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Kentucky Disasters

Multi-Hazard Approach to Mapping Flood Susceptibility and Vulnerability in Kentucky

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1. Abstract

Flooding is the most common and costly natural disaster in Kentucky, with major flood events in 2022 and 2023 highlighting the need for flood risk assessment. In partnership with the National Weather Service Jackson and Paducah Forecast Offices and the Kentucky Climate Center, we mapped flood risk in Kentucky using a multi-hazard approach that considered two dimensions of risk: flood susceptibility based on a weighted combination of seven physical factors and flood vulnerability based on 13 socioeconomic and infrastructure factors. We additionally analyzed NASA Soil Moisture Active Passive (SMAP) observations of surface soil moisture to explore the utility of SMAP observations for future analysis of flood risk. By analyzing flood susceptibility, we found that with equal rainfall, western Kentucky generally displays a higher propensity to flood than eastern Kentucky. In contrast, our flood vulnerability analysis indicated that more vulnerable areas were generally concentrated in the eastern part of the state. Through a combined perspective, our flood risk analysis identified much of the state as having moderate degrees of flood susceptibility and vulnerability. Our parallel analysis of antecedent soil moisture found that SMAP soil moisture levels were variable in the months leading up to each flood event but were drier than normal in the month prior to the 2023 event, as shown by negative soil moisture anomalies. These results were limited by challenges with weighting input parameters and a lack of validation but overall demonstrate the feasibility of using GIS and Earth observations for mapping flood risk and soil moisture.

Key Terms: flood risk, flash flooding, soil moisture, SMAP, analytic hierarchy process.

2. Introduction

2.1 Background Information

Flooding is the most common and costly natural disaster in Kentucky, with annual flood damage totaling over 40 million dollars (Division of Water [DOW], 2018, p. 1). Flood events typically occur annually across the state, and the frequency and severity of such events are projected to increase over time due to climatic changes in weather patterns including increased annual maximum and mean river flows (DOW, 2018, p. 9). Kentucky has the most navigable water miles in the contiguous U.S. and contains a total of 89,431 miles of rivers and streams (DOW, 2018, p. 1; Ecological Society of America [ESA], 2024). During periods of intense precipitation, overflow from this vast river system contributed to recent flash flooding events in July of 2022 and 2023. The 2022 flood in eastern Kentucky was classified as a 1-in-1000-year precipitation event and resulted in 44 deaths and over 9,000 damaged homes, with 13 eastern Kentucky counties declared as federal disaster zones (Jackson, KY Weather Forecast Office [Jackson], n.d.; Klesta, 2023). The 2023 flood in western Kentucky was also classified as a 1-in-1000-year precipitation event, with the Mayfield, Kentucky Mesonet station measuring a record-breaking 11.28 inches of rain in 24 hours on July 18 and 19 (NOAA National Weather Service Hydrometeorological Design Study Center, 2017; Paducah, KY Weather Forecast Office [Paducah], n.d.).

With major flooding events expected to increase, predicting floods and warning communities are critical tasks for Kentucky weather service offices. However, making such predictions is difficult because impacts from flooding vary across the state based on topographic factors. Eastern Kentucky is mountainous, with high elevations and communities built in valleys that are prone to flash flooding (Figure 1). Western Kentucky is generally flat, with flood plains that typically see slower river flooding (Mahmood et al., 2019, p. 1755). Despite the elevation differences, Kentucky's extensive river system traverses the entire state, making it essential to consider regional differences and the greater landscape when characterizing flood risk.

To examine the regional differences and characterize flood risk across the state, we examined flood susceptibility, which estimated the propensity of flooding, based on seven physical factors including topography and river proximity. We analyzed susceptibility parameters with an analytic hierarchy process (AHP), a method well-suited for regional studies, which weighs factors based on their contribution to flooding according to expert knowledge (Tehrany et al., 2014). We performed a preliminary comparison of our susceptibility map with historical inundation data from the Global Flood Database (GFD; Tellman et al., 2021a; Tellman et al., 2021b) . We also analyzed flood vulnerability, which considered the impact of flooding on populations based on socioeconomic factors and infrastructure concerns. These factors allowed us to locate frontline communities, those most exposed to the effects of floods. After examining susceptibility and vulnerability separately, we combined the two perspectives to comprehensively assess flood risk across the state.

In a parallel analysis, we used NASA Soil Moisture Active-Passive (SMAP) remote sensing data to examine soil moisture content prior to the flood events of 2022 and 2023. Studies have found that because soil moisture affects groundwater recharge and run-off ratios, antecedent conditions "can explain the difference between minor and major flooding events," making satellite observations of soil moisture a potentially valuable tool for anticipating floods (Ahlmer et al., 2018, p. 2). Combined with flood risk mapping, antecedent soil moisture may provide an additional dimension to flood management in Kentucky.

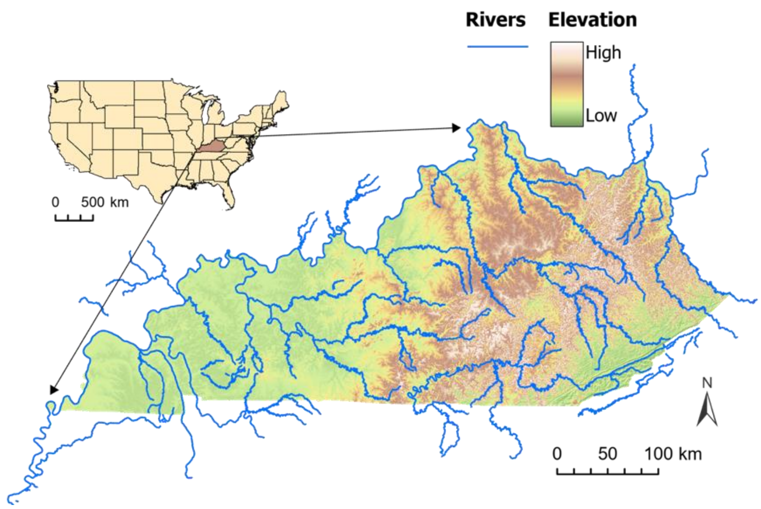

Figure 1. The study area for this project is the entire state of Kentucky. The state's major rivers and elevation are shown in this map.

2.2 Project Partners and Objectives
Our team partnered with the Kentucky Climate Center (KCC) and the National Oceanic and Atmospheric Administration's (NOAA) National Weather Service (NWS) Forecast Offices in both Paducah and Jackson, Kentucky. As Kentucky's official climate office, the KCC collects and distributes weather and climate information, while also supporting research and community outreach. The KCC also maintains the Kentucky Mesonet, a growing statewide weather and climate observation network with sensors at over 70 locations (Mahmood et al., 2019, p. 1753). The NWS provides weather, water, and climate outreach information through data, forecasts, and warnings, with coverage of every county in the United States. The Jackson and Paducah offices oversee the eastern and western regions of Kentucky, respectively, including the areas that experienced severe impacts from the 2022 and 2023 flood events.

