GeoHealth

RESEARCH ARTICLE

10.1029/2023GH000839

Key Points:

- This study examines the mental and behavioral disorder response to changing environmental conditions during summer months in North Carolina, USA
- Socio-demographic compared to environmental factors were more predictive of mental health outcomes in adolescents
- Findings indicate the effect of place-based differences in a youth mental health response to extreme heat

Correspondence to:

L. Wertis,
wertisml@appstate.edu

Citation:

Wertis, L., Sugg, M. M., Runkle, J. D., & Rao, D. (2023). Socio-environmental determinants of mental and behavioral disorders in youth: A machine learning approach. *GeoHealth*, 7, e2023GH000839. https://doi.org/10.1029/2023GH000839

Received 10 APR 2023
Accepted 22 AUG 2023

Author Contributions:

Conceptualization: Luke Wertis, Margaret M. Sugg, Jennifer D. Runkle
Data curation: Luke Wertis
Formal analysis: Luke Wertis
Methodology: Luke Wertis, Margaret M. Sugg, Jennifer D. Runkle, Douglas Rao
Software: Luke Wertis
Visualization: Luke Wertis
Writing – original draft: Luke Wertis
Writing – review & editing: Luke Wertis, Margaret M. Sugg, Jennifer D. Runkle

Socio-Environmental Determinants of Mental and Behavioral Disorders in Youth: A Machine Learning Approach

Luke Wertis[1], Margaret M. Sugg[1], Jennifer D. Runkle[2], and Douglas Rao[2]

[1]Department of Geography and Planning, Appalachian State University, Boone, NC, USA, [2]NC Institute for Climate Studies, NC State University, Raleigh, NC, USA

Abstract Growing evidence indicates that extreme environmental conditions in summer months have an adverse impact on mental and behavioral disorders (MBD), but there is limited research looking at youth populations. The objective of this study was to apply machine learning approaches to identify key variables that predict MBD-related emergency room (ER) visits in youths in select North Carolina cities among adolescent populations. Daily MBD-related ER visits, which totaled over 42,000 records, were paired with daily environmental conditions, as well as sociodemographic variables to determine if certain conditions lead to higher vulnerability to exacerbated mental health disorders. Four machine learning models (i.e., generalized linear model, generalized additive model, extreme gradient boosting, random forest) were used to assess the predictive performance of multiple environmental and sociodemographic variables on MBD-related ER visits for all cities. The best-performing machine learning model was then applied to each of the six individual cities. As a subanalysis, a distributed lag nonlinear model was used to confirm results. In the all cities scenario, sociodemographic variables contributed the greatest to the overall MBD prediction. In the individual cities scenario, four cities had a 24-hr difference in the maximum temperature, and two of the cities had a 24-hr difference in the minimum temperature, maximum temperature, or Normalized Difference Vegetation Index as a leading predictor of MBD ER visits. Results can inform the use of machine learning models for predicting MBD during high-temperature events and identify variables that affect youth MBD responses during these events.

Plain Language Summary There is new evidence showing that really hot weather during the summer make it harder for people with mental and behavioral disorders (MBD) to cope. But not much research has been done on youths. This study used machine learning to look at data from over 42,000 visits to the emergency room for mental and behavioral issues in youths in North Carolina. We examined the association between youth MBD and environmental conditions using different types of machine-learning models. The research found that in some cities, environmental factors like the temperature had a significant impact, while in other cities, factors like where people lived, and their sociodemographic backgrounds were more important. Overall, this study suggests that really hot weather might make it harder for young people with MBD to cope, but this might not be the case in all locations. Other place-based factors and social determinants of health might be more important than environmental conditions like ambient temperature.

1. Introduction

The burden of mental illness in the United States is substantial; one in five individuals experience a diagnosable mental illness each year (Centers for Disease Control and Prevention, 2021). According to the U.S. Department of Health and Human Services Substance Abuse and Mental Health Services Administration (SAMHSA), instances of mental health are the highest among young adults aged 18–25, with one in three reporting having a mental illness (SAMHSA, 2021). The direct cost of addressing and treating mental illness in the United States is growing annually, with the annual cost increasing by 40% in the last 7 years (Roehrig, 2016; SAMHSA, 2014).

