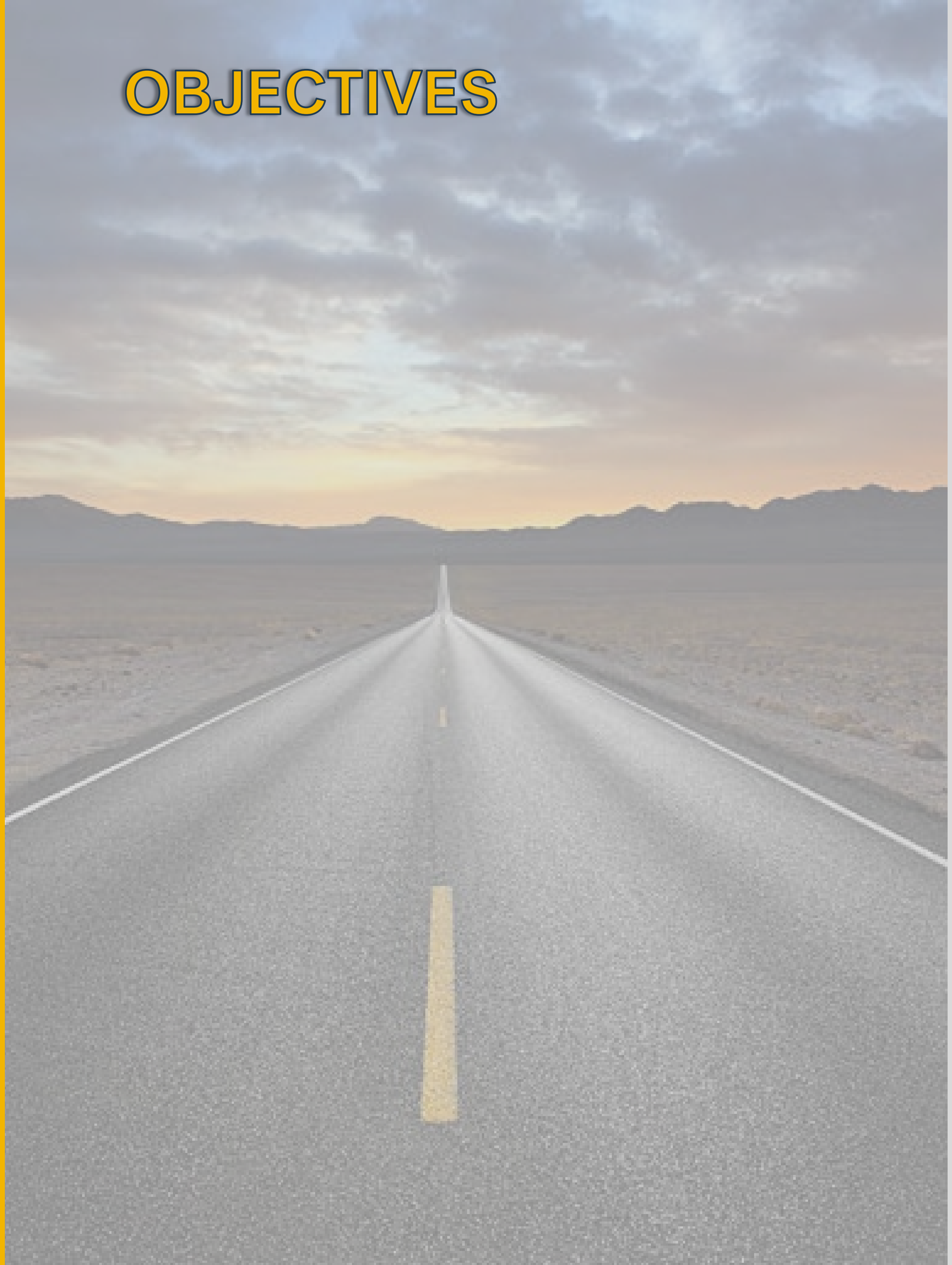
STUDY TWO

CHAPTER4

Applying a Random Forest Modeling Approach to Map Flood Susceptibility in WV, USA

Keywords: Flood vulnerability; Machine Learning; Flood Zone; High Water Marks; West Virginia

OBJECTIVES



STUDY TWO

- A Data-driven approach,
- Identifies flood-prone areas based on observed flooding and environmental conditions,
- Provide a flexible and updatable approach for flood risk assessment.

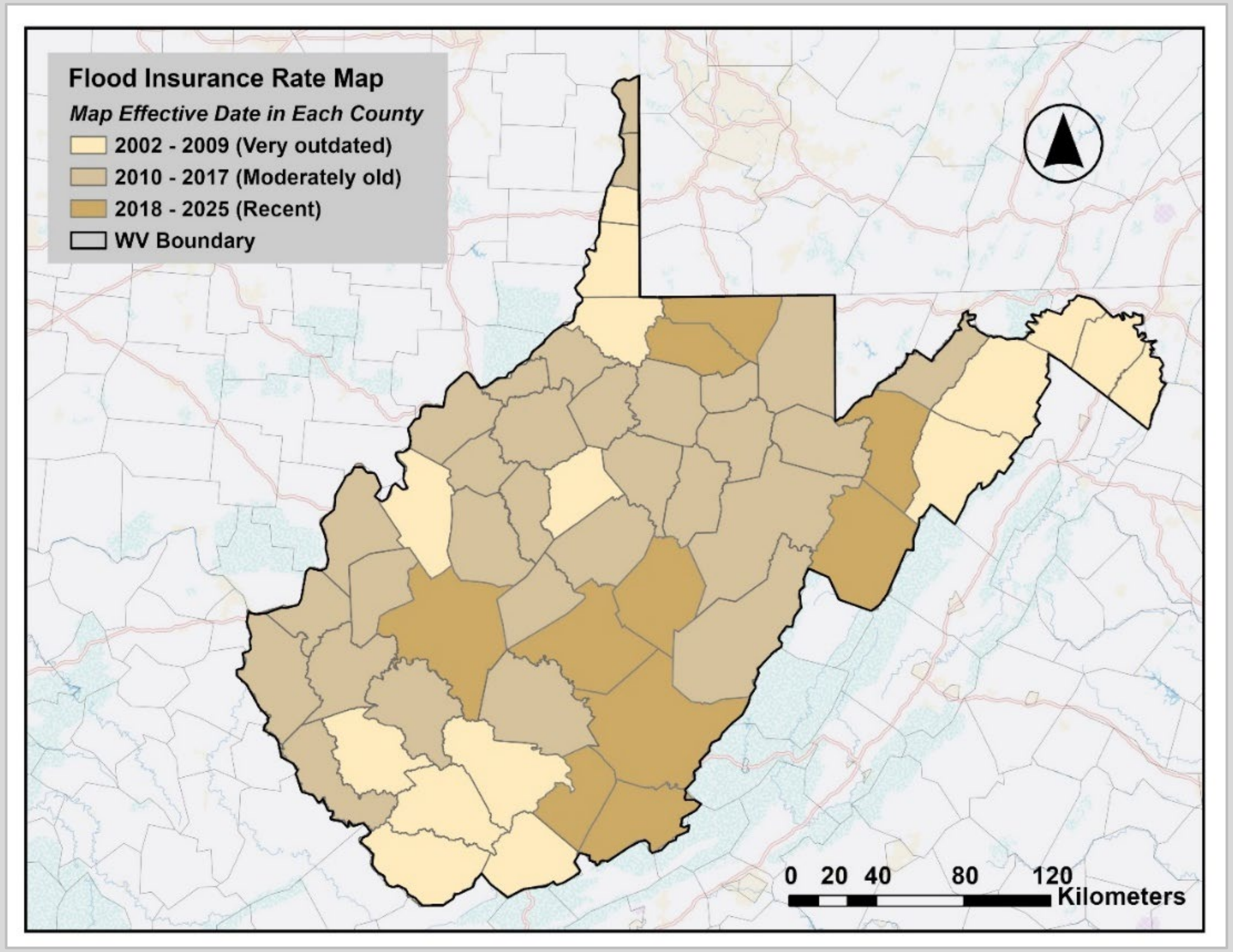
WHY ADDITIONAL FLOOD MAPS?

FEMA's mapping supports insurance, zoning, and building codes, BUT FIRMs categorize risk as inside or outside, a binary distinction that doesn't accurately reflect how risk varies across areas.

Thirty percent of NFIP insurance claims come from areas outside the mapped high-risk flood zones.

FEMA is required to periodically evaluate floodplain areas that require revision, with each area to be assessed at least once within a five-year cycle.

Several WV counties have maps over 10 years old, and some communities lack up-to-date flood maps altogether.



STUDY TWO

STUDY TWO

DATA

Flood Conditioning Factors	Description	Variable Type	Source	Date
Precipitation	Average annual precipitation in inches for three decades	Continuous	USDA	1991 - 2020
Topographic Wetness Index (TWI)	TWI = ln (A / tan(β)) Where: A = upslope contributing area (how much water flows to a pixel) β = local slope (steepness at the pixel) TWI highlights areas where water is likely to pool, flat zones with a lot of flow converging.	Continuous	Calculated by the authors	2025
Impervious surface	The Impervious Descriptor layer provides categorical detail on impervious surfaces by separating road surfaces from other types of built-up urban areas. It classifies impervious pixels from the NLCD land-cover dataset using a supervised classification algorithm, rather than relying on reported urban source data. The layer includes three coded values: 0 for no data, 1 for roads, and 2 for other urban impervious surfaces.	Continuous	MRLC (Multi-Resolution Land Characteristics (MRLC) Consortium)	2023
Land cover	Containing: Open Water, Developed, Open Space, Developed, Low Intensity, Developed, Medium Intensity, Developed, High Intensity, Barren Land (Rock/Sand/Clay), Deciduous Forest, Evergreen Forest, Mixed Forest, Shrub/Scrub, Grassland/Herbaceous, Pasture/Hay, Cultivated Crops, Woody Wetlands, Emergent Herbaceous Wetlands	Categorical (15 classes)	USGS	2023
Ecological land units	Containing: Cliff, Steep Slope, Slope Crest, Upper Slope, Flat Summit, Side slope, Cove, Dry Flat, Moist Flat, Wet Flat, Slope Bottom	Categorical (11 classes)	WV GIS Technical Center	2012
Soil hydrologic group	Soil group in seven classes that describe the rate at which the soil absorbs rainfall	Categorical (seven classes)	USA SSURGO (Imagery Layer and managed by Esri)	Updated on Apr 11, 2025
Soil drainage	Drainage class in sevenclasses, from Excessively drained to Very poorly drained	Categorical (seven classes)	Gridded Soil Survey Geographic (gSSURGO)	2020
WV karst	WVGIS TC	Binary	WV GIS Technical Center	1968

STUDY TWO

METHODOLOGY

Using ArcGIS Pro 3.4.0 and RStudio (R 4.4.1)