Our partners work to increase awareness of flood risk in their communities, and we sought to provide informational products to assist in this mission. We created a static flood risk map incorporating flood susceptibility and vulnerability to better inform our partners and support their community outreach efforts. We also created a pamphlet to allow for more efficient communication with emergency managers and thus frontline communities in the state. Lastly, the examination of antecedent soil moisture before the 2022 and 2023 floods allowed us to explore the feasibility of space-based platforms for flood risk assessment, which could be combined with Mesonet data to improve spatial coverage of weather information across the state.

3. Methodology

3.1 Data Acquisition

3.1.1 Susceptibility Data

We identified seven susceptibility factors from preliminary literature review and expert consultation and included them in the susceptibility map (see Appendix A, Table A1). We imported all susceptibility data directly into ArcGIS Pro from the ArcGIS Online Portal or ArcGIS Living Atlas. Distance to Rivers considers the distance of each point from the nearest river and was included due to the risk of rising waters in periods of heavy rainfall. The Topographic Wetness Index (TWI) measures the effects of slope, aspect, and elevation on hydrologic processes (Sørensen et al., 2006). Kentucky's terrain is also affected by karst areas and mining. Karst areas are areas where bedrock dissolves, forming features such as sinkholes and caves (National Park Service). Karst springs are prone to overflowing during extreme events, leading to flooding (de Waele et al., 2011). Distance to Mines was included based on flood risk from mine slurry impoundments. Land Cover, which includes land categories such as forests, agricultural areas, and developed areas, reflects the fact that water more readily drains through highly permeable materials such as forest soil than through impermeable surfaces such as asphalt or concrete. Drainage Class is a categorization of soil types that considers how quickly water moves through the soil, which was included based on the assumption that areas with poorly drained soils are more prone to flooding (Soil Science Division Staff, 2017). Unlike Land Cover, Drainage Class primarily considers the natural condition of underlying soils, rather than human-built infrastructure. Hydrologic Group is another soil metric that groups soils based on runoff potential when inundated by large storm systems, regardless of vegetation coverage (Soil Science Division Staff, 2017). We included this parameter to account for runoff's contribution to flooding.

3.1.2 Vulnerability Data

For our vulnerability map, we collected ten demographic factors (see Appendix A, Table A2) from the U.S. Census 2022 Planning Database, which includes data from multiple census surveys. We used data at the tract level because it was the highest spatial resolution of census data that contained all the desired variables. After downloading the data as a single CSV file, we removed all non-essential columns. The ten variables were selected in consultation with project partners and their knowledge of flood exposure in Kentucky. We included poverty, population 65 and over, population under 5, and disability as percentages of population in each census tract (U.S. Census Bureau, 2024). We included a factor for manufactured homes (referred to as mobile homes by the Census Bureau) as a percentage of homes in each tract since manufactured homes lack foundations and are thus vulnerable to displacement and damage in floods. We also included four factors that influence the ability to receive information and warnings about flooding: no computer access, no telephone service, no internet access, and limited English speaking each as a percentage of households in each tract. Additionally, we included population density to account for the higher number of people at risk in more populated areas. We also obtained a census tract feature layer entitled "Poverty Inequality of Kentucky Census Tracts 2020_WFL1" and a county feature layer entitled "Kentucky_County_polygons" both from the ArcGIS Online Portal (Kentucky Transportation Cabinet, Division of Planning, 2021; U.S. Census Bureau, 2022b). In addition to census demographic data, we included the number of fire stations, hospitals, and bridges in each polygon as variables, since people living further from medical care and emergency services may be more vulnerable in emergencies, and damage to bridges during floods can disrupt evacuation. Hospital data were collected from the KyGovMaps Open Data Portal, bridge location data were acquired from the Kentucky Geography Network, and fire station data were collected from the Homeland Infrastructure Foundation-Level Data (see Appendix A, Table A3).

3.1.3 Soil Moisture Data

We acquired soil moisture data from NASA's Soil Moisture Active Passive (SMAP) sensor via the Google Earth Engine data catalog (Reichle et al. 2022a; Reichle et al. 2022b). We used the SMAP L4 Global 3-hourly 9 km EASE-Grid Surface and Root Zone Soil Moisture Analysis - Update Version 7.

3.1.4 Comparison of Susceptibility with Global Flood Database Data
We acquired the full set of GFD data from the Google Earth Engine data catalog (Tellman et al., 2021a; Tellman et al., 2021b). The data include 33 flood events in Kentucky from 2001 to 2018 identified based on flood records maintained by the Dartmouth Flood Observatory. One pair of flood events had overlapping dates and regions, despite the GFD categorizing them as two distinct events. The GFD flood extent maps were derived using data from NASA's MODIS Terra and Aqua sensors.

3.2 Data Processing
3.2.1 Susceptibility
We downloaded all the layers for susceptibility as web layers and converted them to feature layers using the Export Features function under the Data tab in ArcGIS Pro to allow editing. We then converted the layers for drainage class, hydrologic group, and karst areas to raster using the Feature to Raster (Conversion) tool as raster format was required for reclassification. We performed a distance analysis on the river and mine layers to determine distance from the features throughout the state using the Distance Accumulation (Spatial Analyst) tool. Since our scale, the entire state of Kentucky, was quite large, we used a geodesic method to account for curve of the Earth and input the Kentucky 5ft Digital Elevation Model (DEM) to account for surface cost in distance. The topographic wetness index (TWI), a means of combining upslope area with slope to quantify topological effects on the local hydrology, was calculated through the following equation, where (a) is the contributing upslope area raster and (tanβ) is the slope raster (Sørensen et al., 2006; Ballerine, 2017; Equation 1).

$$TWI = Ln\left(\frac{a}{\tan \beta}\right) \tag{1}$$

To calculate TWI using ArcGIS Pro, we used the 5ft DEM raster with cell size adjusted to columns of 571,4222 and rows of 249,716 to 15,000 and 4,100, respectively, to meet ArcGIS Pro's image service's maximum cell size requirement for geoprocessing. Following a common protocol, we created the TWI layer through a series of spatial analyst tools (O'Donohue, 2023). Once all the raster layers were prepared, we reclassified each layer on a one to five scale using the Reclassify (Spatial Analyst) tool. The reclassification groups described in Appendix B, Table B1 were based on former susceptibility analyses and descriptions of the factors' impacts on flooding found through literature. The distance to rivers layer was reclassified using five equal intervals under the assumption that impact from rivers decreases linearly with distance if elevation is ignored. Distance to mines was classified using a quantile scale under the assumption that impact on flooding is only strong very near the mines.

3.2.2 Vulnerability
For vulnerability, we created a population density variable by dividing each tract's total population by the tract area. The remaining nine variables collected from the Census required no additional processing. Variables representing the count of selected infrastructure (bridges, hospitals, and fire stations) within each tract were generated using the Summarize Within (Analysis) tool. These steps were then repeated at the county level; however, since county-level data are not provided by the census, we summed the tract-level counts by county for each variable and divided by the appropriate county total depending on the census's formula for calculating each variable (see Appendix, Table A4). All 13 variables were then reclassified at the tract- and county-level on a one to five scale using the Reclassify Field (Data Management) tool and the quantile method of reclassification. For all variables excluding hospitals and fire stations, a larger number or percentage corresponds with higher vulnerability, or a 5. The quantile method was chosen so that the values reflect the relative vulnerability of a tract/county to others in the state.

