Climate Impact on Health in Varying Community Types

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Our natural world is changing; fluctuations in global temperatures and weather patterns in addition to sea level rise are adversely impacting countries around the world (National Oceanic and Atmospheric Administration (NOAA), n.d.). Recently, climate change has led to more severe natural hazard events in the United States that have put individuals and communities at risk. In summer 2023, more than 100 million Americans experienced a local heat advisory warning due to extreme temperatures (Friedman, 2023). These impacts of climate change have been pronounced in the Southeast region of the United States, where communities are experiencing worse and longer heat waves and are at risk to extreme weather like hurricanes and flooding.

These climate events have caused negative public health outcomes in impacted communities. The Center for Disease Control (CDC) found that these events not only cause injuries and fatalities but also can result in long term health outcomes such as asthma, cardiovascular diseases, and vector-borne illnesses. Last year, approximately 1,700 people died in the U.S. due to extreme heat or a heat-related issue (Reese, 2023). Furthermore, climate events can have a negative effect on people's mental health (CDC, n.d.). While some communities are well equipped to handle these natural events, others with significantly vulnerable populations, such as children, the elderly, people of color, and people with low income, have to determine strategies to support these groups (NOAA, n.d.).

The increased risks associated with climate change have prompted an examination of what metrics can be utilized to interpret the relationship between an area's risk to natural disasters and the effect it has on individuals' health. In 2020, the Federal Emergency Management Agency (FEMA) published the National Risk Index (NRI) to better identify the U.S. counties that are most at risk to 18 natural hazards. The NRI is a multifaceted score that considers three different components: the county's expected annual loss due to a natural hazard, its social vulnerability based on its population, and its community resilience to natural hazards (FEMA, n.d.). While the NRI is intended to support community emergency managers' plans for potential natural disasters, our team believes that the NRI has the potential to be an indicator of negative public health outcomes due to the relationship between climate change and community health.

In this study, we investigated our research questions through OLS regression analysis and through predictive modeling using decision trees method. We created variables for community type based on the CDC's classification of rurality to discern the effects of community type in addition to risk score. Based on our models, while we found that the Risk Score was statistically significant in the regression models, the Risk Score had varied success in predicting whether a county's health outcomes were better or worse than the national average.

Research Questions

- How does a county's climate risk affect its population's health?
- How does the impact of climate risk vary by urbanicity?
- Can the FEMA NRI Risk Score be used to accurately predict a county's health outcomes in the Southeast region of the country?

Data Sources

The data for this project came from two key sources: the 2023 FEMA National Risk Index dataset (and corresponding shapefile) and the 2023 County Health dataset.

1. **The FEMA National Risk Index**

The 2023 FEMA NRI is a county-level dataset. The unique identifier is state-county FIPS (Federal Information Processing Standard) and the unit of observation is individual counties in the United States. Each county has an overall composite risk score (*Risk Score*) and risk rating for all 18 natural hazards, plus the overall Expected Annual Loss, Social Vulnerability, and Community Resilience scores and ratings. The FEMA NRI dataset also provided these data points for each natural hazard, but they are not included in our analysis. Other data provided included population and area size of the county. The NRI data is available in two different file types: a .csv table and a shapefile, which enabled us to complete Geographic Information System (GIS) visualizations as part of our analysis.

As stated previously, a county's overall risk index score is calculated based on the three values–the expected annual loss, the social vulnerability index, and community resilience score–using the formula below.

$$\text{Risk} = \frac{\text{Expected Annual Loss} \times \text{Social Vulnerability}}{\text{Community Resilience}}$$

Figure 1. **Formula for calculating the FEMA NRI Score**. (Zuzak et al., 2022)

Each of these components are made up of multiple indicators. Additionally, while FEMA calculated the expected annual loss scores, FEMA utilized pre-existing indicators for the social vulnerability and community resilience indicators.

- ***Expected Annual Loss.*** For this score, FEMA calculated the average economic loss in dollars resulting from natural hazards each year. Specifically, FEMA only quantified loss for relevant consequence types (i.e., buildings, population, or agriculture). Additionally the EAL score considered hazard exposure, annualized frequency, and historic loss ratio (HLR) measurements in its calculation (FEMA, 2023).
- ***Social Vulnerability.*** The Social Vulnerability Index in this dataset is the CDC/ATSDR Social Vulnerability Index (FEMA, 2023). The place-based index consists of 16 socioeconomic variables, such as percent of population over the age of 65, to help characterize communities that are less able to prepare for, respond to, and recover from public health crises.
- ***Community Resilience.*** The Community Resilience Index in this dataset is from the HVRI Baseline Resilience Indicators for Communities (BRIC) dataset (FEMA, 2023); the HVRI BRIC dataset includes a set of 49 indicators that represent six types of resilience: social, economic, community capital, institutional capacity, housing/infrastructure, and environmental.