- Eight flood conditioning factors were imported into R (predictor variables)
- Predictor rasters were combined into one multi-layer raster object (stacking them)
- 1560 High water mark (HWM) dataset (obtained from the West Virginia GIS Technical Center) , which includes records of floods from 1936 to 2016, was imported into R.
- To reduce uncertainty and prevent selecting locations that might have experienced undocumented flooding, absence points were sampled in the 200-meter buffer around the FEMA 100-year flood zone.

```r
#Load Packages and Set Paths
install.packages("raster")
install.packages("terra", type = "win.binary")
install.packages("randomForest", type = "win.binary")
install.packages("gbm", type = "win.binary")
install.packages("dplyr", type = "win.binary")
install.packages("leaflet", type = "win.binary")
install.packages("sf", type = "win.binary")
install.packages("parallelly", type = "source")
install.packages("future", type = "win.binary")
install.packages("caret", type = "win.binary")
```

```r
library(raster)
library(terra)
library(randomForest)
library(caret)
library(gbm)
library(dplyr)
library(leaflet)
library(sf)
library(tmap)
```

```r
raster_dir   <- "E:/MY_THESIS/DISERTATION_STUDY/PAPER2/GIS_Layers
```

```r
# 4) Align rasters (PROJECT + CROP + MASK)
aligned_dir <- file.path(output_dir, "Aligned_WV_Rasters")
dir.create(aligned_dir, showWarnings = FALSE, recursive = TRUE)

aligned_files <- character(length(files))
```

```r
# Build the raster stack (lightweight)
predict_stack_masked <- rast(aligned_files)
names(predict_stack_masked) <- tools::file_path_sans_ext(basename(aligned_files))
```

```r
# 6) HWM Points: load FULL CSV, compute HWM_ft, filter to WV-only
hwm_full <- read.csv(hwm_csv)
stopifnot(all(c("longitude_", "latitude_H", "elev_ft") %in% names(hwm_full)))

hwm_full$HWM_ft <- as.numeric(gsub("[^0-9.-]", "", hwm_full$elev_ft))
hwm_full <- hwm_full %>%
```

```r
# 7) CLASSIFICATION: create pseudo-absences inside WV
absence_strategy <- "WV_RANDOM"   # main analysis

n_abs     <- nrow(hwm_points_proj) # balanced
buffer_m <- 200                    # avoid absences too close to presences
```

```r
library(randomForest)
set.seed(42)
model <- randomForest(label ~ . -ID, data = df, ntree = 500, importance = TRUE)
print(model)

# Variable Importance:
varImpPlot(model)
```

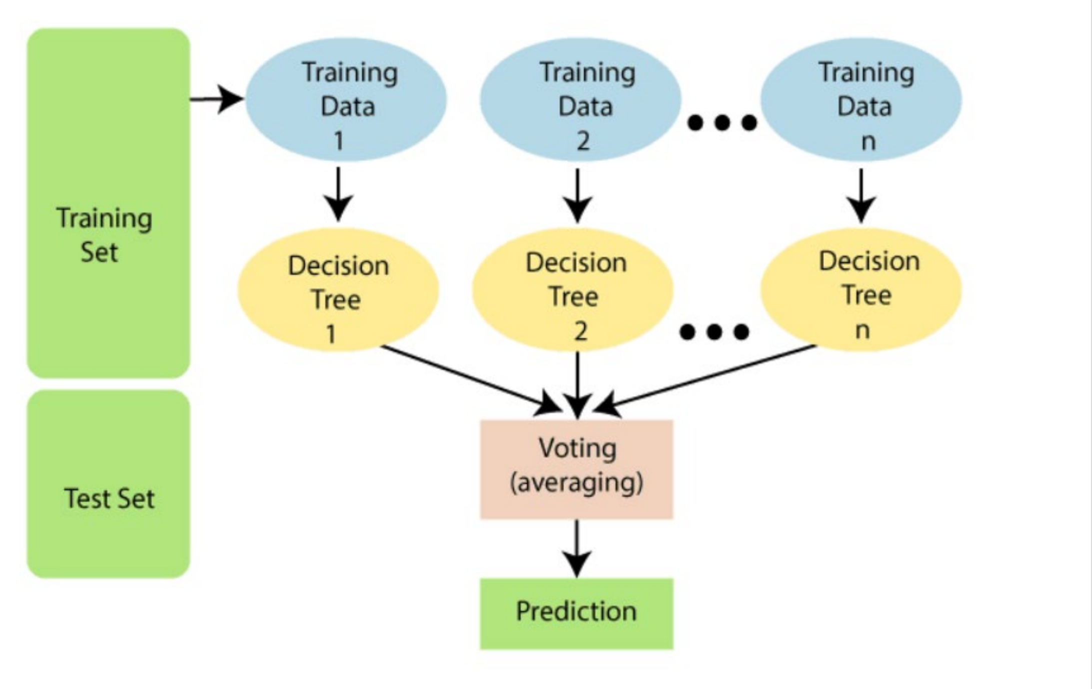
STUDY TWO

METHODOLOGY

- An equal number of absence points (1,560) were randomly sampled (non-flood vs. flood)
- For each flood presence/absence point, the values of the eight flood conditioning factors were extracted from the raster layers.
- Random Forest (RF) is an ensemble learning method that combines many decision trees into a single predictive model
- A decision tree works by repeatedly splitting data into smaller groups based on predictor variables, creating a structure of decision rules.
- The final prediction is made by combining the results of all trees, usually through majority voting in classification problems.

```
# 7) CLASSIFICATION: create pseudo-absences inside WV
absence_strategy <- "WV_RANDOM"   # main analysis

n_abs     <- nrow(hwm_points_proj) # balanced
buffer_m <- 200                    # avoid absences too close to presences
```

```
# Extract predictors
clf_df <- terra::extract(predict_stack_masked, terra::vect(clf_pts), ID = FALSE)
clf_df$label <- factor(clf_pts$label, levels = c(0,1))
```



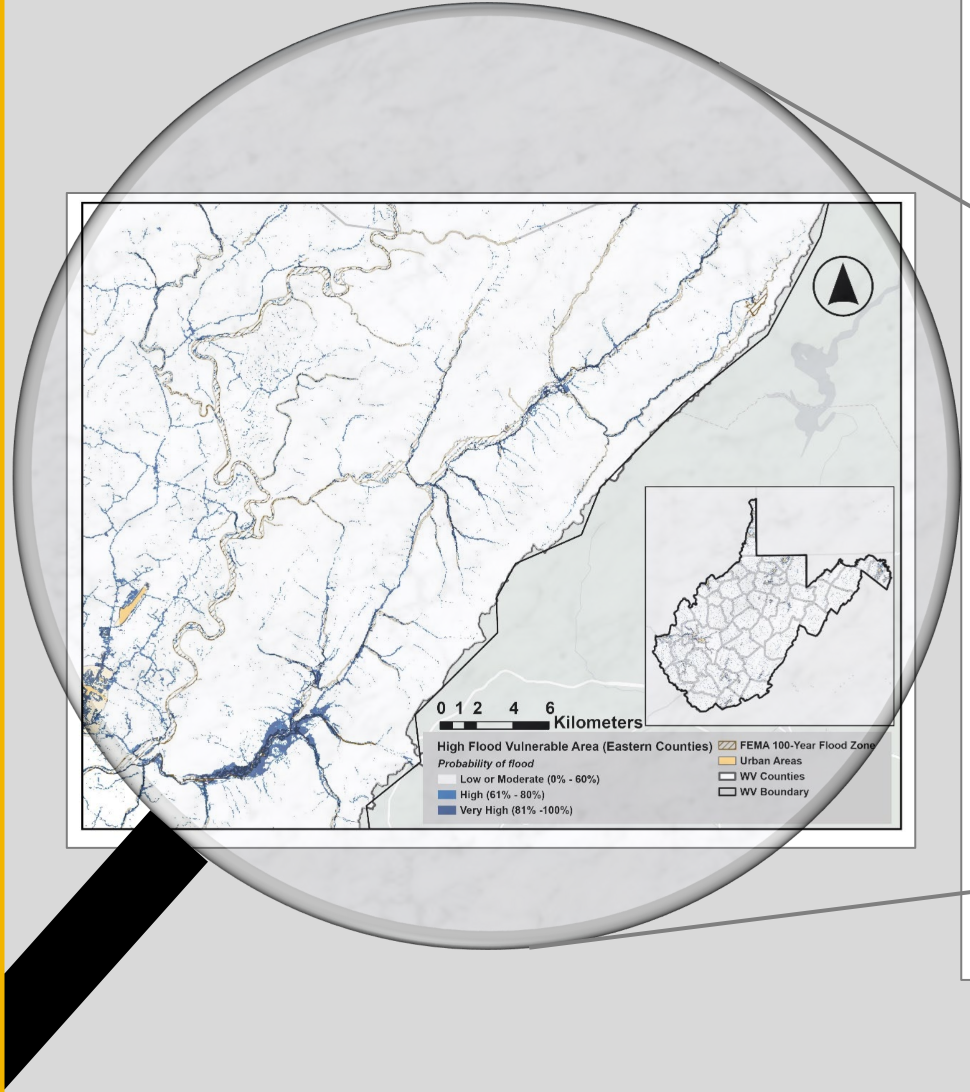
Source: AlmaBetter (n.d.), Random Forest Algorithm in Machine Learning

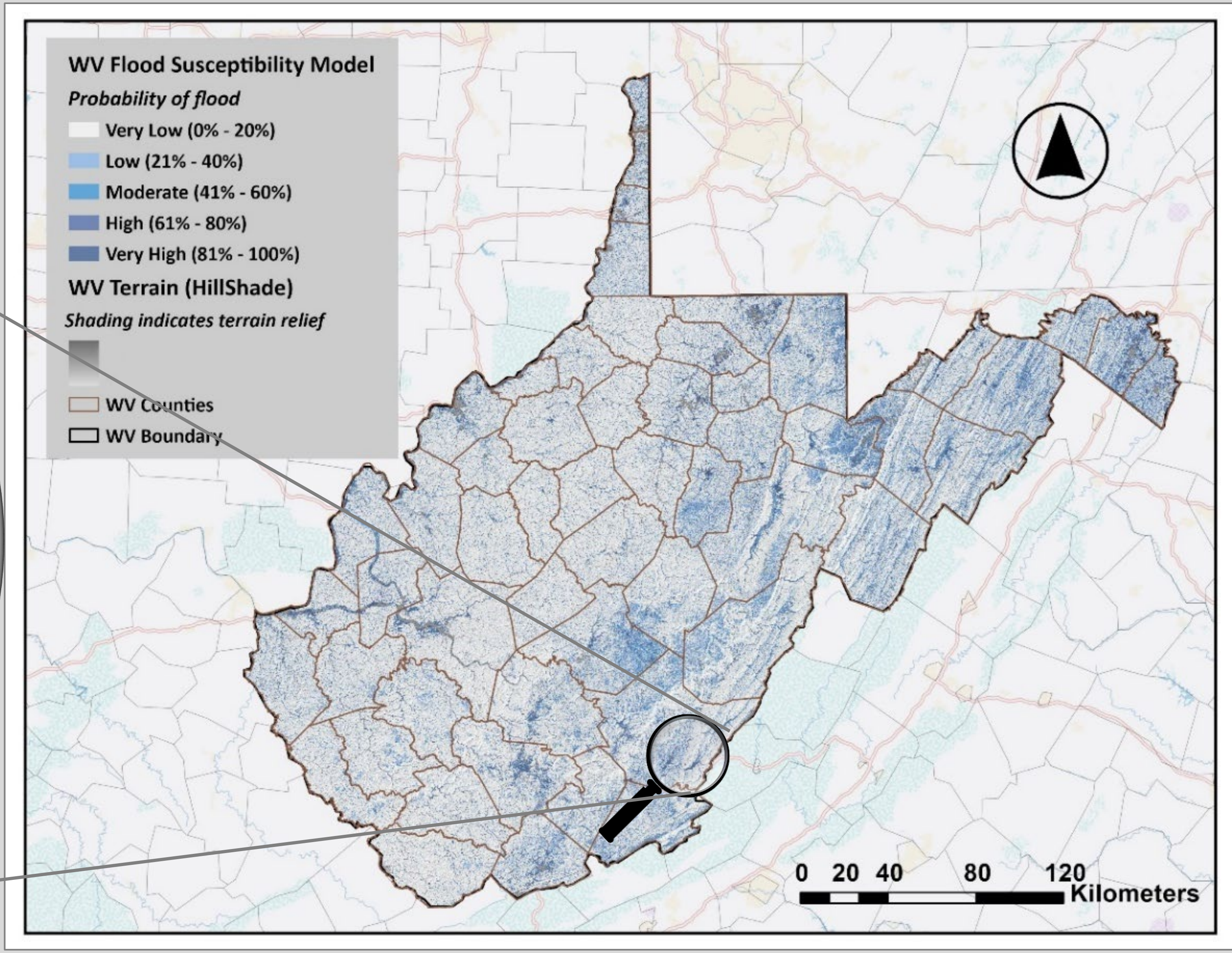
```
# Train/test split
set.seed(42)
train_idx <- caret::createDataPartition(clf_df$label, p = 0.7, list = FALSE)
train_clf <- clf_df[train_idx, ]
test_clf  <- clf_df[-train_idx, ]
```