Exposure to hot environmental conditions such as air temperature has been associated with an increased risk of hospitalizations or emergency room (ER) visits for mental health disorders (Berry et al., 2009; McMichael et al., 2006; Mullins & White, 2019; X. Wang et al., 2014), but the majority of this work has been focused on adult rather than youth populations (Sugg et al., 2018). Despite a strong association, there is no universal temperature threshold for when mental health begins to be negatively affected. Researchers have identified a strong association between high ambient air temperatures (24.5–28°C) over a period of up to 7 days and a strong increase (26%–29%) in mental and behavioral disease emergency visits compared to days below this threshold (Peng et al., 2017; X. Wang et al., 2014). Research has also observed a positive association between increased hospital admissions for MBDs (7.3%) and heat-wave days (Hansen et al., 2008). Previous research has shown an overall increase in mental health admittance during summer months for select locations (Toronto Canada, 10 labor market regions in New York, and Erie and Niagara counties in New York) (C. Wang et al., 2018; Yoo, Eum, Gao, & Chen, 2021; Yoo, Eum, Roberts, et al., 2021).

Despite many studies investigating the susceptibility to extreme heat among persons with a mental disorder, the lack of defined metrics identifying which environmental (e.g., vegetation amount, ambient temperature, humidity) and socioeconomic factors (e.g., income and race) contribute to susceptibility means that there still is a need to better understand this relationship (Park & Kim, 2018; C. Wang et al., 2018). Previous studies have indicated that socioeconomic variables such as unemployment and no high school diploma are proxies for low income and suggest higher vulnerability to temperature-related mental health outcomes (Mullins & White, 2019; Reiss, 2013; Y. Wang et al., 2019).

Future projections show that the Southeastern United States will likely experience an increase in average temperature as high as 8°F along with an increase of up to 50 additional days over 95°F in some areas, all of which will lead to an increase in heat stress and heat-related deaths (EPA, 2022). However, there has been little research on how different geographical and climatological regions respond to high-temperature extremes and the susceptibility of vulnerable populations like children, particularly in the southeastern US, a region regularly impacted by high temperature and humidity (Park & Kim, 2018). The extreme heat and health associations are typically assessed by looking at a select individual area (Hansen et al., 2008; Rocklöv et al., 2014) or multiple urban cities spread across a single country (Ogata et al., 2021). As a result, there is limited information about how neighboring cities differ in their response behavior and what contributes to this differing response and even fewer studies have examined how place-based disparities in access to greenspaces or other mental health-promoting resources influence the heat-health relationship (Mullins & White, 2019). It would be useful to capture the driving risk factors in predicting the occurrence of MBDs for determining interventions to address the effect of climate change on mental health. However, the lack of identifiable risk factors delays an accurate prediction and lowers the utilization of available medical resources, which could be provided more effectively to improve response rates, decrease mortality, and reduce medical costs (SAMHSA, 2021).

Prior studies have relied on statistical models like linear regression and generalized additive model (GAM) because they are easy to interpret but may yield less accurate predictions because these models lack the ability to simultaneously consider the complex and possibly nonlinear relationship between multiple collinear variables (Aragones et al., 2002; Benka-Coker et al., 2020). In general, too few studies have integrated state-of-the-art machine learning approaches (e.g., random forest and XGBoost) alongside standard statistical approaches to complement a priori statistical inference with the predictive performance of tree-based ensembles to enhance medical decision support (Lundberg, 2018). The study aims to identify the factors that predict ER visits for mental and behavioral disorders (MBD) in youths living within six metropolitan cities during the warm season. To achieve this, various machine learning approaches, including the generalized linear model (GLM), GAM, random forest, and extreme gradient boosting, will be explored. These models offer more precise and robust results than traditional linear regression and additive models, especially when dealing with multicollinearity within the data. The SHapely Additive exPlanations (SHAP) method will also be used to allocate contribution values for model outputs among explanatory variables, making it possible to quantify variable contribution in non-linear model results and thereby providing a means of quantifying variable contribution in non-linear model results.