2. 2023 County Health Rankings & Roadmaps (CHR&R) Data

The County Health Rankings & Roadmaps is a dataset from the University of Wisconsin Population Health Institute. The County Health Rankings measure the health of nearly all counties in the United States and include demographic information, health metrics such as *Age-Adjusted Death Rate*, and social determinants of health such as *Access to Exercise Opportunities*. The dataset is compiled using county-level measures from a variety of national and state data sources. These measures are then standardized and combined using scientifically-informed weights. As with the FEMA NRI dataset, the unit of measurement is a United States county and the unique identifier is the state-county FIPS.

From the County Health Rankings & Roadmaps dataset, we focused on four health variables to learn more about the overall health of the population: *Life Expectancy*, *Age-Adjusted Death Rate*, *Average Number of Mentally Unhealthy Days*, and *Average Number of Physically Unhealthy Days*.

- ***Life Expectancy.*** Average number of years a person can expect to live. The data was from the National Center for Health Statistics - Mortality Files and was collected in 2018-2020.
- ***Age-Adjusted Death Rate.*** Number of deaths among residents under age 75 per 100,000 population (age-adjusted). The data was from the National Center for Health Statistics - Mortality Files and was collected in 2018-2020.

- ***Average number of mentally unhealthy days.*** Average number of mentally unhealthy days reported in the past 30 days (age-adjusted). This data came from the Behavioral Risk Factor Surveillance System and was collected in 2020
- ***Average number of physically unhealthy days.*** Average number of physically unhealthy days reported in the past 30 days (age-adjusted). This data came from the Behavioral Risk Factor Surveillance System and was collected in 2020

Data Wrangling.

Even though the FEMA NRI data and the County Health Rankings data were relatively clean CSV files, we still needed to take several data cleaning steps to ensure we could best answer our research questions. We clean and wrangle our data through the following: (1) selecting appropriate columns and renaming; (2) joining datasets by their common identifiers; (3) creating new columns for community type, population density, and binary health outcomes; and (4) subsetting the dataset.

Selecting Columns. We decided to only import necessary columns from our chosen datasets to reduce the time for import and to reduce the number of columns that would need to be deleted later. There were some identical columns, like state and county names, that we decided to just use one dataset's information on these variables to avoid duplicates. Additionally, we looked at the information that was captured in the elements of FEMA's risk score to ensure that we did not import columns with overlapping information. To avoid multicollinearity, we decided to omit the demographic and infrastructure columns that were perfectly correlated with information included in the composite risk score. Additionally, we renamed columns to replace spaces in words with underscores, which made data processing easier in our next steps.

Joining Tables. In each table there was a unique common identifier, the Federal Information Processing Standard (FIPS) code, used for each county record. We used this unique identifier to join the datasets with a left merge approach to ensure that we were looking at the counties provided in the FEMA dataset first and then bringing in matching data from the County Health data set.

Creating New Columns. We needed to create new columns to better visualize groupings and perform predictive analysis on the data. First, we created a *Community Type* variable that categorized each county into either "Rural," "Small Urban," or "Urban" depending on population. Using the CDC's classification of Rural-Urban counties, we classified communities with populations below 50,000 as Rural, those within the range of 50,000 to 250,000 as Small Urban, and communities with populations exceeding 250,000 as Urban. Creating a community type variable was important to view the differences in climate risk effects on health outcomes across distinct levels of urbanicity. Second, we created a *Population Density* variable to aid our research on the effects of not only population in a county but also how dispersed the population is across the county. Finally, we created four binary variables for each of our health outcomes (*Life Expectancy Mean Indicator, Age-Adjusted Death Rate Mean Indicator, Physically Unhealthy Days Mean Indicatory,* and *Mentally Unhealthy Days Mean Indicator)* looking at if a county was above or below the national average for that metric. These binary variables would assist us in our GIS visualizations and with prediction outcomes from our machine learning models.