As the number of trees increases, the model becomes more stable.

```
# RF classification
rf_clf <- randomForest(
  label ~ .,
  data = train_clf,
  ntree = 1000,
  mtry = best_mtry,
  importance = TRUE
)
```

RESULT


0 1 2 4 6
Kilometers
High Flood Vulnerable Area (Eastern Counties)
Probability of flood
Low or Moderate (0% - 60%)
High (61% - 80%)
Very High (81% -100%)
FEMA 100-Year Flood Zone
Urban Areas
WV Counties
WV Boundary


WV Flood Susceptibility Model
Probability of flood
Very Low (0% - 20%)
Low (21% - 40%)
Moderate (41% - 60%)
High (61% - 80%)
Very High (81% - 100%)
WV Terrain (HillShade)
Shading indicates terrain relief
WV Counties
WV Boundary
0 20 40 80 120
Kilometers

STUDY TWO

RESULT

Conditional Permutation Importance (PermImp)

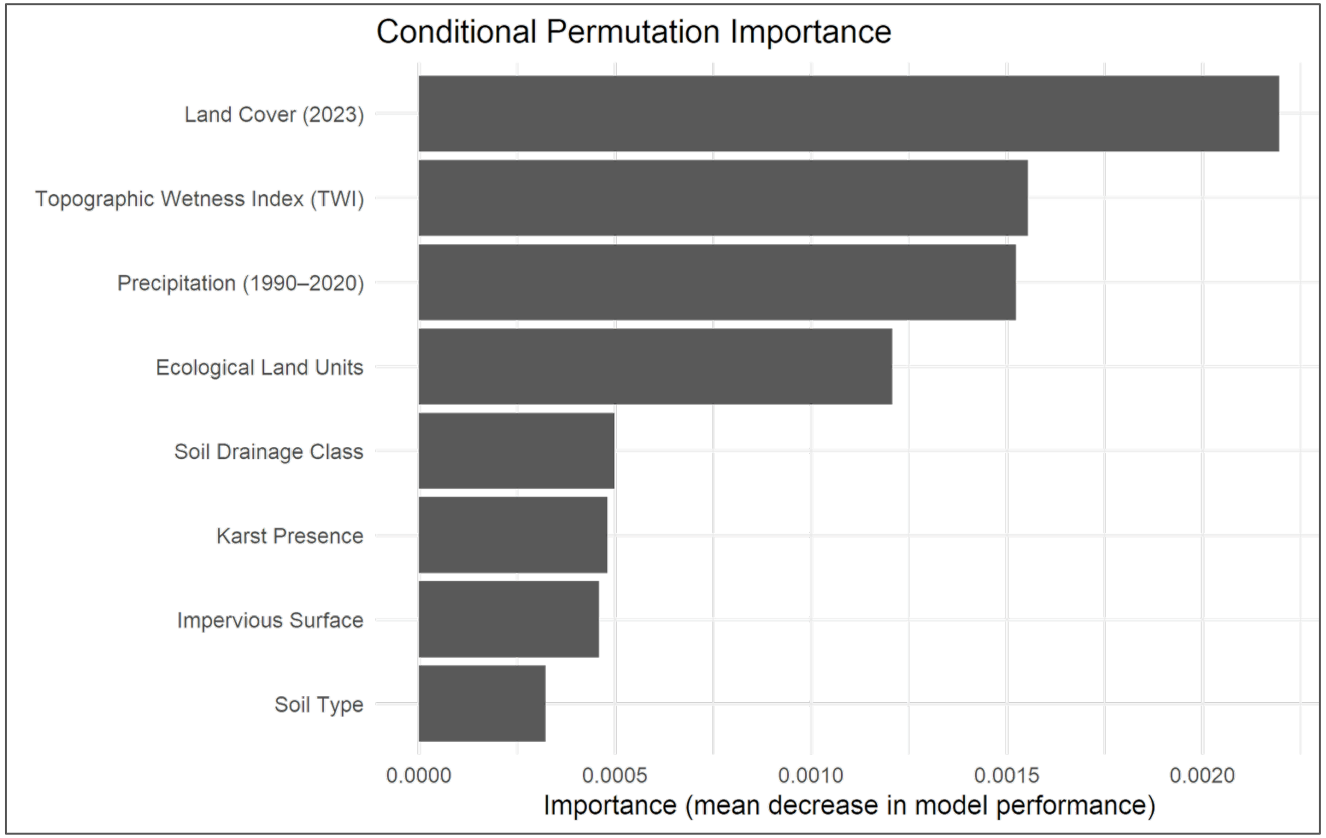
How did different flood conditioning factors influence the model predictions?

Evaluates the contribution of each variable by measuring how much the model's performance decreases when the values of that variable are randomly permuted, while accounting for correlations among predictors.

Land cover is the most influential factor,

followed by the Topographic Wetness Index,

And Precipitation comes third



MODEL PERFORMANCE

Accuracy, expressed as a percentage, represents the proportion of correctly classified locations.

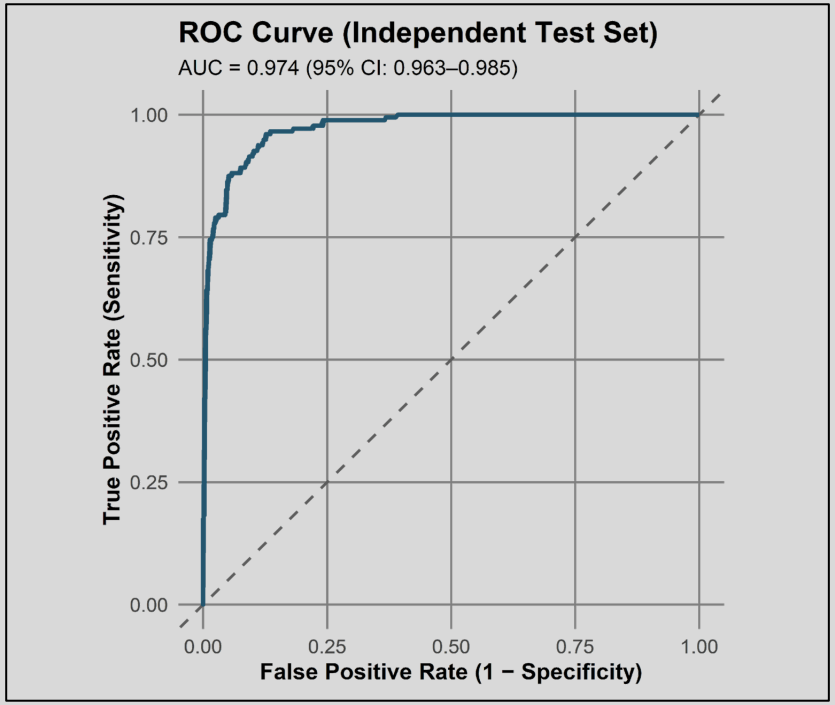
Sensitivity measures the model's ability to correctly identify flooded and non-flooded locations .

How good is the model at separating flooded vs non-flooded areas at ALL possible thresholds?

Model discrimination ability was evaluated using the Receiver Operating Characteristic (ROC) curve.

True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity).

The Area Under the Curve (AUC) provides a single summary measure of this discrimination ability: values closer to 1 indicate stronger predictive performance.



The model gives higher predicted probabilities to locations that actually experienced flooding.

STUDY TWO

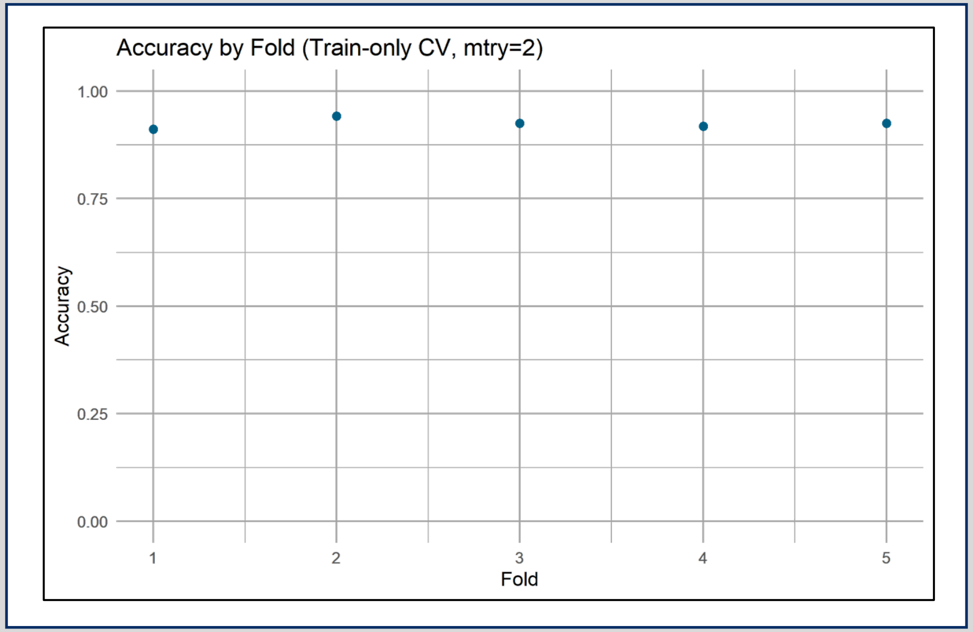
Model Performance

```
          Reference
Prediction   0   1
         0 425  22
         1  26 154

               Accuracy : 0.9234
                 95% CI : (0.8998, 0.943)
    No Information Rate : 0.7193
    P-Value [Acc > NIR] : <2e-16

                  Kappa : 0.8117

 Mcnemar's Test P-Value : 0.665

            Sensitivity : 0.8750
            Specificity : 0.9424
         Pos Pred Value : 0.8556
         Neg Pred Value : 0.9508
             Prevalence : 0.2807
         Detection Rate : 0.2456
   Detection Prevalence : 0.2871
      Balanced Accuracy : 0.9087

       'Positive' Class : 1
```

Five-fold cross-validation was conducted within the training dataset.