The study hypothesizes that there is an association between hot ambient temperatures and youth mental health (ages 5 to 24), but socioeconomic and regional differences are the most influential factors in explaining mental health disparities in youths. Results from this study can provide new guidance on the application of machine learning models for predicting mental health conditions during high-temperature events, as well as help inform what variables contribute to a communities mental and behavioral response during high-temperature events.

10.1029/2023GH000839

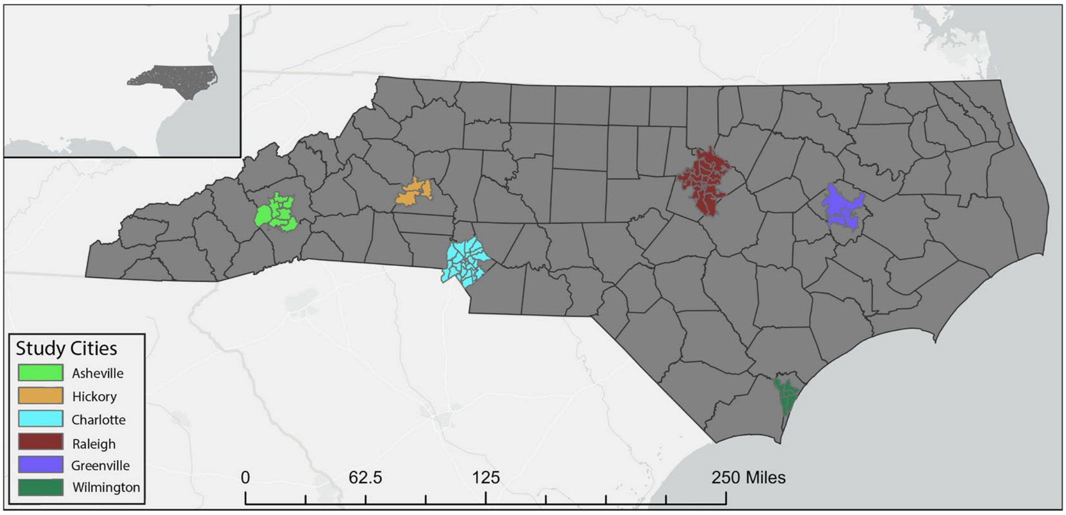

Figure 1. Study area with the ZIP Codes that comprise the six cities in North Carolina that are part of the study highlighted in a unique color, and the ZIP Codes not in the study are shaded gray.

2. Materials and Methods

2.1. Data

2.1.1. Study Population

In this study, the MBD cases were obtained from the Shep's Center for Health and Human Services Research data set, which contains all ER visits across North Carolina (SHEPS, 2022). Diagnosis of mental health and behavioral conditions were identified using ICD-10 diagnosis codes (F00-F99) in any of the diagnostic categories. We collected the daily case counts of mental and behavior-related visits in Asheville, Hickory, Charlotte, Raleigh, Wilmington, and Greensville from the summer (June, July, and August) of 2016–2019 of individuals between the ages of 5 and 24, which was used as the outcome variable (Figure 1). The study locations were selected because they represent a range of climates across NC while supporting a large enough sample size for the statistical analysis. ER visits were selected for between 2016 and 2019. This time period was selected due to the change from ICD-9 to ICD-10 codes in 2016, leading to a classification change in several mental health-related codes. Additionally, 2019 was chosen as an endpoint, not to include data during the COVID-19 pandemic, as hospital visits decreased for mental health in the early phase of the pandemic. The cities were treated as a categorical variable (i.e., Asheville = 1, Hickory = 2, etc.) in the all city's model and as a dichotomous variable (Asheville (yes/no)) in the individual city analysis. Cities received a categorical value depending on which of the three geographical regions of North Carolina they were located in: Mountains, Piedmont, and Coastal Plains. Additionally, the month of the year and day of the week were notated in the data set and incorporated into the final models (Table 1).