Subsetting Data. After cleaning the columns of the data, we wanted to focus primarily on the effects in the Southeast region of the United States. Therefore, we created a subsetted dataset only including states in the Southeast – Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee, West Virginia, and Virginia. We did this because of the Southeast's latitude and geography that causes it to be more susceptible to harsh climate conditions and natural disasters (Gutierrez, 2016). Additionally, creating a subset of the data allowed us to better discern the correlations between the FEMA NRI Risk Score variable and the health dependent variables, as seen in the figures below. Our Southeast regional dataset consisted of 924 unique observations (counties) – 625 Rural counties, 237 Small Urban categories, and 62 Urban counties.

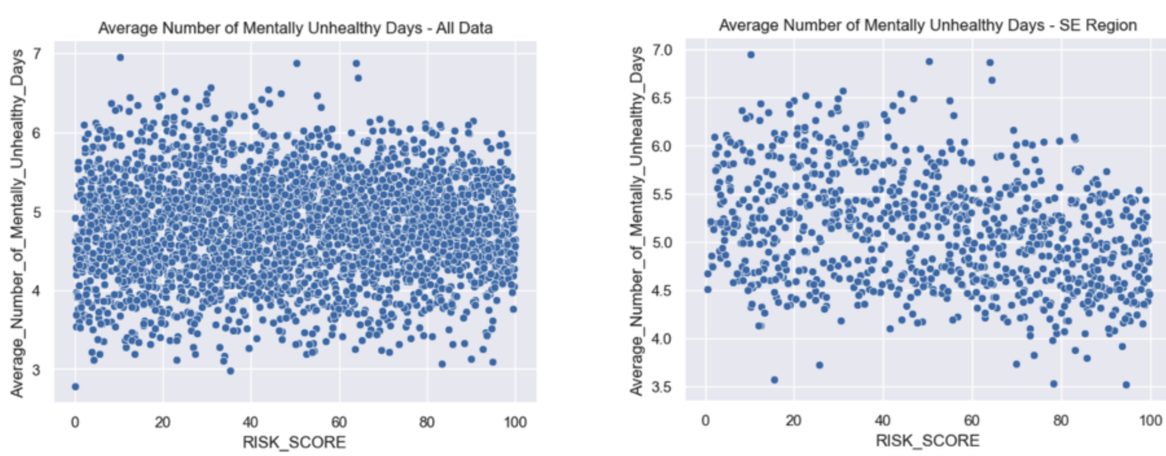

Figure 2. Example of the Differences between National and Southeast Regional Data

Methods & Analysis

Strategy. Once our data was clean, we started to complete exploratory analysis to understand what our data initially looked like before deciding on specific models to explore. We began by creating various scatter and density plots, such as the figure below, to examine the distribution and potential relationships between *Risk Score*, *Community Type,* and our four different health outcomes.

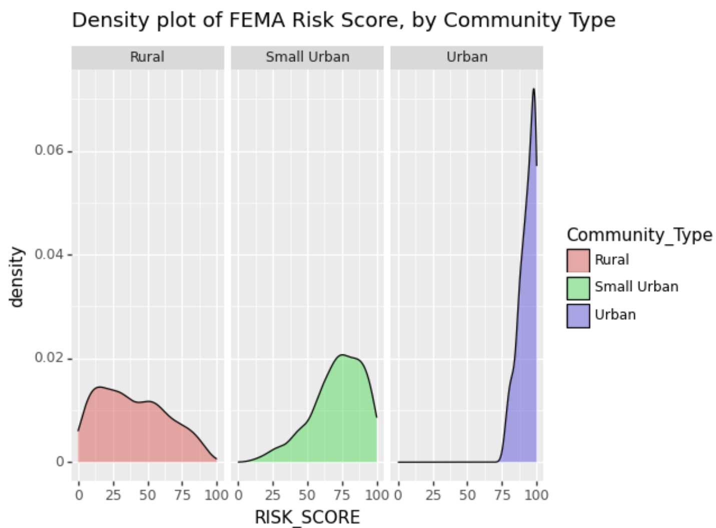

Figure 3. Density Plot for FEMA Risk Scores in the Southeast Region, by Community Type

In addition to investigating the composite risk score, we considered the effects of the different components of the Risk Score – social vulnerability, expected annual loss, and community resilience – on the dependent health outcomes. We created these exploratory plots for both the national dataset and the Southeast regional dataset to understand patterns in these metrics throughout the United States and Southeast region. Our final exploratory measure was to look at GIS visualizations to learn about the spatial distribution of the risk score and dependent health variables.