The training data were divided into five equal subsets (folds): four folds were used to fit the model, and the remaining fold was used for validation.

The process was repeated five times so that each fold served once as validation data.



The model achieved high accuracy across all folds, ranging from about 92% to 94%, with an average accuracy of approximately 93%.

Fold	AUC	Accuracy	Kappa	Sensitivity	Specificity	Balanced Accuracy
1	0.963	0.918	0.804	0.898	0.926	0.912
2	0.969	0.923	0.815	0.898	0.933	0.915
3	0.974	0.923	0.813	0.881	0.940	0.910
4	0.964	0.940	0.850	0.880	0.963	0.921
5	0.979	0.925	0.819	0.897	0.936	0.917

The confusion matrix provides a detailed view of how the model classified flooded and non-flooded areas.

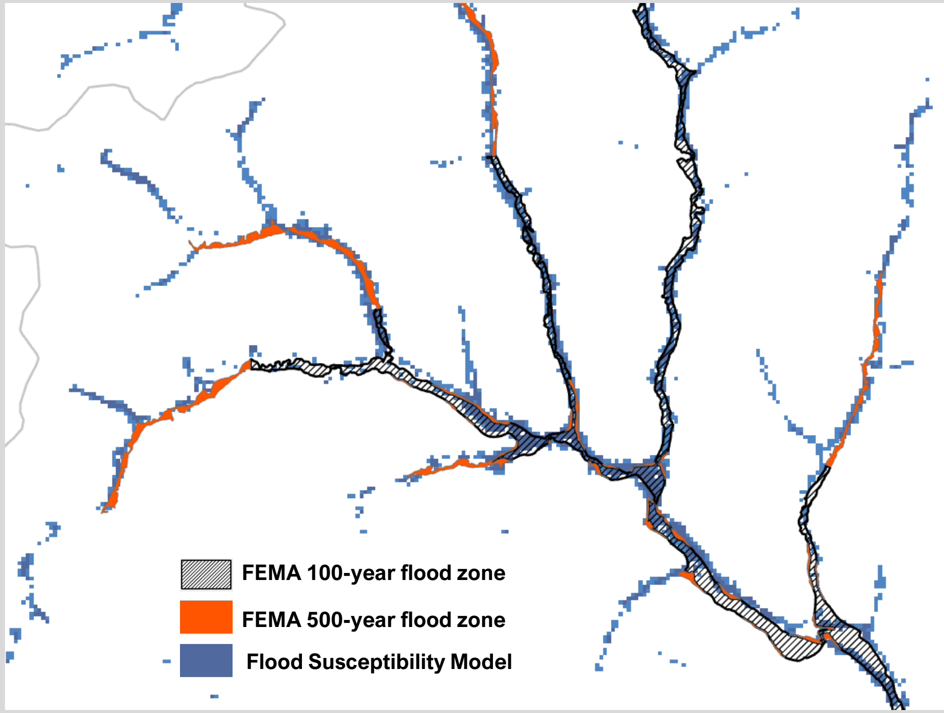
	Observed: non-flood	Observed: flood
Predicted: non-flood	425	22
Predicted: flood	26	154

The model correctly identified 87.5% of flooded locations (sensitivity) and 92.4% of non-flooded locations (specificity)

KEY FINDINGS

- ❑ The model shows strong predictive performance (Accuracy ≈ 92%).

- ❑ Although the model was made based on natural indicators, its coverage and the pattern of flooding are more similar to the FEMA 100-year flood zone, and not the 500-year flood zone. While in some areas some overlap between the model and 500-year flood zone is seen.



- ❑ Flood susceptibility is not limited to FEMA flood zones.

- ❑ High-susceptibility areas are mainly concentrated along river valleys and mountainous regions, particularly in the eastern and southern parts of West Virginia.

STUDY TWO

STUDY THREE

CHAPTER5

Abstract

Flooding ost persistent and destructive natural hazards in West Virginia.
Howev le assessments that connect social vulnerability with physical
flood v limited. Existing floodplain management plans often focus on
infrastr ogy, overlooking how socioeconomic disparities shape resilience.
This stud od resilience in West Virginia communities by connecting socioeconomic vulnerability with physical flood vulnerability. Using data from the American Community Survey (ACS) and state floodplain maps, we developed a Socioeconomic Vulnerability Index (SEVI) and combined it with physical indicators, such as the percentage of residential buildings in the 100-year floodplain, the share of mobile homes in flood-prone areas, the presence of essential facilities and community assets within flood zones, and the proportion of roads submerged by at least one foot of water. Incorporated and unincorporated communities were analyzed separately to reflect differences in governance and service capacity. The results reveal that high flood vulnerability areas often coincide with high socioeconomic vulnerability, especially in the southern and southeastern counties, where long-term economic decline has increased risks. Communities like McDowell and Mingo face a combined challenge of social and physical vulnerability, adding pressure

Keywords: flood vulnerability; socioeconomic vulnerability; community resilience; spatial analysis; West Virginia

sustainability

IMPACT FACTOR 3.3

CITESCORE 7.7

Article

Assessing Flood Resilience in West Virginia Communities Using Socioeconomic and Physical Vulnerability Indicators: Implications for Sustainable Planning

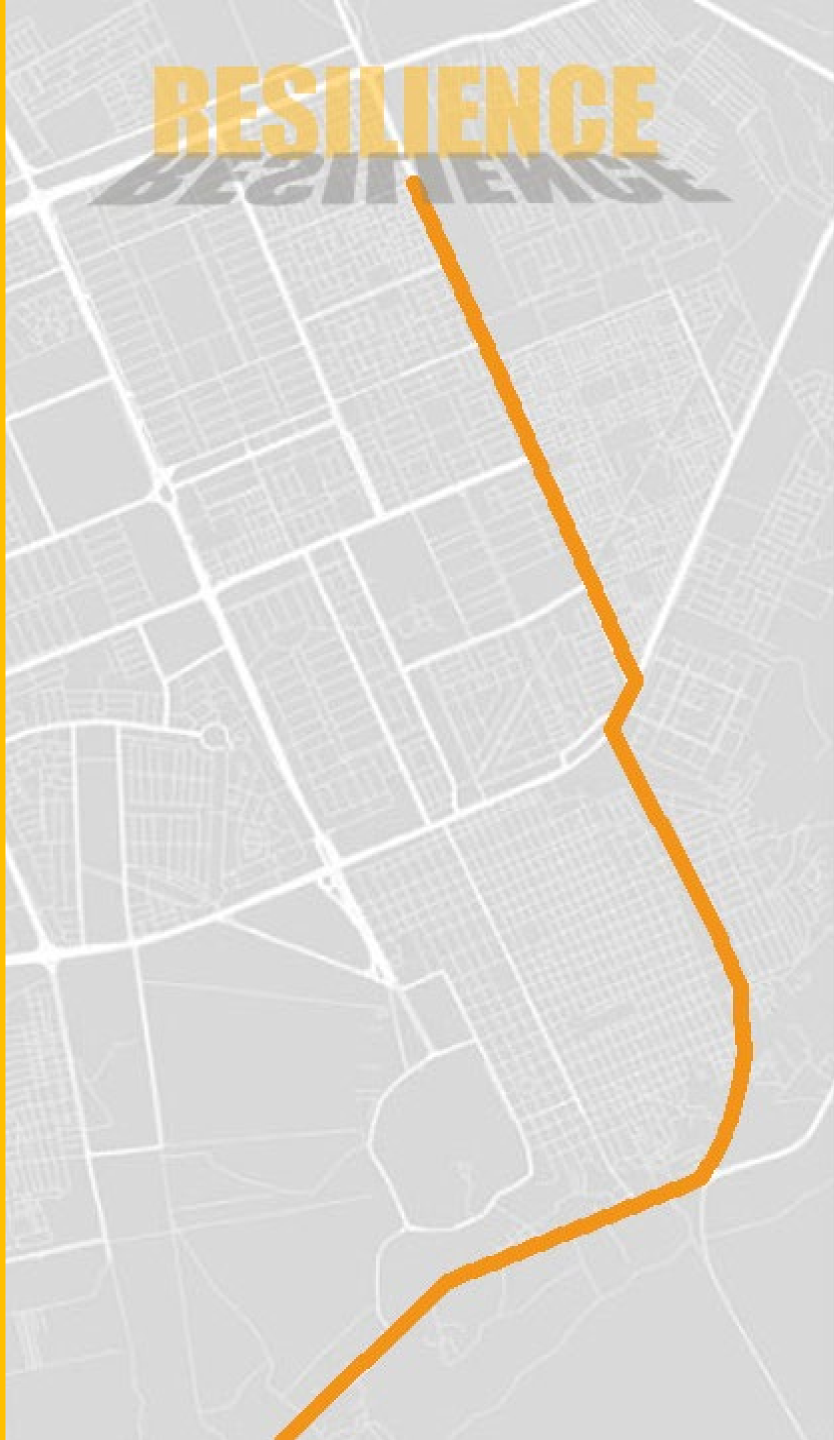
Annie Mahmoudi, Michael J. Dougherty, Peter M. Butler and Michael P. Strager

Sustainability **2026**, *18*(7), 3321; https://doi.org/10.3390/su18073321

MDPI

https://doi.org/10.3390/su18073321

STUDY THREE



OBJECTIVES

Developing Socioeconomic Vulnerability Index for WV Communities

Identifying the overlaps between flood vulnerability and socioeconomic vulnerability across incorporated and unincorporated areas.

STUDY THREE

DATA

Socioeconomic indicators

Socioeconomic data were obtained from the 2021 American Community Survey (ACS) 5-year estimates.

West Virginia GIS Technical Center (WVGISTC)
(100-year and 500-year floodplains and structures located in the flood zone)

STUDY THREE

METHODOLOGY

Socioeconomic indicators

Using TidyCensus

```r
install.packages("tidycensus", dep=T)
library(tidycensus)
```

```r
# Set your API key
census_api_key("88d804c4ea24d3d1d23d6f703c9befe91ffe72e4", install = TRUE, overwrite=TRUE)
```

Popular for its ability to acquire, process, and analyze demographic and socioeconomic data.
Connecting with the Census Bureau's Application Programming Interface (API)

Selected variables based on vulnerability assessment frameworks like the Social Vulnerability Index (SoVI), FEMA's Resilience Analysis and Planning Tool (RAPT), and related flood vulnerability studies.

Demographic Indicators	Percentage of the population younger than 15 or older than 60 (vulnerable age groups)
	Percentage of the population with a disability (related to independent living, self-care, ambulatory, cognitive, vision, or hearing difficulties)
	Percentage of uninsured population
Economic Indicators	Percentage of households with an income below $50,000
	Percentage of unemployed population
	Percentage of households below the poverty line
	Percentage of households receiving assistance (food stamps/SNAP)
Education Indicator	Percentage of the population with less than a high school education
Housing Indicator	Percentage of rental residential units
	Percentage of overcrowded households (with less than one room per person)
	Percentage of mobile homes in housing units
Access & Infrastructure Indicators	Percentage of households without a vehicle

METHODOLOGY

Physical indicators

- ❑ Ratio of residential buildings in 100-year flood zone
- ❑ Ratio of manufactured buildings (mobile homes) in the 100-year flood zone
- ❑ Ratio of essential facilities in the 100 and 500-year flood zones (hospitals, schools, nursing homes, fire stations, police stations, and E911 centers)
- ❑ Ratio of community assets in the 100-year flood zones (religious organizations, post-secondary educational facilities, government buildings, and utilities)
- ❑ Ratio of Roads Inundated by Flood Water of one Foot or more

STUDY THREE

METHODOLOGY

Physical indicators

All indicators were assigned equal weight when constructing the Socioeconomic Vulnerability Index.