3.2.3 Soil Moisture
We used Google Earth Engine to create gifs and charts displaying SMAP L4 surface soil moisture data before, during, and after the two major floods in 2022 and 2023. For the July 2022 flood in eastern Kentucky, the study period was for June 25 through August 4, 2022. Then for the July 2023 flood in western Kentucky, the study period was for June 19 through July 26, 2023. For the charts, we defined smaller areas of interest

within our study area boundaries to pinpoint soil moisture behavior in the regions where major flooding occurred (Figure 2). For the 2022 flood event, we used Breathitt, Clay, Floyd, Johnson, Knott, Leslie, Letcher, Magoffin, Martin, Owsley, Perry, Pike, and Wolfe Counties based on the federal disaster declarations for the event (The White House, 2022). Whitley county was also included based on additional evidence suggesting it was seriously affected (Kentucky Governor Andy Beshear, n.d.). For the 2023 Flood event, we used Carlisle, Fulton, Graves, and Hickman Counties, which declared states of emergency during the flood event according to Kentucky news site WYMT (Ruch, 2023). The same article notes that Lee County also declared a state of emergency, but since Lee County is in the eastern part of the state and thus completely disconnected from the rest of our study area in western Kentucky, we omitted it in our quantitative analysis.

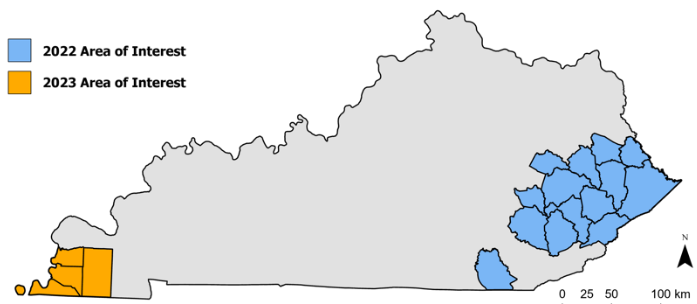

Figure 2. The study areas for our soil moisture analysis are shown. The 2022 study area includes 14 counties in eastern Kentucky impacted by the 2022 flood event, while the 2023 study area includes four counties in western Kentucky impacted by the 2023 event.

For each region, we used Google Earth Engine to filter the SMAP L4 surface soil moisture band data by the study period dates and export the entire three-hourly dataset for the study period. In addition to the absolute soil moisture values, we also created charts of soil moisture anomaly data for the same time periods and areas of interest. The anomaly values are derived from the experimental derived SMAP L4 surface soil moisture anomaly band product, which was created for Google Earth Engine. They represent the difference of the 30-day average of SMAP L4 surface soil moisture band values centered on each date and time compared to the mean of the same 30-day periods in the years 2015 to 2023, excluding the flood event year. Due to limited documentation in Google Earth Engine, it is unclear whether 2023 is included in the mean calculation for the 2022 anomaly. Like with the absolute soil moisture data, we took the spatial mean of the band data in Google Earth Engine for the appropriate area of interest and exported the dataset for analysis.

3.2.4 Comparison of Susceptibility with Global Flood Database Data

We first filtered the GFD dataset to only images within or overlapping with the Kentucky state boundaries. We converted the individual flood extent maps into a single binary layer, where pixel values of "1" represented one or more historical inundation events included in the GFD, and pixel values of "0" represented no historical inundation events. We applied a mask to remove pixels with permanent water (based on the JRC Global Surface Water dataset, included in the GFD data as the "jrc_perm_water" band), so that only flood inundation areas would be included. Then we scaled up and reprojected the binary flood layer pixels to match the susceptibility map pixels, since the susceptibility pixels were larger. To accomplish this, we used the reduceResolution function in Google Earth Engine with a mean reducer, so that the mean value of the input pixels (weighted by area within the output pixel) became the value of the output pixel. We then created a binary inundation layer with a 25% threshold, meaning that if the GFD had inundation data for at least 25% by area of the smaller input pixels, the larger output pixel was considered "inundated" and assigned a value of "1." If there were gaps in the smaller input pixels due to the surface water mask or missing data in the GFD dataset, the 25% threshold only applied to however many input pixels had data and were not masked. This means that for some output pixels assigned a value of "1," less than 25% of the output pixel may have been inundated if there were missing pixels in the input data. This threshold was chosen based on visual assessment. The reprojection was accomplished using Google Earth Engine's reproject function, using the flood susceptibility layer's projection as the target projection. We also used the susceptibility map as a mask for the binary inundation layer and vice versa, so that pixels without data in one or both maps would be excluded from the analysis (Figure 3).

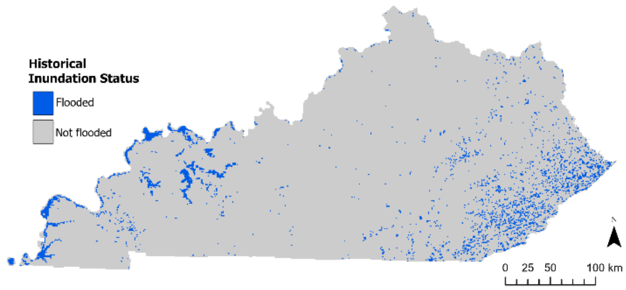

Figure 3. Kentucky's historical inundation status based on 33 Global Flood Database (GFD) records from 2001–2018. A pixel has "flooded" status if at least 25% of input pixels from the GFD (masked to exclude permanent water) by area had one or more flood inundations in the GFD. The data have been processed to scale up the pixels to match our Flood Susceptibility map and exclude pixels that had no data in the Flood Susceptibility Map.

3.3 Data Analysis

3.3.1 Susceptibility Map

To determine the importance of each susceptibility factor, three outside scientists considered subject matter experts (SME) on regional flooding performed an AHP individually using a Microsoft Excel-based template (Goepel, 2013). These individual weighting schemes were then combined, resulting in the weights shown in Appendix B, Table B2. The SMEs' combined analysis resulted in a 3.6% consistency ratio. The consistency ratio is a measure of how logical an evaluator's judgement of criteria is based on their pairwise rankings; this value of 3.6% is deemed acceptable as it is under the 10% threshold considered ideal for published AHPs (Saaty, 1991).

We created a susceptibility measurement using the rounded combined weights from our AHP and the Weighted Overlay (Spatial Analyst) tool in ArcGIS Pro, which accepts each factor as a reclassified raster and creates an average score based on the weighting scheme. This created a map with pixels ranked 1–5, where a "1" describes lower susceptibility and a "5" describes higher susceptibility. Using census tracts and Kentucky county lines as boundaries, we aggregated the pixels and found an average for each polygon to create a more meaningful resolution for our partners.

3.3.2 Vulnerability Map

After reclassification, the vulnerability data were exported into R 4.2.2 to calculate an average vulnerability score for each tract and county. This score was calculated by summing the individual reclassified scores and dividing this value by the number of columns (1–13) that contained data. This ensured tracts with missing data were adequately represented. After analysis, data tables were exported as CSV files, imported into ArcGIS Pro, and joined with polygons by tract ID and county names for visualization.