2.1.2. Socio-Demographic Data

Additional sociodemographic information was obtained from the U. S. Census Bureau (2023) for each city including the median age, total population, the population of our study age, male-to-female ratio, percent of the population without a high school diploma, percent unemployment, percent English speakers, percentage of mobile homes, and the Index of Concentration at the Extremes (ICE) metrics (Krieger et al., 2016) (Table 2). Variable selection and justification can be found in Table 2. The ICE metrics are used in public health monitoring to capture extremes of economic and residential segregation (Conner et al., 2010; Krieger et al., 2016). The ICE income ratio is the number of persons in the 80th percentile of income subtracted from the 20th percentile, divided by the total population with a known income; where by the majority low-income are compared to the majority high-income communities. The ICE race metric is derived from the ratio of white to black individuals and represents a comparison between majority Black compared to majority White communities at each extreme (Krieger et al., 2016). The ICE metrics range from −1 (least privilege) to 1 (most privileged) (Krieger et al., 2016). Lastly, the rural-urban commuting area (RUCA) codes collected from the United States Department of Agriculture, which use population density, urbanization, and daily commuting, were used to delineate metropolitan (RUCA

Table 1
Sociodemographic Information for Each of the Six Cities in the Data Set Between June and August From 2016 to 2019

	Asheville	Hickory	Charlotte	Raleigh	Greenville	Wilmington
Total Population	194,953	103,044	907,489	739,710	140,723	169,921
Population between 5 and 24	42,633	26,607	240,923	199,645	50,559	47,975
Median Age of City	42.15	40.17	34.78	35.71	31.7	37.96
Male to Female Ratio	91.48	93.30	93.62	95.41	90.33	90.28
ICE Income[a]	−0.14	−0.27	0.06	0.28	−0.21	−0.16
ICE Race[a]	0.82	0.79	0.19	0.48	0.27	0.61
Total Mobile Home, %	2.08	2.07	0.58	0.81	1.53	1.22
Does not Speak English, %	8.03	14.80	18.81	15.34	7.58	7.30
Below Poverty Line, %	14.83	17.23	15.64	12.56	22.40	20.94
No High School Diploma, %	17.89	22.7	13.15	11.69	16.48	18.04
Unemployment, %	3.775	5.5	5.796	3.97	7.03	5.48

[a]ICE metrics range from −1 (least privilege) to 1 (most privileged).

1–3), micropolitan (RUCA 4–6), small-town (RUCA 7–9), and rural (RUCA 10) commuting areas based on the size and direction of the primary (largest) commuting flows (USDA, 2020), for the ZIP Codes comprising the area within the chosen city's city limits.

2.1.3. Weather Data

Daily gridded raster temperature data at 4 km resolution was obtained from the PRISM Climate Group (PRISM, 2022); the raster was aggregated to the city level by taking a weighted mean average of daily climate metrics; minimum temperature (TMIN) (°C), average temperature (TAVG) (°C), maximum temperature (TMAX) (°C), and dew point for all grid points within a city, where the values from each grid point are combined to calculate the mean value within the grid. In addition to the metrics obtained by PRISM, several other metrics were derived; the TMAX 24-hr difference (°C), TMIN 24-hr difference (°C), and TAVG 24-hr difference (°C), which were obtained by subtracting the current days' value by the previous day's value. Relative humidity (RH) (%) was obtained as a product of TAVG and dew point, and the heat index was calculated using TAVG and RH. Lastly, excess heat factor (EHF) was calculated using TAVG and following the methodology from Nairn and Fawcett (2014). R 4.2.0 was utilized to perform this raster analysis at the city level.

2.1.4. Green Space Data

The Normalized Difference Vegetation Index (NDVI) was obtained from the National Oceanic and Atmospheric Administration (NOAA, 2022). NDVI is used to quantify vegetation greenness and is used to understand vegetation density, ranging from 1 to −1 from dense vegetation to barren rock (USGS, 2018). The spatial resolution of the data set was 5 km with a daily temporal resolution. The raster was aggregated to the city level by taking a weighted mean average of daily NDVI value for all grid points within a city, where the values from each point are combined in order to calculate the mean value within the grid. R 4.2.0 was utilized to perform this raster analysis at the city level.

All variables calculated at the ZIP Code level were then aggregated with the other ZIP Codes corresponding to their given city.