Percentage_of_household_with_income_lower_50k	percentage_unemployment	Percentage_education_lower_highschool	Percentage_of_Rental_Residential	Percentage_Uninsured_Population	Mobilehome_Percentage	Vulnerable_Population_Percentage	Poverty_Percentage	Disability_population_Percentage	Percentage_Gov_Assistance	Percentage_with_No_Vehicle_Access	Percentage_of_Overcrowding_Households	Socioeconomic_Index_Average_Percentage	Ranking
84.21%	16.42%	100.00%	50.00%	53.78%	60.81%	63%	12.3%	10.9%	61.4%	64.91%	0.00%	=(SUM(E2:P2))/12	1

$$Rankc = RANK(Sc,\{S_1,S_2,\ldots,Sn\},0)$$

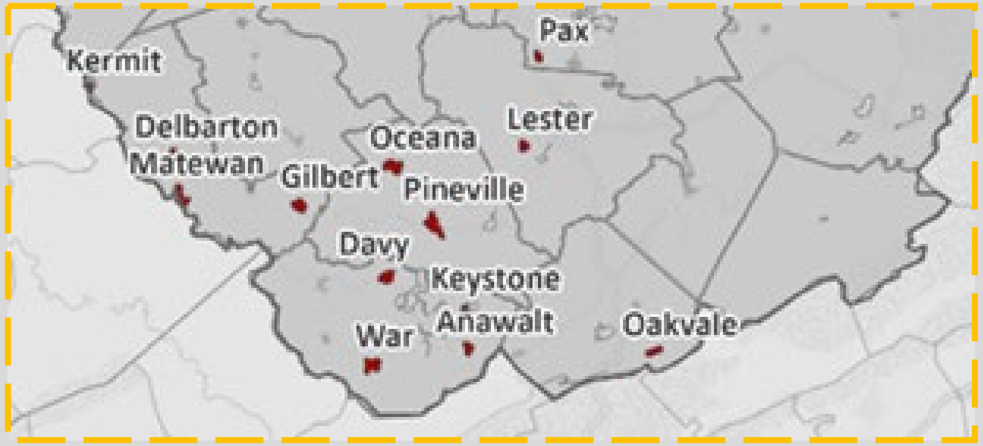
- *$Rank_c$ is the rank of community c*
- *S_c refers to the socioeconomic index average percentage (s) for community c*
- *$\{S_1,S_2,\ldots,S_n\}$ is the set of average scores for all communities*
- *The final argument, 0, indicates descending order (i.e., the highest vulnerability score gets rank 1).*

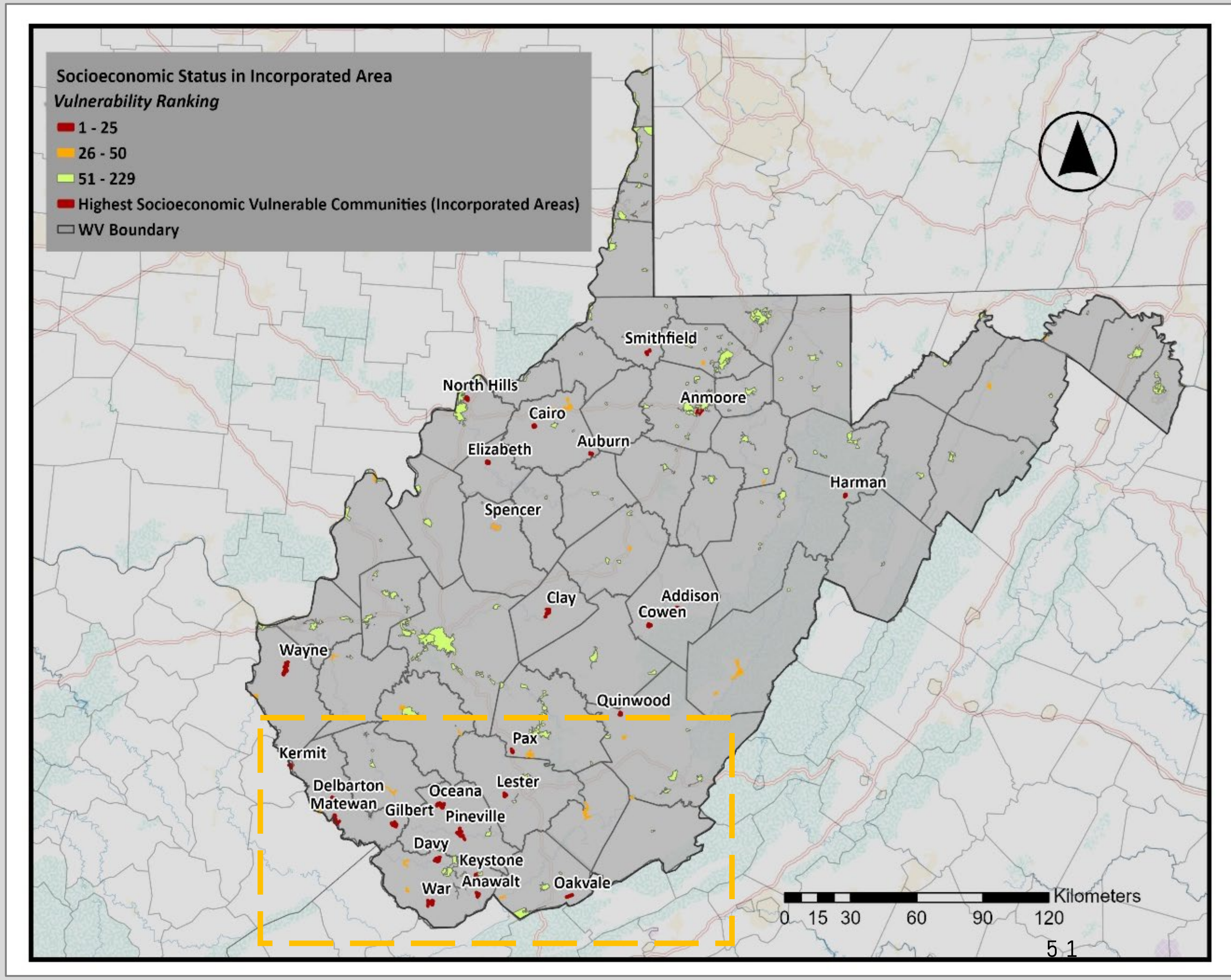
STUDY THREE

RESULT

Socioeconomic Vulnerability in Incorporated Areas

Uneven distribution of vulnerability. Notably, many vulnerable areas are located in the southern part of the state.