3.3.3 Risk Map

Once the susceptibility and vulnerability maps were created at the census tract and county resolution, the layers were joined into a single table in ArcGIS Pro and displayed using a bivariate color symbology. This visualization displays combined flood risk while still depicting the separate susceptibility and vulnerability rankings.

3.3.4 Soil Moisture

After exporting soil moisture and soil moisture anomaly data from Google Earth Engine, we plotted the data in charts to quantitatively display the progression of soil moisture behavior. For the surface soil moisture data, we added a 24-hour running mean to display a smoothed version of the data in addition to the raw three-hourly time series. For the soil moisture anomaly data, we did not compute a running average since the anomaly band data already represents a 30-day average centered on the date.

3.3.5 Comparison of Susceptibility with Global Flood Database Data
We created a series of binary layers for each susceptibility class from the susceptibility map, which was masked to omit any "no data" pixels from the GFD inundation map. Then, the reduceRegion tool on Google Earth Engine was used to compare the maps and calculate statistics. We found the number of pixels in the union of the target susceptibility class and the GFD binary inundation layer for each susceptibility class. Then, we determined the total number of pixels per class in the masked susceptibility map. Outside of Google Earth Engine, we divided the number of pixels that have historical inundation data in each class by the total number of pixels in that class to determine the percentage of each susceptibility class that had historical inundation data represented in the GFD.

4. Results & Discussion

4.1 Susceptibility

Our final susceptibility map assigned each pixel a value from one to five based on the weighted average of the seven topographic parameters. No pixels were classified into group 5, the highest classification. The majority of Kentucky was classified into group 3, which comprises about 74% of total pixels (Table 1). Group 2 was the next largest, with about 22% of pixels, leaving less than 5% of pixels made up of groups 1 and 4 combined.

Table 1
Distribution of Susceptibility Classifications

Classification	Number of Pixels	Area of State (km^2)	Percent of State Coverage
1 (Lower)	6	7.2	<0.01
2	15,871	19,045.2	22.1
3	53,210	63,852	74.2
4 (Higher)	2,603	3,123.6	3.6
5	0	0	0
Total:	**71,690**	**86,028**	**100**

The final flood susceptibility map (Figure 4; Appendix C1*)* shows the weighted susceptibility with darker blue areas corresponding to higher susceptibility, and green/yellow areas corresponding to lower susceptibility. It is important to note that this map does not claim to identify areas with no, or even low, susceptibility to flooding. The analysis only compares the susceptibility across the state, so that areas classified as "1" may still have high susceptibility to flooding during intense precipitation events, but they are generally less susceptible to areas classified as "4." Generally, susceptibility appears to be higher in western Kentucky, with clusters of the highest susceptibility along the Ohio River on the northwestern border. However, areas of high susceptibility can also be seen in eastern Kentucky, where major flooding does occur. In this region, areas of lower susceptibility correspond to higher elevation, with higher susceptibility appearing in the valleys of the mountainous region.

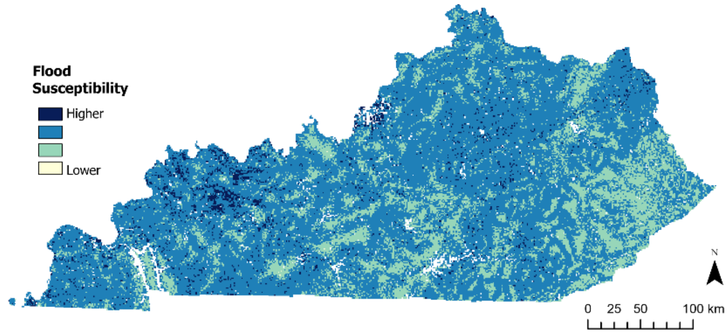

Figure 4. Final flood susceptibility map showing the weighted susceptibility score by pixel, approximately 1.2 km², for Kentucky. The darker regions correspond to higher susceptibility, while lighter regions correspond to lower susceptibility.

4.2 Vulnerability

Through an analysis of vulnerability score distribution (Table 2), we found over 95% of Kentucky's population and land area falls within a tract in the range of 2 to 3.99. A small number of tracts and their associated land area and population have a vulnerability score below 2. Around 2.4% of Kentucky's population lives in a tract with a vulnerability score of 4 or greater, with these tracts being more concentrated in eastern and southeastern regions.

Table 2
Distribution of Vulnerability Classifications

Classification	Number of Tracts	Percent of State Coverage	Number of People	Percent of Population
1–1.99	5	0.1	17,353	0.4
2–2.99	481	19.8	1,877,462	42.1
3–3.99	782	77.0	2,460,373	55.1
4–4.99	38	3.1	106,764	2.4
Total:	**1,306**	**100**	**4,461,952**	**100**

Our final vulnerability map (Figure 5; Appendix C2*)* shows the average vulnerability score by census tract, with a range of values from about 1.77 to 4.31 and a mean vulnerability score for all tracts of approximately 3.13 out of 5. Darker pink areas correspond to higher vulnerability scores while lighter pink areas correspond to lower vulnerability scores. Higher vulnerability scores are generally found in eastern Kentucky, but some tracts in other regions of the state also have higher scores.

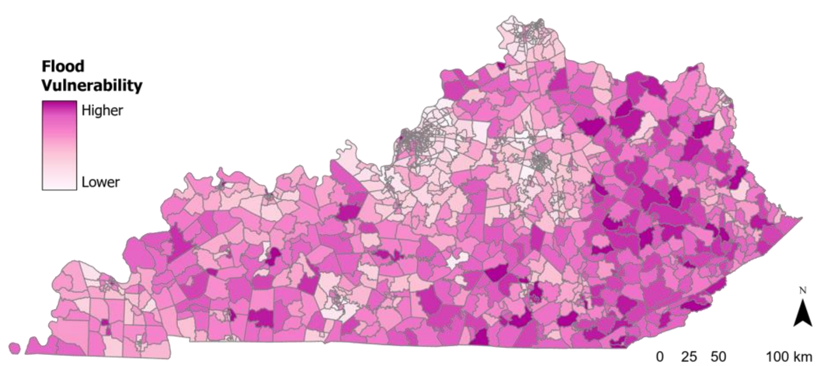

Figure 5. Final flood vulnerability map showing the average vulnerability score by census tract for the state. Darker regions are associated with higher vulnerability scores, while lighter regions are associated with lower

vulnerability scores. Higher vulnerability scores are generally seen in the eastern part of the state, but high vulnerability tracts can be found in other regions as well.

4.3 Flood Risk

Our combined flood risk map (Figure 6; Appendix C3) shows the overlap between susceptibility (based on physical geography) and vulnerability (based on socioeconomic factors) in Kentucky, largely reflecting the trends seen in each map. Areas of higher vulnerability (pink) are generally more frequent in eastern Kentucky, while areas of higher susceptibility (blue) are more frequent along the Ohio River in northwestern Kentucky. The resolution of our susceptibility map was reduced to combine it with vulnerability, which is recorded at the census tract level. Pixels inside each census tract were aggregated to the census tract level, and an average susceptibility was assigned to each tract. As a result, spatial resolution is reduced, and at this lower spatial resolution, isolated areas of both high and low susceptibility are lost. This is especially true of eastern Kentucky, where a higher concentration of lower susceptibility pixels of mountaintops was averaged with the sparser high susceptibility pixels of valleys, creating an average susceptibility that is not reflective of the true risk posed to communities in valleys. Still, much of the state is moderately susceptible and moderately vulnerable.