After completing our exploratory analysis, we decided to run various OLS models to test our hypothesis that risk scores would have a significant impact on health outcomes. Moreover, we wanted to test if controlling for *Community Type* would provide further clarity on this relationship.

Following OLS modeling, we utilized machine learning to predict if the climate risk score with controlling variables was able to accurately predict binary health outcome metrics across the Southeast region. Using a test and training split dataset, we were able to test various machine learning models with differing parameters to find the best model. After finding our best machine learning model, we wanted to visualize the predictions and accuracy via GIS. Using the prediction outcomes and the actual values, we were able to visualize our model's accuracy geographically to detect any accuracy patterns across regions and states.

OLS Modeling. To better understand the relationships between the FEMA NRI risk scores and the four dependent health variables, we ran several multivariate regression models. Based on the scatterplots that visualized a county's NRI Risk Score and health outcomes, we recognized a potential quadratic relationship between the variables. Therefore, we created the variable *Risk Score Squared* and added it into our OLS models. Additionally, we controlled for the categorical variable *Community Type* and added *Population Density* as a covariate. Lastly, we added an interaction term between *Community Type* and *Risk Score* to discern whether there was a significant interaction between the two variables.

For each health outcome, we created hierarchical regression models. We started with a bivariate model that utilized *Risk Score* as the only independent variable. Then in each additional model added *Risk Score Squared, Community Type* (Community Type Rural served as the reference category)*, Population Density,* and the interaction variable, one variable at a time. Ultimately, the last model created resembled the following model:

$$HealthOutcome_i = B_0 + B_1 RiskScore_i + B_2 RiskScore_i^2 + B_3 CommunityType_i + B_4(CommunityType_i * RiskScore_i) + B_5 PopulationDensity_i$$

Figure 4. Formula for Regression Analysis

In cases where *Risk Score Squared* did not appear significant, we took out the variable and ran with only *Risk Score* to determine whether *Risk Score* was significant in the model.

Based on the results of the multivariate linear regressions, seen below in Table 1, *Risk Score* and *Risk Score Squared* appear to be statistically significant for *Life Expectancy, Age-Adjusted Death Rate,* and *Average Number of Mentally Unhealthy Days.* This suggests that *Risk Score* may have a quadratic relationship with these health dependent variables and that the effect of *Risk Score* varies depending on its value. *Risk Score Squared* was not statistically significant for the dependent variable *Average Number of Physically Unhealthy Days,* but the variable *Risk Score* was statistically significant, suggesting a negative relationship.

Community Type was statistically significant in all four regression models, which suggests that the average scores for the health dependent variables are different for Rural, Small Urban, and Urban community types. The interaction effect varied based on the community type; compared to the reference category Rural, Small Urban did not appear to have a statistically significant interaction effect for any of the dependent variables but the interaction effect between *Risk Score* and Community Type Urban was statistically significant for three of the dependent variables. However, Urban counties make up a small percentage of the total sample (less than 10%).

Table 1: Regression Output for Dependent Health Outcomes

	Life Expectancy	Age-Adjusted Death Rate	Physically Unhealthy Days	Mentally Unhealthy Days
RISKSCORE	-0.0686***	2.2283***	-0.0019**	0.0045
	(0.0146)	(0.6207)	(0.0009)	(0.0030)
RISKSCORESQ	0.0006***	-0.0198***		-0.0001***
	(0.0002)	(0.0069)		(0.0000)
CommunityType[T.Small Urban]	2.4717***	-117.3983***	-0.2906*	-0.3073*
	(0.8123)	(34.6395)	(0.1557)	(0.1648)
CommunityType[T.Urban]	9.2681*	-599.1343***	-3.9066***	-4.0316***
	(5.2595)	(224.3500)	(1.1445)	(1.0672)
RISKSCORE:CommunityType[T.Small Urban]	-0.0109	0.4196	-0.0017	0.0034
	(0.0122)	(0.5192)	(0.0022)	(0.0025)
RISKSCORE:CommunityType[T.Urban]	-0.0658	4.9157**	0.0361***	0.0440***
	(0.0573)	(2.4426)	(0.0123)	(0.0116)
PopulationDensity	0.0009***	-0.0310***	-0.0002***	-0.0002***
	(0.0001)	(0.0054)	(0.0000)	(0.0000)
Observations	922	924	924	924
R^2	0.2384	0.2318	0.2468	0.1787
Adjusted R^2	0.2326	0.2259	0.2418	0.1725
Residual Std. Error	2.5729	109.7610	0.5728	0.5221
F Statistic	40.8727***	39.4853***	50.0695***	28.4781***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1. Regression Results for the Four Dependent Variables