2.2. Model Development

2.2.1. Preprocessing

Prior research has documented a strong association between exposure to high temperatures and increased risk of MBD-related ER visits in the summer season (Ogata et al., 2021; Son et al., 2016; X. Wang et al., 2014; Y. Wang et al., 2019); therefore, this study focused on the warmer period (June through August). Multicollinearity

10.1029/2023GH000839

Table 2
Variables Considered as Predictors of Youth Mental and Behavioral Disorders in North Carolina, 2016–2019

Category	Variable and operational definitions	Association with mental health outcomes	Citation
Socioeconomic Status	% **Unemployment**—the percentage of individuals unemployed % **Total Mobile Homes**—The percentage of mobile homes in a city % **Non-English Speakers**—The percentage of individuals who do not speak English in a city % **No High School Diploma**—The percentage of the cities population without a high school diploma % **Below Poverty Line**—The percentage of the cities population that is below the poverty line	These variables are proxies for low income and low educational attainment; prior studies suggest that individuals with access to fewer resources have a greater risk of temperature-related shocks to mental health	Reiss (2013), Mullins and White (2019), and Y. Wang et al. (2019)
Green Space	**Normalized Difference Vegetation Index (NDVI)**—Method of quantifying vegetation greenness	In urban environments green space has been shown to lower temperatures and provide protection to pedestrians	Schatz and Kucharik (2015) and Kianmehr and Lim (2022)
Climate Conditions	**Maximum temperature (TMAX)**—The daily maximum temperature **Minimum temperature (TMIN)**—The daily minimum temperature **Average temperature(TAVG)**—The mean value of the daily maximum and minimum temperature **Relative humidity (RH)**—The daily mean relative humidity **24-hr TMAX**—Current day maximum temperature subtracted from the previous day's maximum temperature **24-hr TMIN**—Current day maximum temperature subtracted from the previous day's minimum temperature **Excess Heat Factor (EHF)**—Method of calculating the severity of a heatwave	High-temperature values have been found to increase mental health outcomes risks Increased relative humidity values are associated with an increase in adverse health outcomes A lower 24-hr temperature difference has been shown to increase an individual's health risk during the summer months EHF is an established method of identifying heatwaves, heatwaves have been shown to increase an individual's risk of adverse health outcomes	Mullins and White (2019), Y. Wang et al. (2019), and Ogata et al. (2021)
Residential and economic segregation	**ICE Race**—Ratio of residential segregation **ICE Income**—Ratio of economic segregation	These metrics have shown to be useful for public health monitoring, as they capture the full range of privilege and deprivation and are more versatile than traditional poverty metrics	Conner et al. (2010) and Krieger et al. (2016)
Demographic	**Male-Female Ratio**—The ratio of males for every 100 females in a city **Median age**—The average age of the cities population	Sex was considered due to higher rates of help-seeking behavior being identified in females The median age was considered due to more resources being allocated to the older population than the younger population which will be more present in cities with an older median population	Oliver et al. (2005) and The Government Office for Science (2019)

10.1029/2023GH000839

Table 3
Variable Inflation Factor of the Chosen Variables for Generalized Linear Model, Generalized Additive Model, RF, and XGBoost Models

Variable	GLM and GAM	RF and XGBoost
Total Population	–	6.12
Median Age	3.546	3.15
Male to Female Ratio	8.31	–
Population 5–24 per 1,000	6.62	–
City	3.71	2.79
ICE Income[a]	–	3.01
Day of the week	1.00	1.00
Month of the year	1.12	1.12
NDVI	1.04	1.04
TMIN	6.95	6.73
TMAX	6.17	6.16
TMIN 24-hr difference[b]	1.71	1.70
TMAX 24-hr difference[b]	1.62	1.63
EHF[c]	1.28	1.28
Relative Humidity	3.48	3.43
Above 95th	1.38	1.38

Note. "–" Indicates that variable was not used in model.
[a]ICE metrics range from −1 (least privilege) to 1 (most privileged). [b]24 hr difference, current days temperature subtracted by previous days temperature, values range from negative to positive. [c]Excess Heat Factor (EHF) values begin at 0.

among the sociodemographic and environmental variables was assessed against the outcome variable, mental and behavioral health conditions, using the variance inflation factor (VIF) (Dormann et al., 2012; Graham, 2003; O'brien, 2007). Independent variables were removed when they had a VIF value greater than 10, an indication of multicollinearity (Mason et al., 2003; Menard, 1995; Neter et al., 1989). To select the best variables with low multicollinearity, the variable with the largest VIF value was removed, and the model was retested until all variable's VIF values remained under 10 (Craney & Surles, 2002) (Table 3).