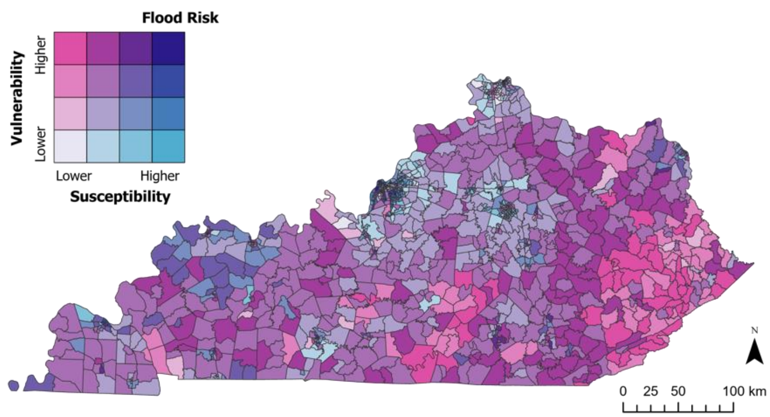

Figure 6. Combined flood risk map showing 16 levels of risk at the census tract level, highlighting the intersection of susceptibility and vulnerability in Kentucky. Pink areas show higher vulnerability but lower susceptibility, blue areas show higher susceptibility but lower vulnerability, and purple areas show a high combination of both factors.

4.4 Soil Moisture

For both flood events, the highest SMAP L4 modeled surface soil moisture values occurred on the date of peak flooding (Figure 7). However, both regions showed substantial variation in soil moisture in the month prior to the floods.

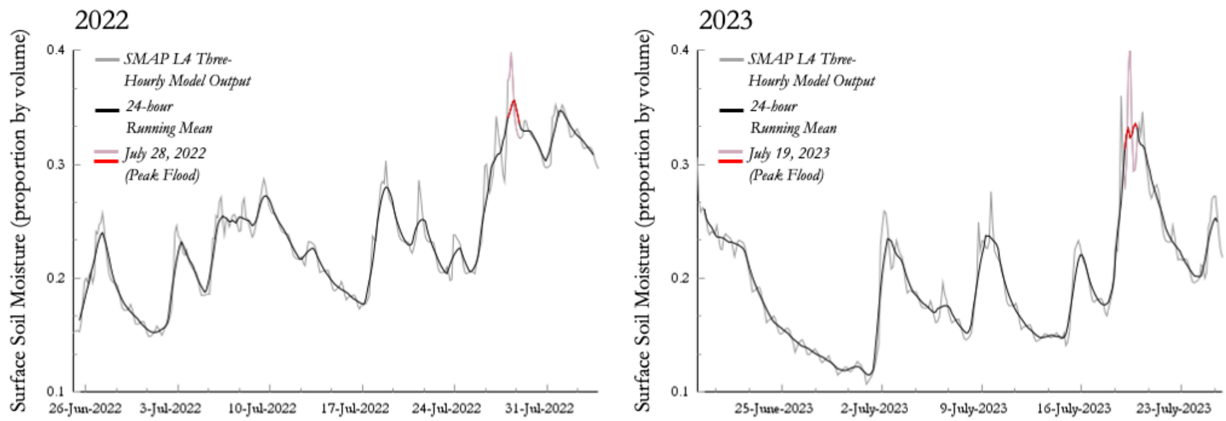

Figure 7. The variation in surface soil moisture in selected counties the month before and week after the major flood events of 2022 (left) and 2023 (right) are shown. Soil moisture values are derived from SMAP L4 Surface Soil Moisture band data. "Proportion by volume" refers to the volumetric proportion of moisture estimated in the top five centimeters of soil.

For both flood events, there were modeled surface soil moisture anomaly values both above and below zero, with values above zero suggesting that soil was more saturated during that time than other years on average, and values below zero suggesting that soil was less saturated during that time than other years on average *(*Figure 8*)*. However, for the 2023 event, a large majority (94%) of the soil moisture anomaly values before the peak flood date were negative, suggesting that many days were drier than that time in previous years. For the 2022 event, the balance of positive and negative anomaly values before the peak flood date is more even, although the majority (63%) of the values were also negative. For both years, the highest anomaly values can be seen on the peak flood dates.

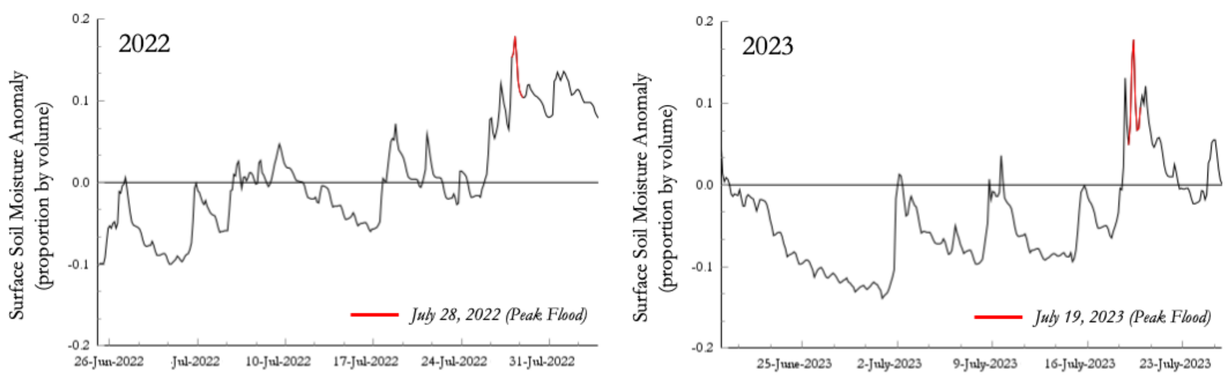

Figure 8. Surface soil moisture anomalies in selected counties from the month before and week after the major flood events of 2022 (left) and 2023 (right) are shown. The anomaly values are derived from the experimental SMAP L4 surface soil moisture anomaly band. They represent the difference of the 30-day average of SMAP L4 surface soil moisture band values compared to the mean of the same 30-day periods in the years 2015 to 2023, excluding the flood event year. Due to limited documentation in Google Earth Engine, it is unclear whether 2023 is included in the mean calculation for the 2022 anomaly. The x axis represents the halfway point in each 30-day period. "Proportion by volume" refers to the volumetric proportion of moisture estimated in the top five centimeters of soil.

4.5 Comparison of Susceptibility with Global Flood Database Data

Out of the 71,292 pixels with data for both maps, 5.04% had historical inundation events represented in the GFD (Table 3). The highest susceptibility class (4) had the highest percentage of historically inundated pixels

(13.98%), while the lowest susceptibility class (1) had the lowest percentage of historically inundated pixels (0.00%). However, classes 2 and 3 do not display a consistently increasing pattern, with a slightly higher percentage of pixels in class 2 having inundation data than class 3.