Machine Learning. We used the binary indicator variables *Age-Adjusted Death Rate Mean Indicator, Life Expectancy Mean Indicator, Physically Unhealthy Days Mean Indicator,* and *Mentally Unhealthy Days Mean Indicato*r that we created in our data wrangling stage as the dependent variables to predict with our machine learning model; we were interested in predicting if Southeast counties would be above or below the national average in these health metrics. We identified four independent variables to use as prediction variables: *Community Type, Population Density, Risk Score, and Risk Score Squared. Risk Score Squared* was included in all models except for the prediction of *Average Number of Physically Unhealthy Days* because it was not statistically significant, as shown in Table 1. *Community Type* and *Population Density* were both included to account for differences in population dispersions and county classifications, consistent with our research questions.

After checking the data types of each column, we identified that the *Community Type* variable was an object and contained string categorical variables. To make this column a compatible input in a model while keeping the categorical values of the variables, we opted to use the one-hot encoding technique to classify the three different community types as dummy variables. We did this by using the get_dummies function in the Pandas library; this allowed us to create two new columns for two different community types that were coded 0 for counties that did not match the community type and 1 for counties that did match the community type. A third column was not created for the third community type as it was used as the reference/excluded variable in model.

We chose to use a decision tree machine learning model to predict the above or below national average health outcomes for Southeast counties. This model was selected for several reasons. After trying several types of classifier models including logistic regression, k-nearest neighbors, and support vector machines, it was clear that the other models either overfit or underfit our data and were not suitable for our predictions. When tuning and selecting the appropriate parameters, the decision tree model gave us the best prediction of the dependent variables without overfitting the data. Further, the specific type of decision tree model that we used allowed us to easily classify the predictions of the binary columns.

The Southeast data was subsetted to only include the newly created community type dummy variables, as well as the other identified independent and dependent variables. We then used the Sci-kit Learn library to create our decision tree machine learning model. Using the train_test_split package, we split the data into training and testing data for our decision tree model; 80% of the data went to training, while 20% was set aside for testing. To fine tune and improve accuracy of the model, we used the k-fold cross validation technique to further split and train our data an additional five times.

We created a DecsionTreeClassifer model to classify the predictions as 0 and 1, consistent with the values of the binary health metric indicator columns. In this model, a value of 0 meant a county was below the national average in the health metric while a value of 1 meant a county was above the national average in the health metric. We then tuned and trained our model using best parameters, including limiting the depth of our trees to three. We fit the model with the X_train and y_train data and predicted counties' position relative to the national average in *Average Number of Physically Unhealthy Days* by using the X_test data; this prediction was then applied to all counties in the dataset. We appended these predictions to a new column and repeated the steps for the *Average Number of Mentally Unhealthy Days* predictions. We also created models that used the same inputs to predict *Age-Adjusted Health Rate* and *Life Expectancy,* but focused our analysis on the *unhealthy days* variables.

GIS. Utilizing GIS was important to understand our data from an exploratory perspective and also to visualize patterns in our machine learning prediction results. We used the Python package Geopandas to manipulate and plot the shape file provided from FEMA's website. We were able to plot continuous and binary variables by county to see patterns across state lines and regions. To better conceptualize our data and findings, we updated the color mapping to associate green with healthier outcomes and red with unhealthy outcomes in our maps plotting health outcomes. For our accuracy maps, we used green as a correct prediction and yellow as an incorrect prediction.

Results

The four models that we created predicting if counties were above or below the national average in *Age-Adjusted Death Rate, Life Expectancy, Average Number of Physically Unhealthy Days,* and *Average Number of Mentally Unhealthy Days* had varying levels of prediction accuracy.