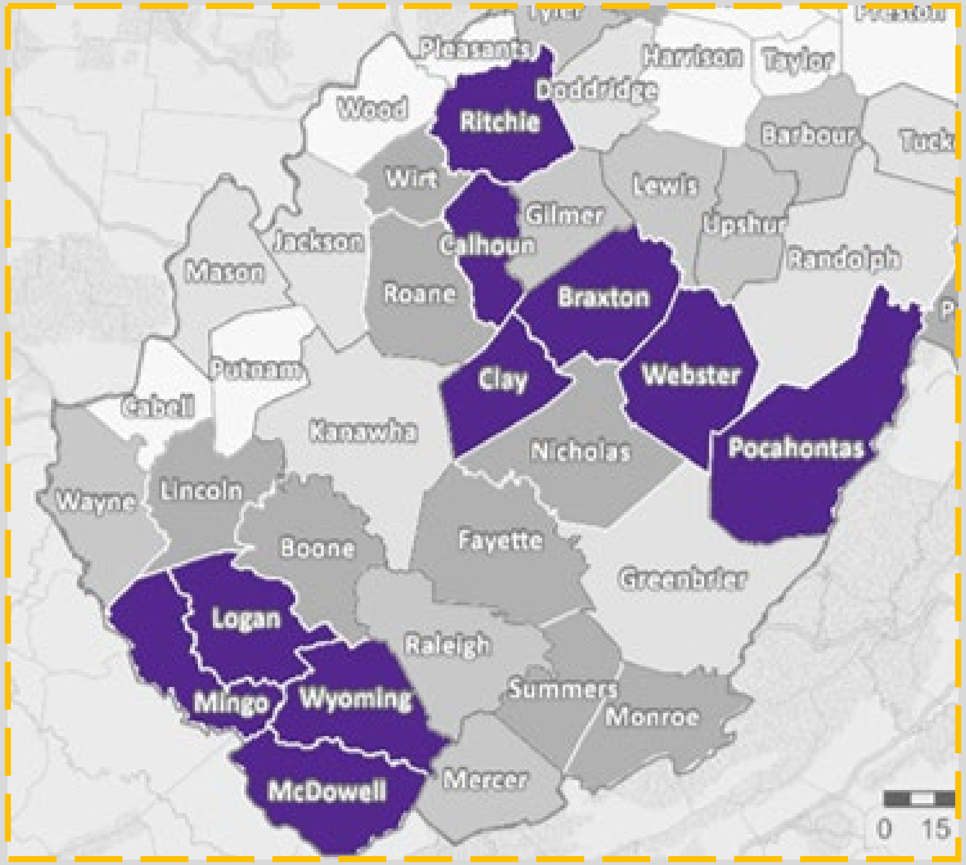


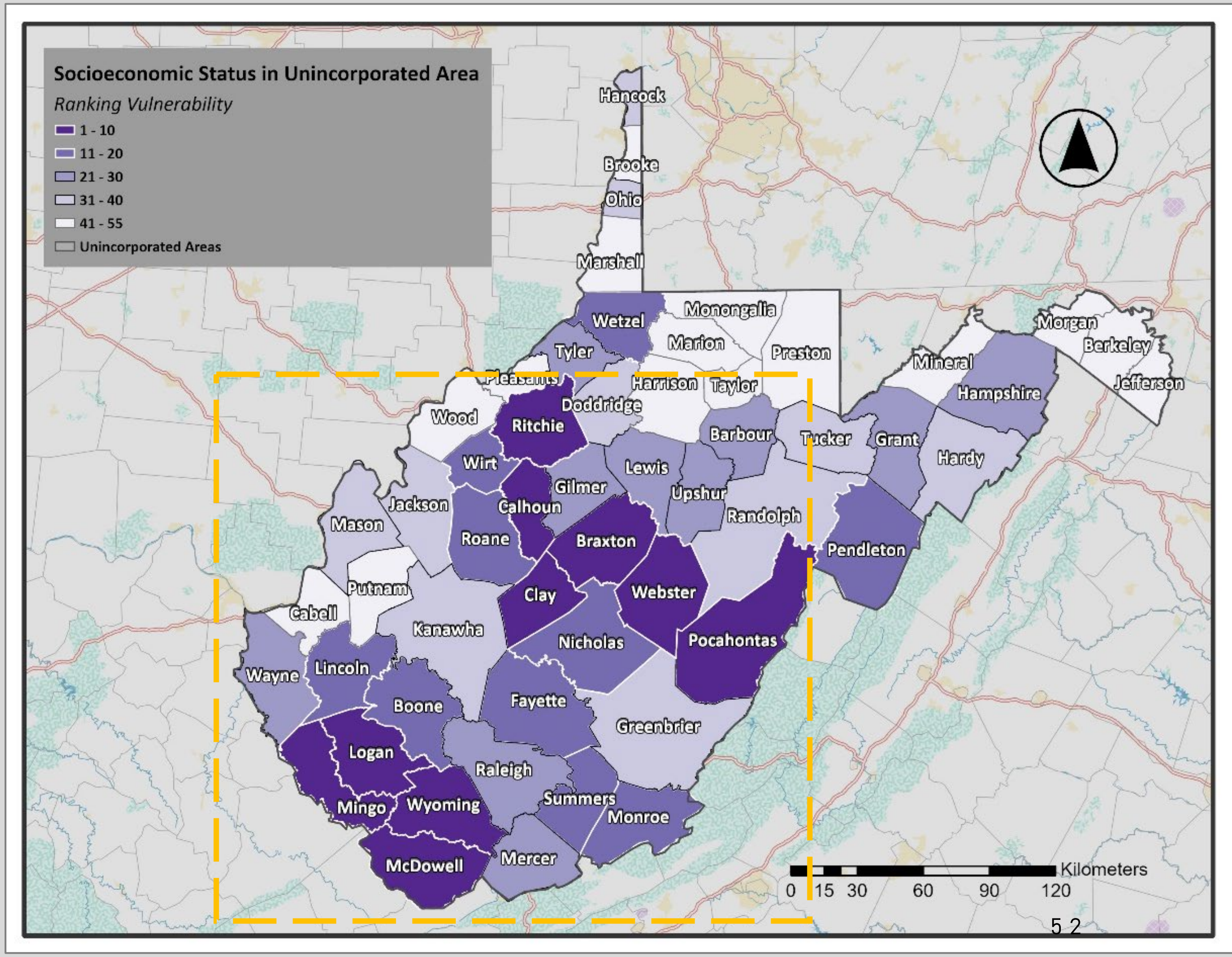
STUDY THREE

RESULT

Socioeconomic Vulnerability in Unincorporated Areas

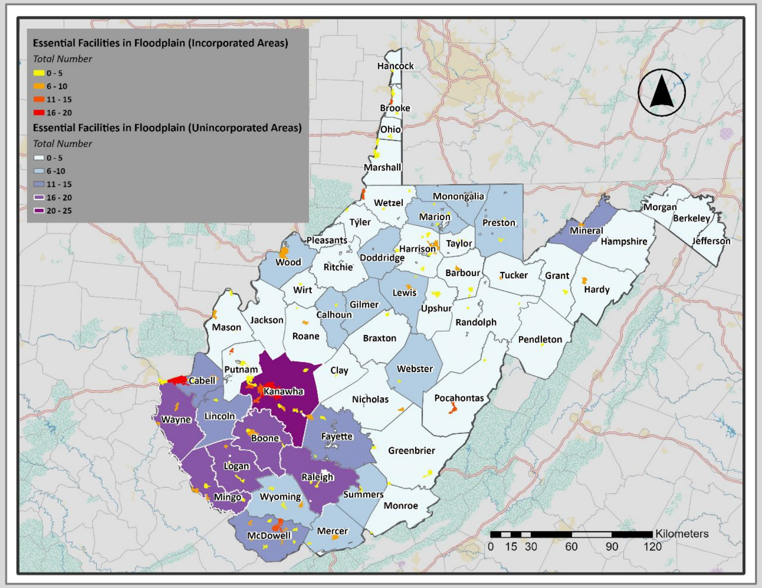
At-risk unincorporated areas are primarily located in the southern and central parts of the state.