Table 3
Comparison between Susceptibility Map and GFD Inundation Map

Susceptibility Class	Number of inundated pixels in class	Total number of pixels in class	Percent of inundated pixels in class
1 (Lower)	0	6	0.00
2	867	15,666	5.53
3	2,364	53,017	4.46
4 (Higher)	364	2,603	13.98
All Classes	**3,595**	**71,292**	**5.04**

4.6 Feasibility for Partner Use
Using seven weighted topographic factors, we created a susceptibility map showing areas of Kentucky that are most prone to flooding. This can aid our partners as an efficient decision-making tool to better assist communities that have a higher exposure to the effects of flooding. However, to improve the accuracy of our AHP, we had the SMEs remove slope, aspect, and elevation from the analysis under the assumption that they are properly encapsulated in TWI, which used these three factors as inputs in its equation. We based this on literature suggesting that seven is the maximum preferred number of factors for AHPs (Saaty, 1980; Saaty and Ozdemir, 2003, cited in Bahurmoz, 2006). This may affect the accuracy of our map as slope and elevation are important in determining runoff, which greatly contributes to flooding. Therefore, a future analysis including these variables through possibly a different weighting scheme that can include more inputs may be worth pursuing.

The results from the comparison of our susceptibility map with the GFD inundation map are promising; however, as remotely sensed, algorithmically derived products, the historical inundation data cannot be considered "ground truth" data. The creators of the GFD note errors in the classification process and exclusion of some flood events due to factors including cloud cover, terrain, and short duration (including flash floods) (Tellman et al., 2021). The bias against flash floods may make this database less suitable for assessing historical flooding in Eastern Kentucky, since flash floods are particularly common there. While the GFD does show historical inundation in southeastern Kentucky, the data is spottier, suggesting that the GFD may not be as representative of flooding in this region of Kentucky. Beyond biases due to the data collection method, the relatively short time span of the historical inundation data means that it may not accurately represent typical flood behavior. Future work could carry out a more detailed validation including data collected via alternate methods to account for biases in optical remote sensing.

We also created a flood vulnerability map using both socioeconomic and infrastructure data to help identify areas that are most exposed. Though we used important criteria, none of them served as a remoteness indicator. This is important, particularly in eastern Kentucky, where many communities are remote, some with only one access point through bridges that can be damaged during flooding. Understanding the location and quality of access points in and out of communities could help our partners better identify frontline communities and aid emergency managers in determining evacuation plans. Still, this map provides our partners with valuable information on vulnerability across the state and can be used to locate areas that may require extra resources and more preparation in the event of a large storm.

The flood risk map was created by combining the susceptibility and vulnerability maps. This can help emergency managers identify areas that are not only most prone to flooding but may experience the most exacerbated impacts from a severe flood. This type of map can be used as an input to hydrologic models for flood forecasting.

Finally, while our soil moisture analysis was the most exploratory part of our study, we have created both visual and quantitative assessments of soil moisture using SMAP Earth observations. The SMAP Level 3 brightness observations upon which the SMAP Level 4 model output is based may have regions of poor quality in Kentucky based on its quality assurance band. Additionally, SMAP anomalies are based on a relatively short time period that cannot be considered authoritative on the region's true climatology. Still, our data can be used by the KCC to assess the agreement between Earth observations and *in situ* data. To assist with this, we have provided the KCC with numerical data of the daily mean soil moisture data at the points of the KCC's Mesonet stations to allow for a direct comparison. Ultimately, although there were limitations to all four components of our study, we have created products that are feasible for partner use.

4.7 Future Recommendations

Our partners could best integrate our products into their decision-making practices by keeping the map layers up to date and ensuring that they are easily accessible. By following these two recommendations, the maps that we made will stay relevant and can continue to inform emergency management decisions well into the future. To assist our partners with keeping the maps up to date, we included a GIS tutorial that outlines the steps to create our map layers for the susceptibility and vulnerability maps and combine them to form a comprehensive flood risk map. By following this set of instructions, the map products can be remade when data are updated on the demographics, infrastructure, and geomorphology of Kentucky. To make our map products accessible, we recommend that our partners host the maps online. The KCC has offered to host the maps, which would allow agencies and stakeholders to interact with our map and share it in a convenient web format. This would also allow for better data interpretation as smaller details can be viewed and layers can be toggled as necessary to fit the user's goals.

5. Conclusions

In just over 12 months, Kentucky experienced two catastrophic flooding events that devastated communities and highlighted the need for continued flood risk assessment. This project demonstrated the viability of using aerial and ground-based measurements to complete such an assessment while also coordinating with Kentucky-based partners to create products that best supplement their community outreach efforts.

Our flood susceptibility map showed that the propensity to flood is relatively higher in western Kentucky, although points of higher susceptibility are scattered throughout the state due to the extensive river system and varying terrain. Our flood vulnerability map showed that communities in eastern Kentucky may experience heightened impacts from flooding, although there are hotspots of higher vulnerability across the state due to fluctuations in socioeconomic factors. Our flood risk map highlighted these trends and reflected the fact that much of the state is moderately susceptible and moderately vulnerable to flooding. Our exploratory analysis of antecedent soil moisture conditions showed the feasibility of incorporating SMAP data into future analyses on the relationship between soil moisture and flood severity in Kentucky.

Additional work could use an alternative weighting scheme or pursue refinements to the AHP used for this project. Such refinements could include considering more criteria, especially variables related to precipitation, consulting more SMEs, or using a weighting scheme for vulnerability. Moreover, future work could incorporate additional data on historical flood occurrence, including in situ data if it can be located, to facilitate a validation of flood susceptibility. While these avenues were outside the scope of our project, we believe they could provide value to the goal of producing accurate and current flood risk maps for Kentucky and other regions.

Together, our maps provide a snapshot of flood susceptibility, vulnerability, and risk in Kentucky and our methodology builds on a reproducible method that allows for the creation of updated maps in the future.

Presently, our maps can serve as resources that aid the community outreach efforts of our partner organizations and enable a greater understanding of flood risk statewide. Our work can also be shared with emergency managers to provide another dimension of preparedness to flood warning and response operations in Kentucky.