Figure 5 demonstrates how our prediction model labeled each county in the Southeast region as being either above or below the national average. For counties that are colored red, it indicates that their health outcome is worse than the national average (for *Life Expectancy,* it is counties whose life expectancy is below the national average; for *Age-Adjusted Death Rate, Physically Unhealthy Days,* and *Mentally Unhealthy Days,* it is counties whose variables are above the national average). For counties that are colored green, it indicates that their health outcome is better than the national average.

Figure 6 highlights where our prediction model was correct and incorrect in its labeling. Counties that are colored green are ones where the actual value matches the predicted value, and counties that are colored yellow are ones where the actual value does not match the predicted value.

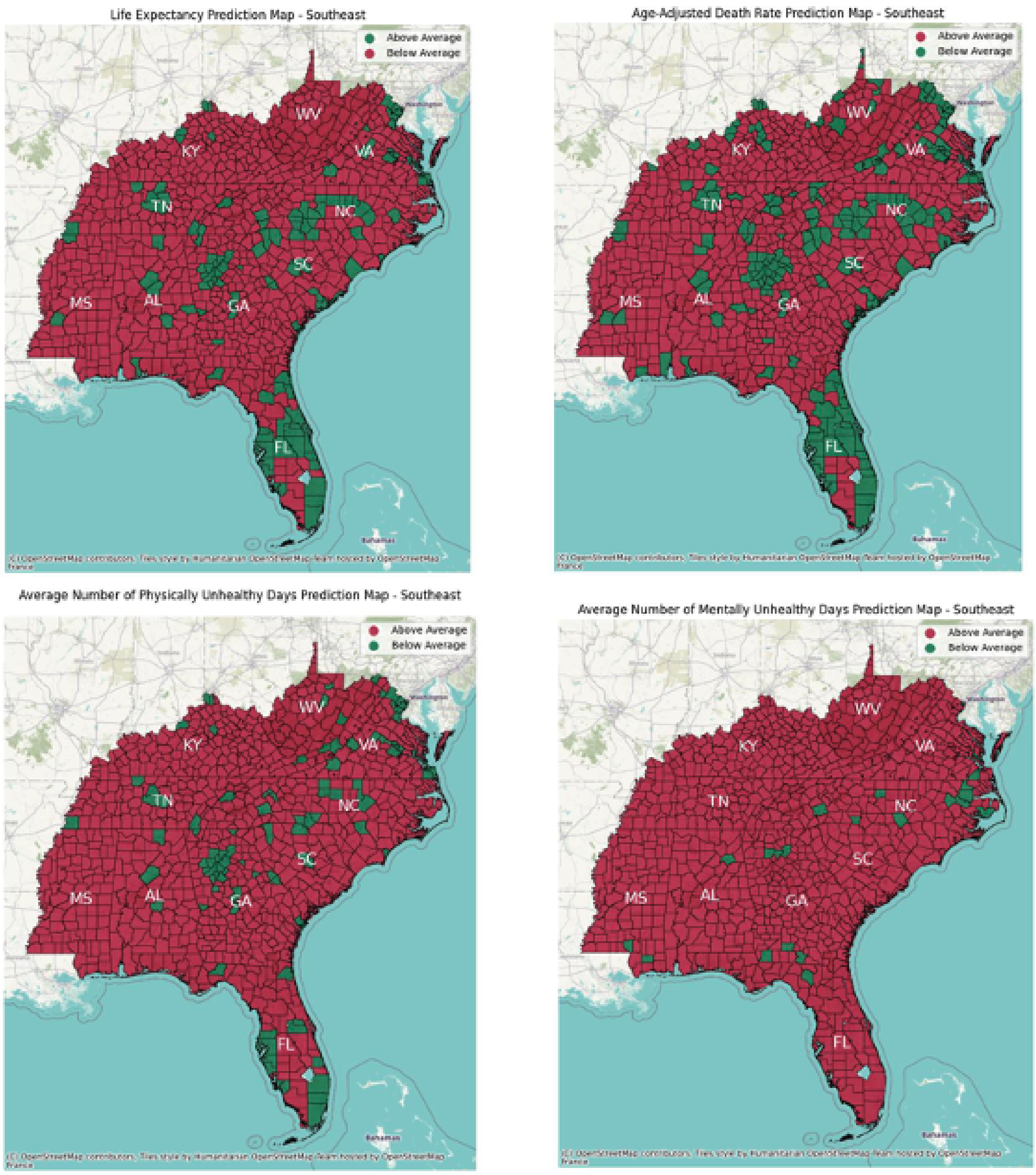

Figure 5. Predicted Values for the Health Dependent Variables. Top Left: Life Expectancy. Top Right: Age-Adjusted Death Rate. Bottom Left: Physically Unhealthy Days. Bottom Right: Mentally Unhealthy Days