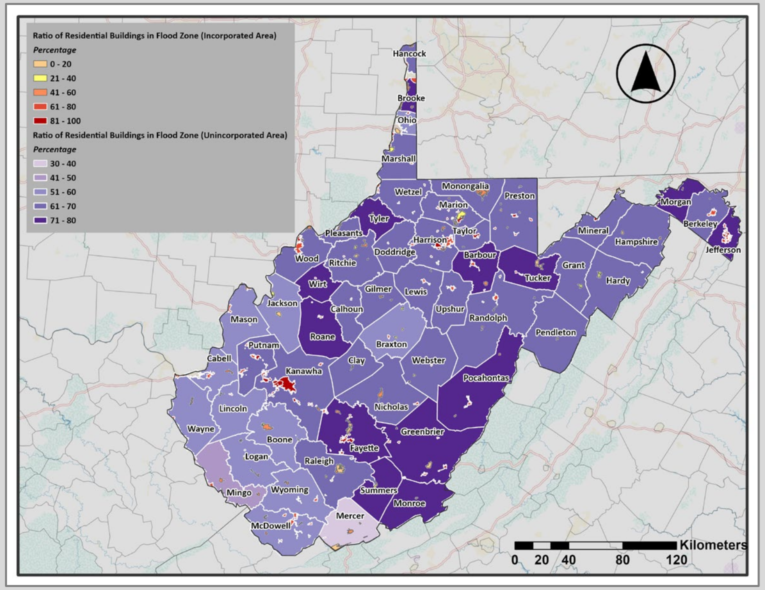


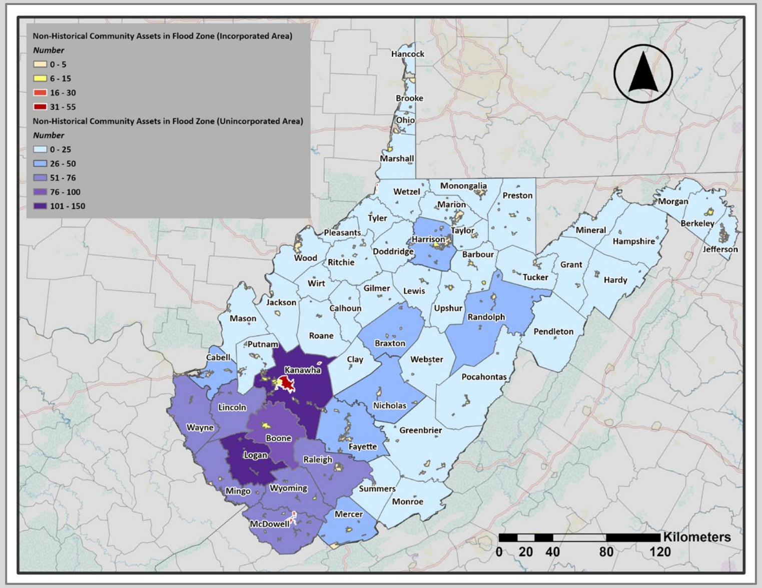


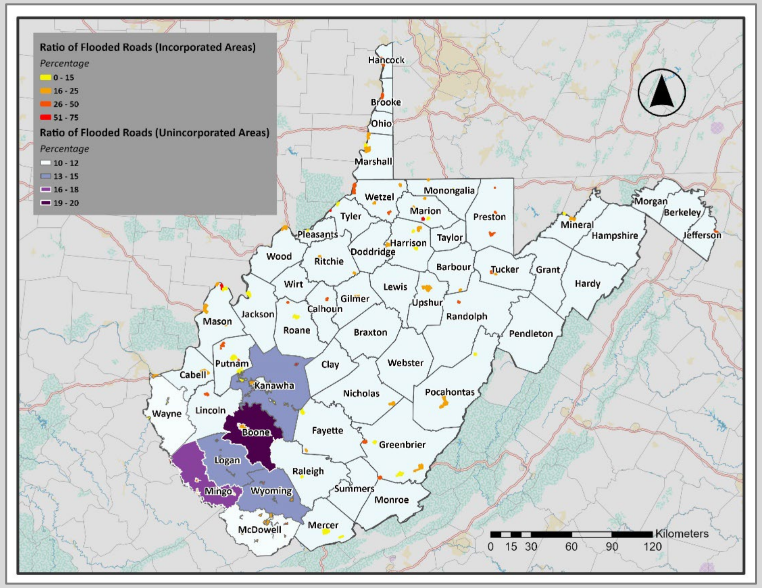
RESULT

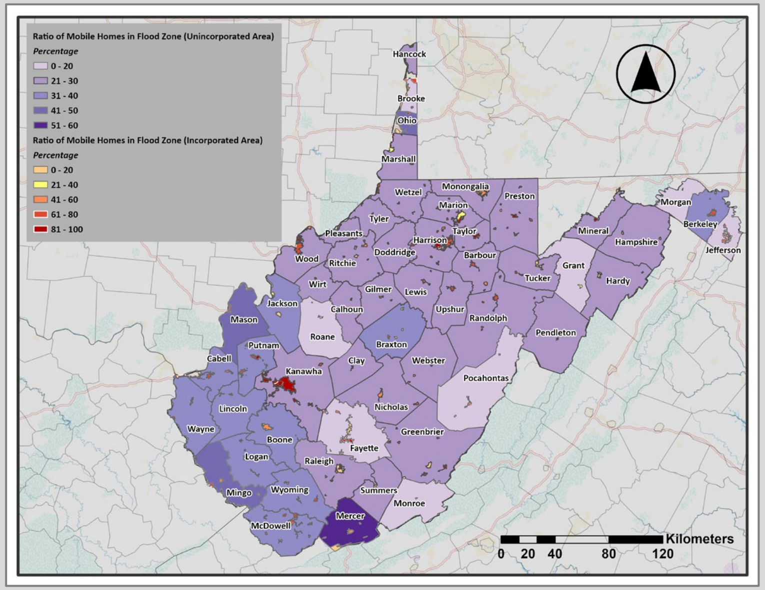
Physical Vulnerability









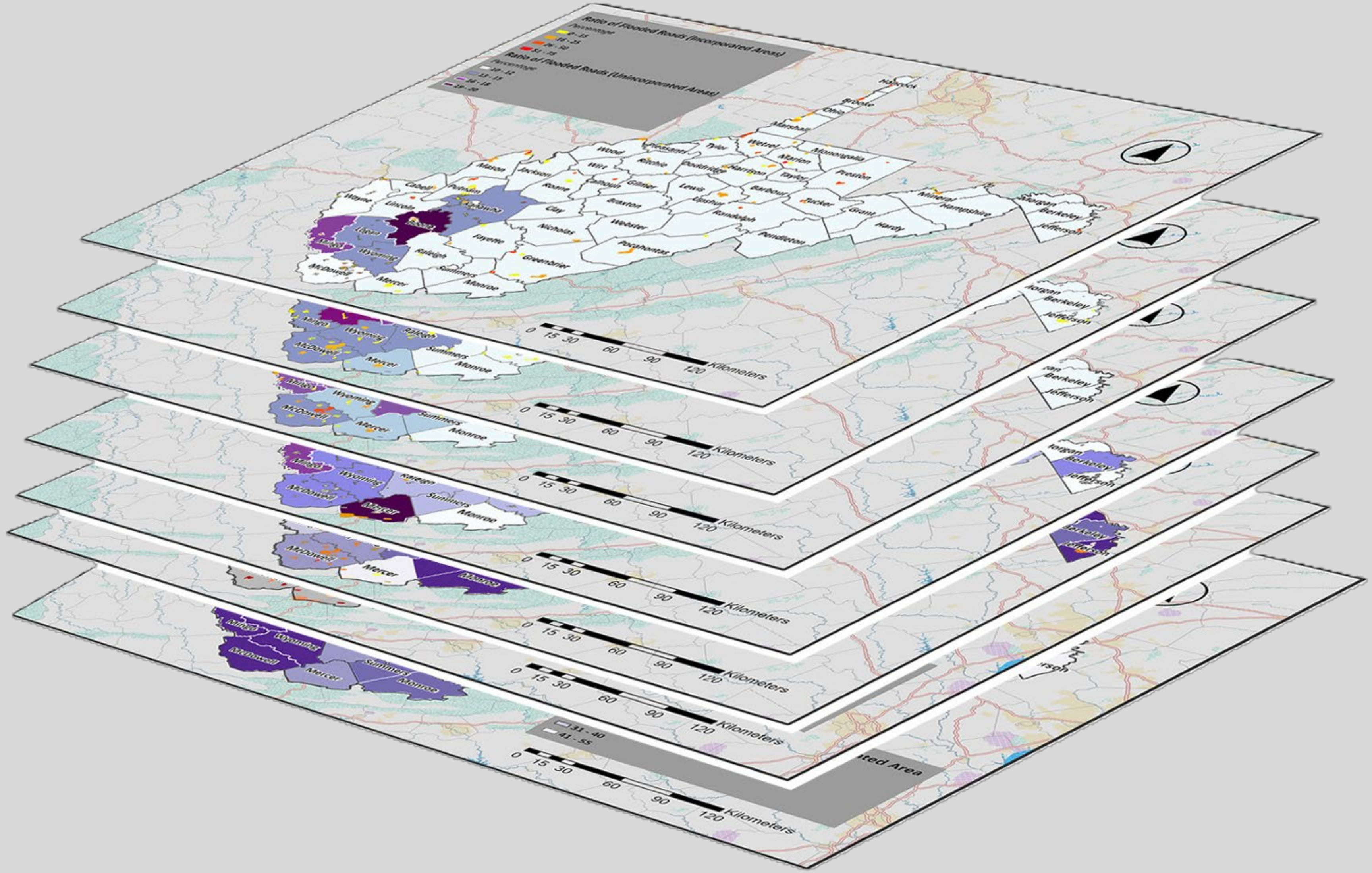


STUDY THREE

STUDY THREE

RESULT

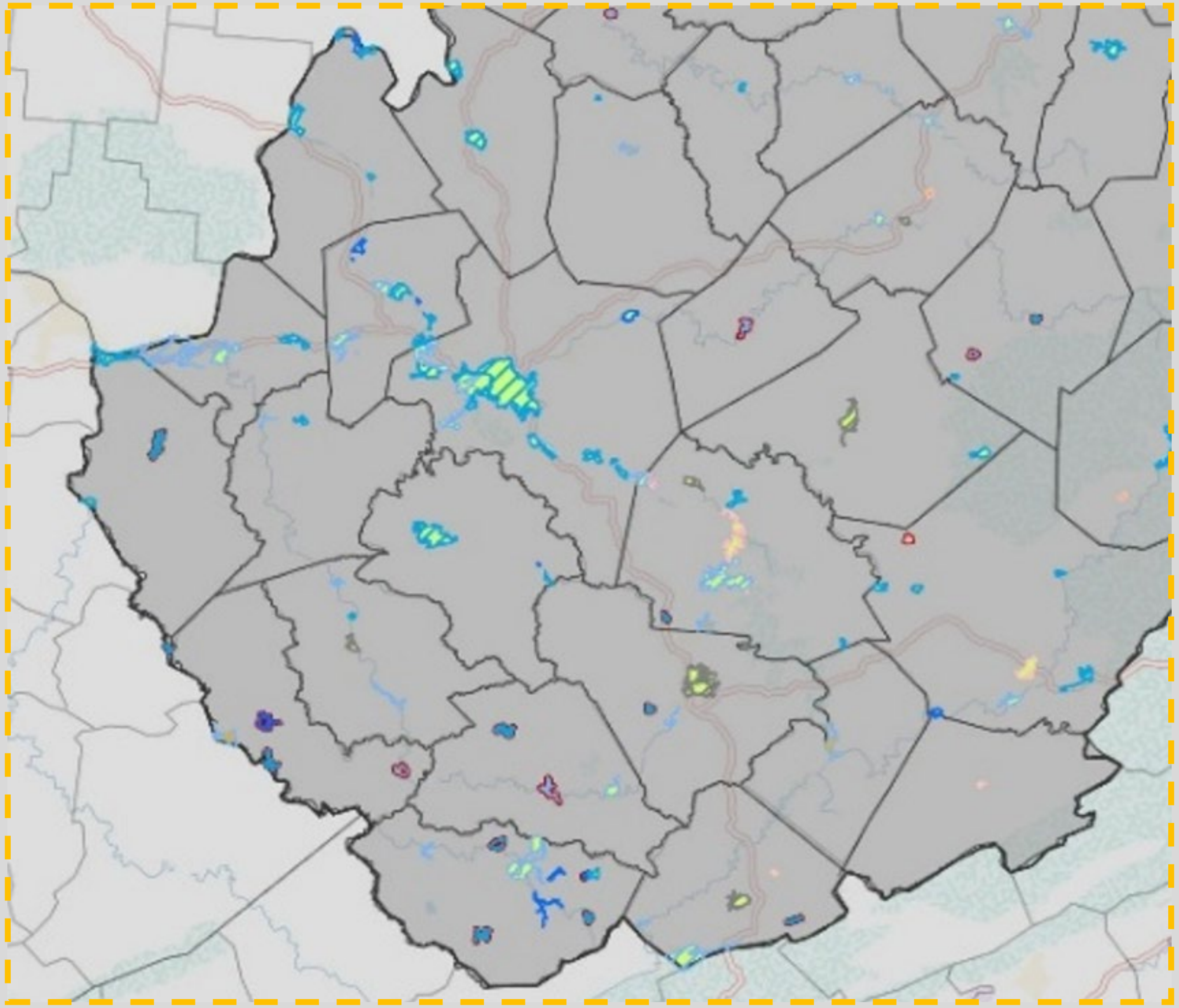
Overlapping the Socioeconomic and Physical layers

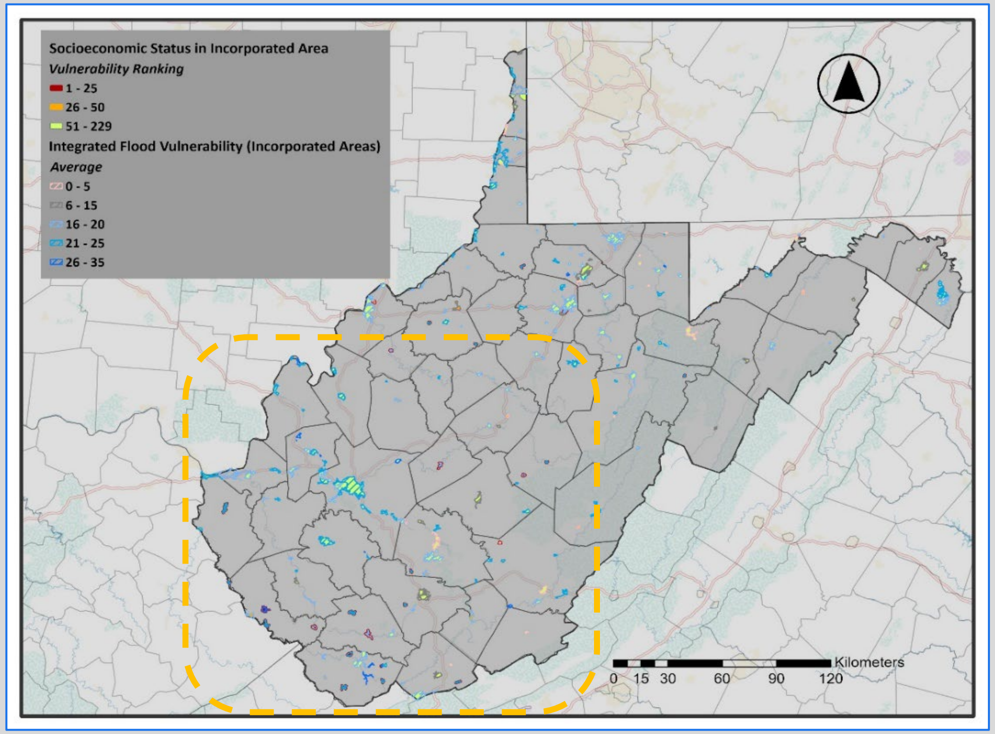


STUDY THREE

RESULT

Incorporated communities in southern West Virginia show strong alignment between socioeconomic and flood vulnerabilities.