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7. Glossary

AHP – Analytic Hierarchy Process, a method using pairwise comparisons to determine the relative importance/weights of criteria
ArcGIS Pro – a professional desktop GIS application from Esri
CSV – Comma-Separated Values, a text file format using commas to separate values and lines to separate records
DEM – Digital Elevation Model, a three-dimensional representation of elevation data and terrain
Flood Susceptibility – the propensity of an area to flood based on topographic factors
Flood Vulnerability – the potential of a community to be severely impacted by a flood disaster
GIS – Geographic Information System, a system to manage and analyze geographic data related to positions on Earth's surface
Google Earth Engine – a cloud-based geospatial analysis platform
Karst – landscape produced by the dissolution of soluble rocks such as limestone and characterized by caves, sinkholes, and other features
Mine Tailings – the leftover material from mining operations, consisting of finely ground rock, water, and chemicals
Slurry Impoundments – a natural or artificial pond used for the storage of mine tailings
SMAP – Soil Moisture Active/Passive, a NASA satellite that measures soil moisture across the globe
TWI – Topographic Wetness Index, used to quantify the impact of topography on hydrological processes

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9. Appendices

Appendix A

Table A1

Susceptibility Map Data

Susceptibility Factor	Dataset Title(s)	Data Source	Details and Justification for Inclusion
Distance to Rivers	Full Set of Rivers	National Weather Service (National Weather Service, 2007)	Rivers and stream levels rise in periods of heavy rainfall.
Topographic Wetness Index (TWI)	Kentucky Elevation Data (5ft DEM)	KyFromAbove (KyFromAbove, 2013)	TWI measures the effects of slope, aspect, and elevation on hydrologic processes (see Sørensen et al., 2006).
Land Cover	NLCD 2021 Land Cover (CONUS)	Multi-Resolution Land Characteristics Consortium [MRLC] National Land Cover Dataset [NLCD] (Dewitz, 2021)	Land Cover shows areas of (for example) forest, agriculture, and developed areas. Water can drain better through permeable materials such as forest soil than through impermeable surfaces like asphalt or concrete. Land cover type impacts runoff rates.
Hydrologic Group	Hydrologic Group	Kentucky Natural Resources Conservation Service [NRCS] (USDA-NRCS, 2020)	Hydrologic Group groups soils based on runoff potential when inundated by long storms, regardless of vegetation coverage (see Soil Science Division Staff, 2017).
Drainage Class	Drainage Class	Kentucky NRCS (USDA-NRCS, 2017)	Drainage Class is a categorization of soil types that considers how quickly water moves through the soil (see Soil Science Division Staff, 2017). Areas with poorly drained soil may be more prone to flooding as the soil can absorb less water from rainfall and at a slower rate.
Karst Areas	Karst Occurrence in Kentucky	Kentucky Geological Survey (Kentucky Geological Survey, 1988)	Karst areas are those where bedrock dissolves, forming features such as sinkholes and caves (National Park Service). Karst springs are prone to overflowing during extreme events, leading to flooding (de Waele et al., 2011).
Distance to Mines	Ky Permitted Mine Boundaries	KyGovMaps Open Data Portal (Horn, 2021)	Mine slurry impoundments may be a flood risk. Surface mines strip the land of soil and vegetation, leading to more runoff.

Table A2
Vulnerability map demographic data

Vulnerability Factor	Long Title*	Data Title**
Poverty	Percentage of people classified as below the poverty level.	pct_Prs_Blw_Pov_Lev_ACS_16_20
Limited English Speaking	Percentage of households in which members 14 and over have difficulty with English.	pct_ENG_VW_ACS_16_20
Population 65+	Percentage of people over the age of 65 years.	pct_Pop_65plus_ACS_16_20
Population Under 5	Percentage of people under the age of 5 years.	pct_Pop_under_5_ACS_16_20
Disability	Percentage of people with a disability.	pct_Pop_Disabled_ACS_16_20
Mobile Homes	Total number of mobile homes.	Mobile_Homes_ACS_16_20
No Internet Access	Percentage of households with no internet access.	pct_HHD_No_Internet_ACS_16_20
No Telephone Service	Percentage of housing units without telephone service.	pct_NO_PH_SRVC_ACS_16_20
No Computer Access	Percentage of households with no computing device of any kind.	pct_HHD_NoCompDevic_ACS_16_20
Population Density	Calculated by dividing the Total Population variable by the Shape_Area variable of the polygon in ArcGIS.	Tot_Population_ACS_16_20

*Long Titles for the US Census 2022 Planning Database Tract Data describe the data in words based on labels provided by the US Census API (U.S. Census Bureau, n.d.).
**Data Titles for the US Census 2022 Planning Database Tract Data refer to the column titles in the CSV.

Table A3
Vulnerability map infrastructure data

Vulnerability Factor	Data Title	Data Source
Bridges	Bridge Locations	Kentucky Geography Network
Hospitals	Ky Hospitals	KyGovMaps Open Data Portal
Fire Stations	Fire Stations	Homeland Infrastructure Foundation-Level Data (HIFLD)

Table A4
County-level vulnerability map demographic data

Vulnerability Factor	Numerator Label*	Numerator Data Title**	Denominator Data Title***

Population Under 5	Persons less than age 5 in the ACS	Pop_under_5_ACS_16_20	Tot_Population_ACS_16_20
Population 65+	Persons aged 65 and over in the ACS	Pop_65plus_ACS_16_20	Tot_Population_ACS_16_20
Poverty	Number of people classified as below the poverty level in the ACS	Prs_Blw_Pov_Lev_ACS_16_20	Pov_Univ_ACS_16_20
Disability	Total population with a disability in the ACS	Pop_Disabled_ACS_16_20	Civ_Noninst_Pop_ACS_16_20
Mobile Homes	Mobile Homes in the ACS	Mobile_Homes_ACS_16_20	Tot_Housing_Units_ACS_16_20
No Computer Access	Households that do not have a computing device of any kind in the ACS	HHD_NoCompDevic_ACS_16_20	Tot_Occp_Units_ACS_16_20
No Internet Access	Households that have no Internet access in the ACS	HHD_No_Internet_ACS_16_20	Tot_Occp_Units_ACS_16_20
Limited English Speaking	Limited English-speaking household (Use Tot ACS Occ HU as denominator) in the ACS	ENG_VW_ACS_16_20	Tot_Occp_Units_ACS_16_20
No Telephone Service	Number of housing units without telephone	Occp_U_NO_PH_SRVC_ACS_16_20	Tot_Occp_Units_ACS_16_20

	service in the ACS		
Population Density	Total Population in the ACS	Tot_Population_ACS_16_20	Shape_Area

*Labels for the US Census 2022 Planning Database Tract Data are taken directly from the US Census API labels for the numerator data (U.S. Census Bureau, n.d.).
**Numerator Data Titles refer to the column titles in the US Census 2022 Planning Database Tract Data.
***Denominators were used to divide the absolute numbers to obtain a percentage according to the method the census uses to calculate the tract-level percentage versions of these variables included in the Planning Database dataset. Denominator Data Titles refer to the column titles in the US Census 2022 Planning Database Tract Data CSV, except for the Shape_Area variable used to calculate population density, which was an attribute of the county polygons in ArcGIS Pro.