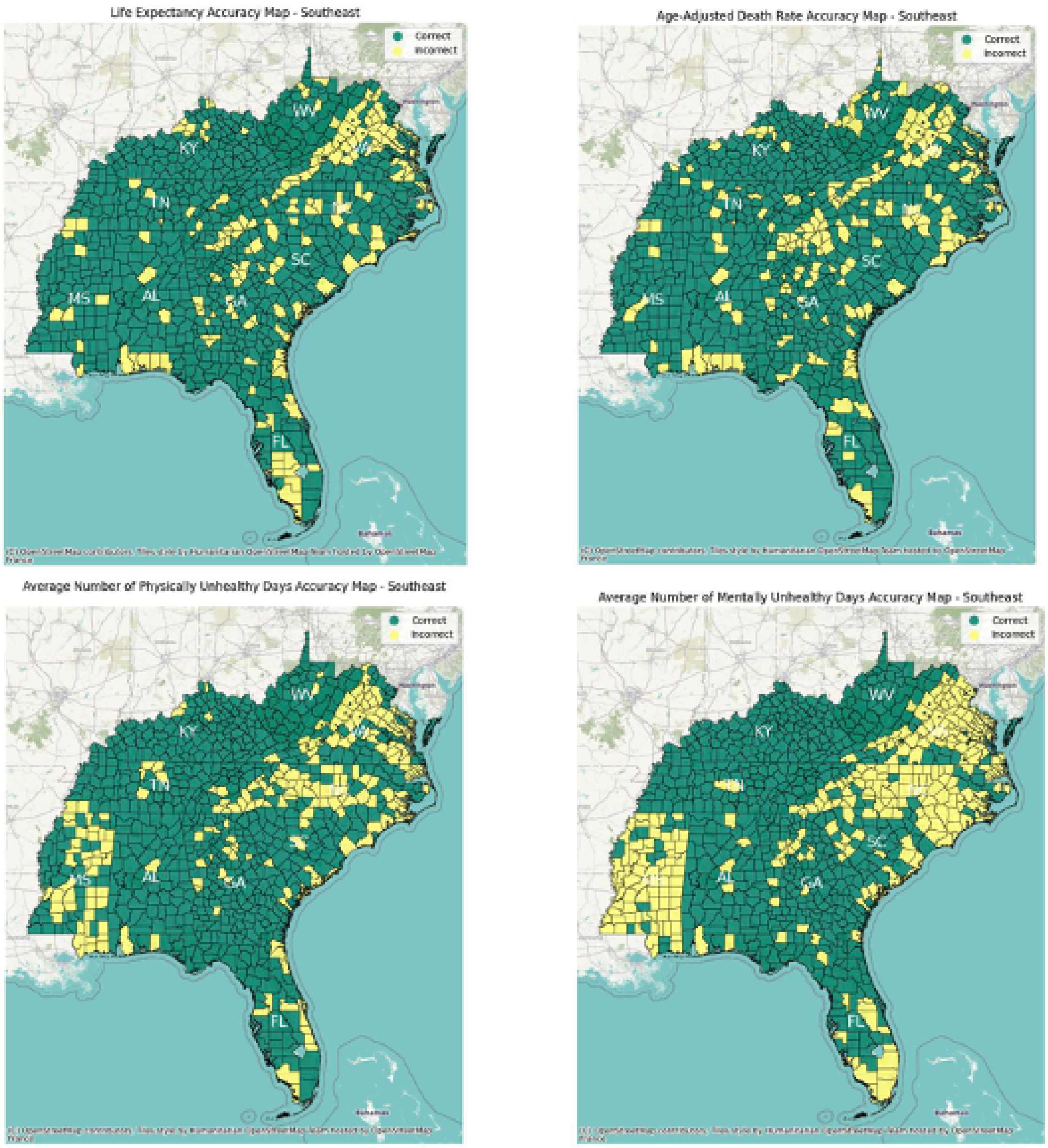

Figure 6. Accuracy of the Machine Learning Prediction Model for the Health Dependent Variables. Top Left: Life Expectancy. Top Right: Age-Adjusted Death Rate. Bottom Left: Physically Unhealthy Days. Bottom Right: Mentally Unhealthy Days