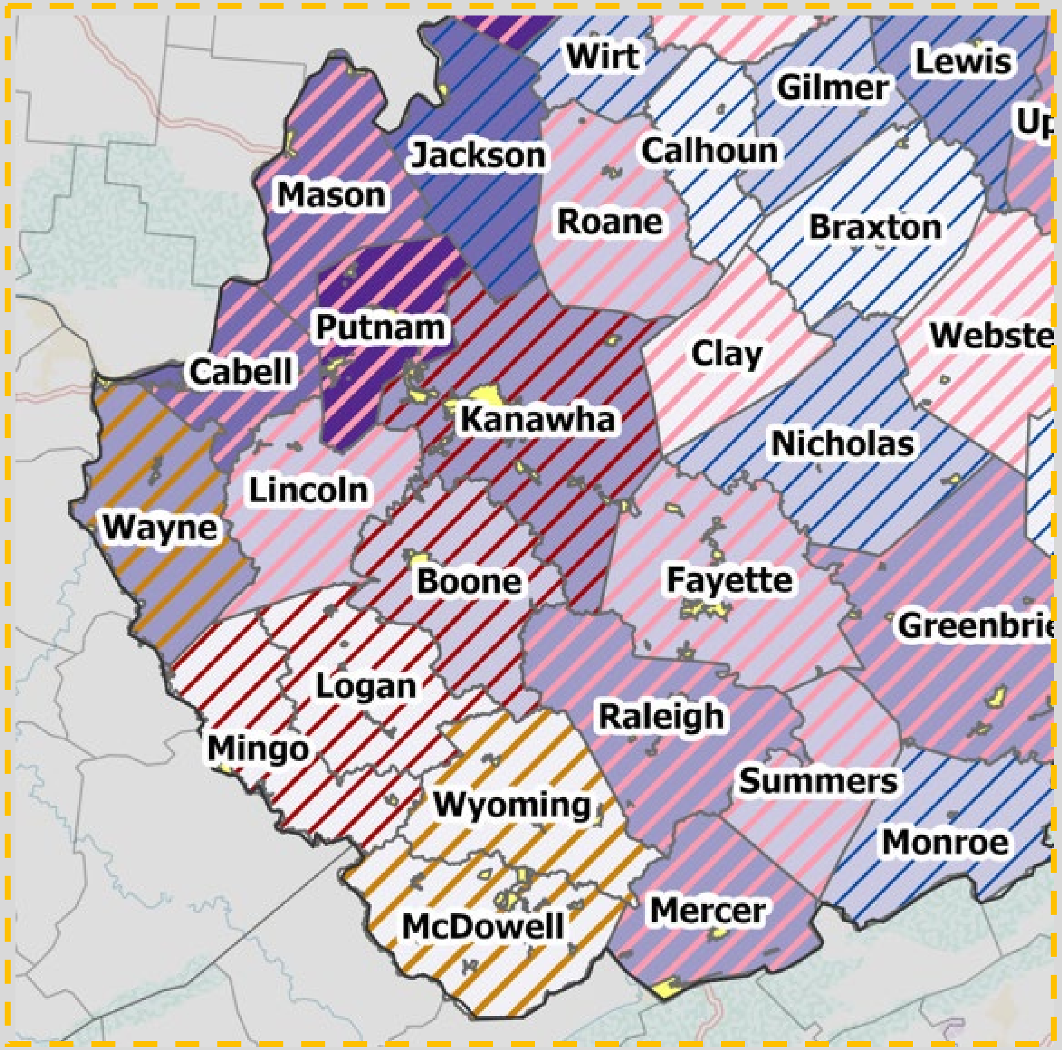


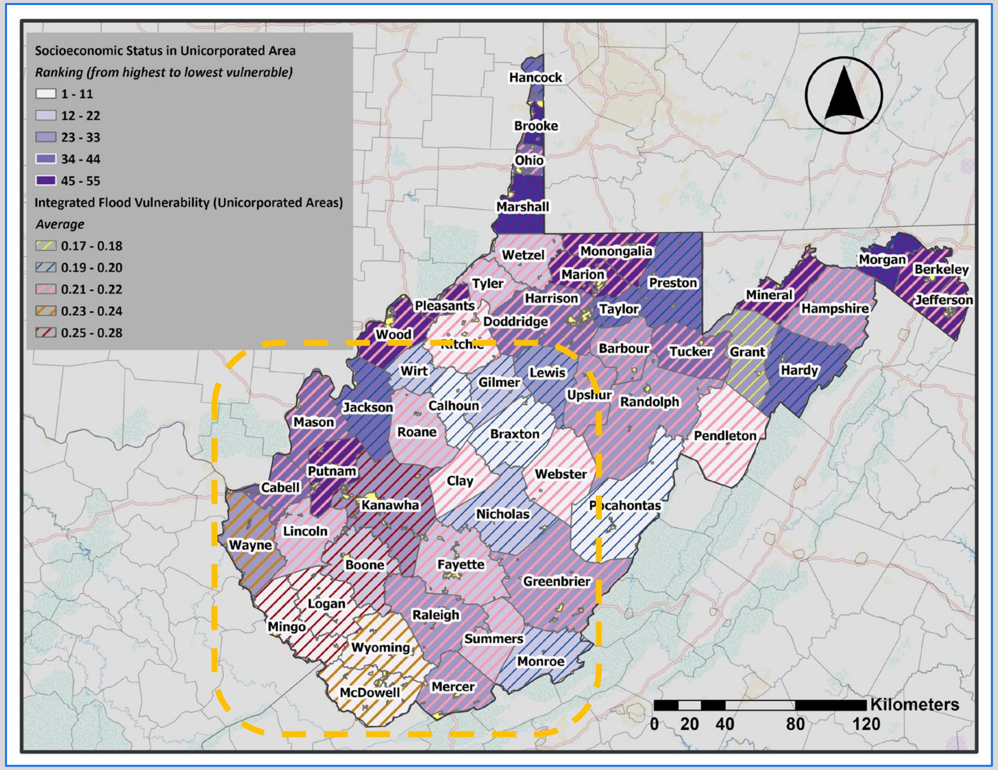


STUDY THREE

RESULT

Unincorporated communities in southern West Virginia also show strong alignment between socioeconomic and flood vulnerabilities.





STUDY THREE

KEY FINDINGS

Incorporated

- 31% of the communities are high or very high Physically Flood Vulnerable (With the Physical Vulnerability Index between 21 and 35).
- 48% of the communities with the highest Socioeconomic Vulnerability Index (top 25) are in the category of high or very high physically vulnerable.

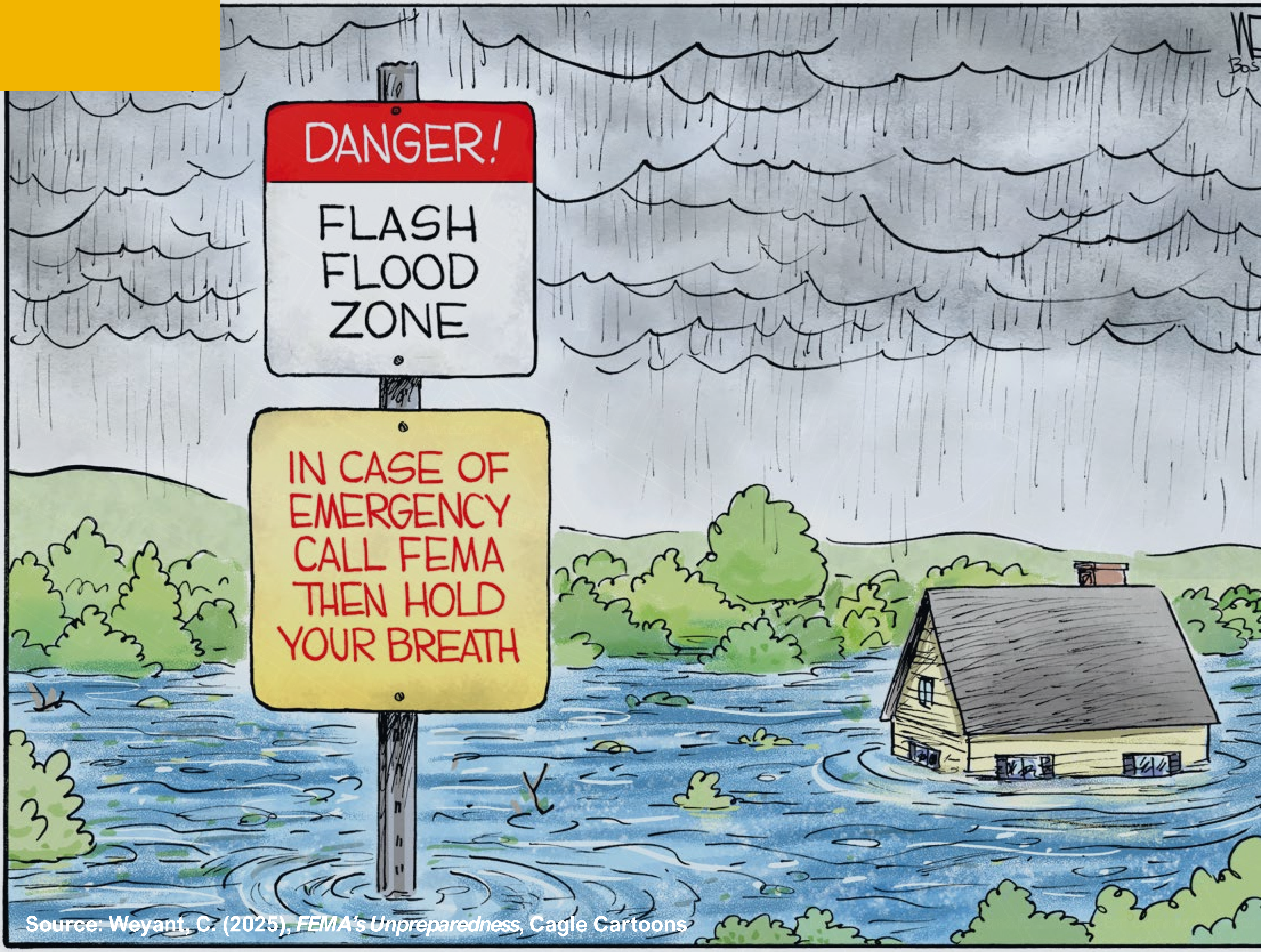
Unincorporated

- 10% of the communities are high or very high Physically Flood Vulnerable (With the Physical Vulnerability Index between 23 and 25).
- 18% of the communities with the highest Socioeconomic Vulnerability Index are in the category of high or very high physically vulnerable.

There is a clear overlap between socioeconomic and physical vulnerability, indicating that many socially vulnerable communities are also flood vulnerable.

CONCLUSION

CHAPTER6



Source: Weyant, C. (2025), *FEMA's Unpreparedness*, Cagle Cartoons

SUMMARY OF FINDINGS

- ❑ Flood vulnerability is multi-dimensional (physical, institutional, environmental, socioeconomic)
- ❑ Vulnerability shows clear spatial clustering, especially in southern WV
- ❑ Machine learning confirms that flood risk extends beyond FEMA flood zones
- ❑ Some communities experience compounded risk
- ❑ Strong overlap between physical and socioeconomic vulnerability

LIMITATIONS

- Dependence on FEMA flood zones (especially in the study one)

- Limited representation of social and community dynamics:
  The analysis does not fully capture the role of social engagement, local organizations, and community networks in post-disaster recovery.

- Focus on measurable socioeconomic indicators:
  The socioeconomic assessment is based on available quantitative data and may not reflect rural-specific vulnerabilities such as losses related to land, livestock, and agricultural resources.

- Mitigation measures not explicitly accounted for
  The analysis does not distinguish between original and mitigated (elevated or flood-proofed) structures

FUTURE RESARCH

- Combining physical, socioeconomic, institutional, and environmental dimensions into a fully integrated resilience model.
- Combining remote sensing and historical data with environmental indicators to improve flood mapping beyond traditional floodplain boundaries.
- Comparing the locations of recently damaged buildings with predicted flood-prone areas to evaluate model performance.
- Incorporating subsurface characteristics (e.g., soil properties, karst systems, and drainage behavior) into flood susceptibility modeling.
- Investigating the interaction between flooding, landslides, and terrain dynamics using high-resolution DEMs and geospatial analysis
- Develop flood susceptibility models for areas lacking reliable flood maps.

POLICY AND MANAGEMENT RECOMMENDATIONS

- In addition to structures within the 100-year flood zone, consider flood-related claims occurring outside mapped floodplains (especially those with repetitive losses) to define the true extent of flood risk better.

- Not only Pre-FIRM, but also Post-FIRM buildings, especially those without flood insurance or not compliant with NFIP or community flood standards, require careful evaluation.

- Identifying and maintaining reliable evacuation pathways and mapping facilities such as hotels, resorts, or gymnasiums located outside flood-prone areas can serve as emergency shelters.

- Flood-sensitive building codes should be integrated into community comprehensive plans, especially in areas where new development occurs within flood-prone regions.

- Property buyout programs

POLICY AND MANAGEMENT RECOMMENDATIONS

- Faith-based organizations and volunteer groups play a crucial role in disaster response and recovery. Creating small emergency funds or financial support systems for these groups could greatly enhance their ability to help communities during disasters.

- Flood mitigation planning should also include the direction of stream flow, debris pathways, and sediment buildup zones when assessing flood risks.

- Insurance should not be unified for the property owners. It should be a discount for special cases (low incomes or with a disabled person at home)

- Adjust insurance costs through targeted discounts or coefficients for vulnerable households, including low-income residents and those with disabilities.

- Establish standards for the placement and protection of livestock, pets, and related structures to reduce flood-related losses.

THANK YOU!

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CHAPTER7

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