Appendix B

Table B1
Susceptibility Reclassification Systems

Parameter	Reclassification	
Distance to rivers (m) (Vojtek & Vojteková, 2019, p. 8)	**1**	11411.355469 - 14264.194336
	2	8558.516602 - 11411.355469
	3	5705.677734 - 8558.516602
	4	2852.838867 - 5705.677734
	5	0 - 2852.838867
TWI (Ballerine, 2017, p. 3)	**1**	≤1.8
	2	≤2.6
	3	≤3.4
	4	≤4.2
	5	≤5.0
Land cover (Nix et al., 2021)	**1**	Deciduous Forest, Mixed Forest, Evergreen Forest, Woody Wetlands
	2	Grassland/Herbaceous, Shrub/Scrub, Emergent Herbaceous Wetlands
	3	Pasture/Hay, Cultivated Crops
	4	Barren Land
	5	Developed Open Space, Developed Low Intensity, Developed Medium Intensity, Developed High Intensity
Soil drainage class (USDA-NRCS, 2017)	**1**	Excessively drained, Somewhat excessively drained
	2	Well drained
	3	Moderately well drained
	4	Somewhat poorly drained
	5	Very poorly drained, Poorly drained

Hydrologic group (USGS, n.d.)	**1**	**Group A** - “Group A soils consist of deep, well drained sands or gravelly sands with high infiltration and low runoff rates”
	2	**Group B** - “Group B soils consist of deep well drained soils with a moderately fine to moderately coarse texture and a moderate rate of infiltration and runoff”
	3	**Group C** - “Group C consists of soils with a layer that impedes the downward movement of water or fine textured soils and a slow rate of infiltration”
	4	**A/D, B/D, C/D** - “If a soil is assigned to a dual hydrologic group (A/D, B/D, or C/D), the first letter is for drained areas and the second is for undrained areas. Only the soils that in their natural condition are in group D are assigned to dual classes.”
	5	**Group D** - “Group D consists of soils with a very slow infiltration rate and high runoff potential. This group is composed of clays that have a high shrink-swell potential, soils with a high-water table, soils that have a clay”
Karst areas (de Waele et al., 2011)	**1**	Non-karst
	2	-
	3	Prone to karst
	4	-
	5	Intense karst
Distance to mines (m) (Maaß & Schüttrumpf, 2018)	**1**	75,893.721936 - 171,264.59375
	2	40,969.177328 - 75,893.721936
	3	12,089.265441 - 40,969.177328
	4	671.625858 - 12,089.265441
	5	0 - 671.625858

Table B2

Analytic Hierarchy Process

Parameter	Subject Matter Expert			Combined Weight*
	SME 1	SME 2	SME 3	
Distance to Rivers	27.0	27.1	30.1	**29.9**
Topographic Wetness Index (TWI)	30.2	16.2	30.1	**25.3**
Land Cover	9.5	16.0	17.7	**14.0**
Soil Drainage Class	9.0	17.6	9.7	**11.5**
Hydrologic Groups	11.8	13.7	7.3	**10.7**
Karst Areas	8.8	4.8	3.4	**5.4**
Distance to Mines	3.8	4.6	1.8	**3.3**

*Combined weights were rounded to the nearest whole number during analysis due to limitations of the Weighted Overlay (Spatial Analyst) tool in ArcGIS, which does not accept decimals for weights.

Appendix C

Figure C1. Full-page combined flood susceptibility map at the pixel level.

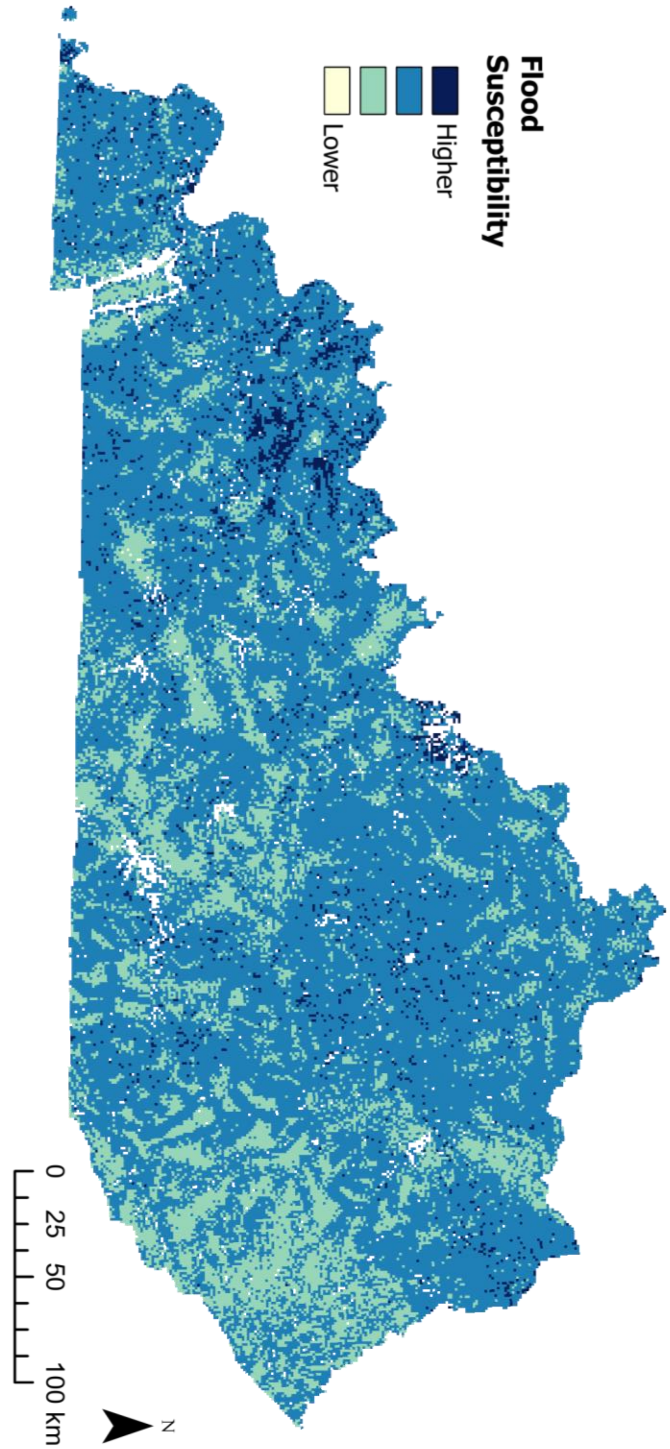

Figure C2. Full-page combined flood vulnerability map at the census tract level.

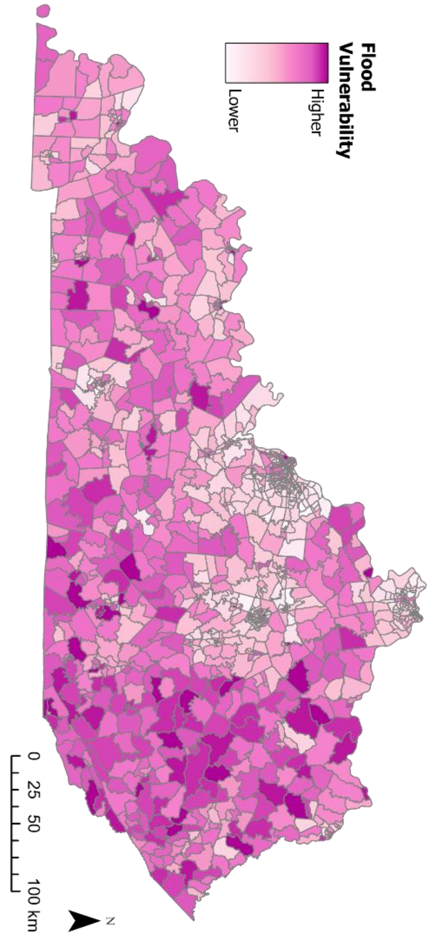

Figure C3. Full-page combined flood risk map at the census tract level.