Table 2: Overall Model Accuracy and Accuracy by Community Type

	Age-Adjusted Death Rate	Life Expectancy	Physically Unhealthy	Mentally Unhealthy
Overall Accuracy	0.745600	0.794500	0.729700	0.670200
Rural Accuracy	0.838400	0.843200	0.812800	0.740800
Small Urban Accuracy	0.670886	0.696203	0.607595	0.582278
Urban Accuracy	0.774194	0.790323	0.774194	0.532258

Table 2. Overall Model Accuracy and Accuracy by Community Type

From Table 2, we can see that the best overall model is our *Life Expectancy* model with an accuracy of 79.4%. We see that the accuracies differ by community type. Across the models, we see that Small Urban counties are very difficult to predict, while Rural counties' predictions are most accurate.

Additionally, the accuracy percentages varied across states. For example, our GIS maps of the *Physically* and *Mentally Unhealthy Days* models show clear and identifiable differences along state lines; specifically, the models did not predict well in Mississippi, North Carolina, and Virginia. Moreover, both models struggled in some specific urban and suburban areas, such as the Atlanta metro area, while the *Mentally Unhealthy Days* model also struggled in correctly predicting outcomes in the Nashville and Miami metro areas.

Discussion

From our analysis, we continue to suspect a relationship between climate risk and community health outcomes, but it requires further review. In the regression analysis, the results were different from what we initially expected. Three of the four dependent variables appear to have a quadratic relationship with *Risk Score*, and one has a possible negative linear relationship with *Risk Score*. We had been expecting that an increased score would result in more negative outcomes, which in the case of *Age-Adjusted Death Rate, Mentally Unhealthy Days,* and *Physically Unhealthy Days*, would mean increased scores. However, the estimated coefficients on *Risk Score* and/or *Risk Score Squared* are negative, suggesting the opposite relationship. Therefore, we suspect that there may be a variable not captured in the Risk Score that affects a county's community health outcomes. Additionally, as *Community Type Rural* served as the reference category in the regression model, only the interaction effect between *Risk Score* and *Community Type Urban* was significant, which suggests a stronger relationship between Risk Score and Urban counties. The estimated relationship between *Risk Score* and Rural/Small Urban counties, which make up the majority of the dataset, is similar and not as strong.

Overall, the *Risk Score* and other independent variables were fairly accurate in predicting health outcomes in comparison to the national average for the four health metrics, but had varying levels of accuracy. Additional variables are needed to improve the accuracy of these models.

There could be many reasons for the regression results and prediction inaccuracies, possibly relating to state policies, geographic location or state identification surrounding these health metrics. All four health prediction models were reasonably accurate in predicting outcomes for rural counties, but they struggled in accurately predicting outcomes in small urban counties. This could be related to the variety of counties within this classification - our classification of small urban counties encompassed both medium size cities as well as suburban counties in large metro areas. These differences in proximity to large cities and geographic location could explain the inaccuracies of predicting health outcomes for small urban counties.

Going forward, we would want to explore more about why certain states clearly had more or less physically or mentally unhealthy days. We imagine that there could be specific state policies that either encourage healthier practices or maybe the results were gathered at a state level that influenced how questions were asked that skewed results. Additionally, we would want to consider geographic location and neighboring counties as additional independent variables to account for inaccuracies identified in our models. Since we did not originally account for geographic location and state identification of counties, these variables did not influence our predictions; however, it is likely that relevant state policies do in fact influence whether counties are above or below the national average in these health metrics.

We would also be interested in learning more about if the climate risk score would have any real life implications for resource allocation or program qualification. These implications would be especially interesting to look at the impacts of areas that report bad levels of health conditions, but have a relatively low risk score due to other impacts. This leads us to look further at the calculation for the composite risk score – maybe the impact of dividing by community resilience is too much or social vulnerability is not amplified enough by just multiplication. Generally, we would want to include additional variables and explore different calculations to learn more about the effects of climate risk on health outcomes.

Author Contributions & Acknowledgements

Each author contributed substantially to the conception, execution, and completion of this research paper. Each analysis component was completed by each of the following authors:

- Bridgette Sullivan: GIS Plotting
- Holt Cochran: Machine Learning Modeling
- Katharyn Loweth: OLS Modeling

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