2.2.2. Procedure of Prediction Models

Four kinds of machine learning models, ranging from more simple to complex, were assessed including (a) GLM assuming Poisson distribution with multivariable predictors and log of population size as the offset; (b) GAM assuming Poisson distribution with multivariable predictors and log of population size as the offset; (c) random forest models with multivariable predictors; and (d) extreme gradient boosting trees (XGBoost) with multivariable predictors (Table 4). Among the four approaches, the best prediction model was determined to be the model with the lowest root-mean-square error (RMSE) and mean absolute error (MAE) (Ogata et al., 2021). GLM is a generalized linear model in which a dependent variable is linearly related to independent variables by a log link function when using a Poisson distribution (IBM, 2011). By using spline functions, GAM can model non-linear associations between the independent variables and the dependent variable. Random forest is a tree-based machine learning model with an ensemble by fitting a number of decision trees on different subsamples of the training data set and combining their predictions for a more accurate result (Breiman, 2001). XGBoost is an optimized distributed gradient-boosting decision tree model (XGBoost, 2022). XGBoost trains a sequence of decision trees, with each iteration attempting to correct the errors of the trees already in the previous model.

2.2.3. Feature Selection and Hyperparameter Optimization

In each model, a 5-fold cross-validation (CV) technique was utilized to ensure the robustness of the model. This technique involves randomly selecting hold-out test data for each fold to evaluate the performance of the training model; this was performed using a randomly selected 80% of the data from the original data set. The procedure is repeated based on the number of folds selected, resulting in a more reliable model. Recursive feature selection (RFE) was used to identify the optimal predictors (i.e., feature selection), and grid search was used to identify the optimal hyperparameters (i.e., hyperparameter tuning) (Chen et al., 2018). The optimal model and hyperparameters were chosen based on having the lowest RMSE. RFE is a wrapper method of backward feature selection that searches a defined subset of predictors by first training a model by using all possible predictors, calculating the models' performance, and then calculating the variable importance of the model. After the first round, the model subsets the top-performing variables. This process occurred for each group of predictors in the first round. In the second iteration, an updated model of the optimally selected predictors was tested in the same manner as before; this process was repeated until the best subset of predictors was determined by having the lowest RMSE (Kuhn, 2019).

In the final models, city-level socioeconomic information included median age, population per 1,000 individuals between the ages of 5 and 24, ICE race ratio, and ICE income ratio. Calendar information included the day of the week and the month of the year. Landcover and location information included NDVI and geographic region. Climate information included TMIN (°C), TMAX (°C), the TMIN 24-hr difference (°C), TMAX 24-hr difference (°C), EHF, and RH (%). The total population was modeled into a log of population per 1,000 as the offset term in GLM and GAM but was excluded from the random forest and XGBoost.

Table 4
Summary Characteristics of Machine Learning Algorithms, Packages, and Optimized Hyperparameters for the Training Data Set

Model	R package	Optimized hyperparameters	Advantages
Generalized Linear Model	Glmnet	penalty = 0.096 mixture = 0.1	- Linear regression is straightforward to understand and explain and can be regularized to avoid overfitting - In addition, linear models can be updated easily with new data
Generalized Additive Model	gamSpline	Degrees of freedom = 1	- Can model non-linear associations of independent variables with a dependent variable by using spline functions; provides straightforward visual interpretation for nonlinear response variables
Random Forest	Ranger	mtry = 1 trees = 506, min_*n* = 101	- Can use the Boruta algorithm as a preliminary selection of model variables to reduce the calculating time of final random forest models - Capture the potential non-linear relationship between heat-health outcome occurrence and other meteorological and socioeconomic variables
Extreme Gradient Boosting	XGBoost	nrounds = 51 max_depth = 3 eta = 0.1 gamma = 0.3 colsample_bytree = 0.8 min_child_weight = 5 subsample = 0.4	- Able to handle missing data, can be optimized on different loss functions and provides several hyperparameter tuning options that make the function fit very flexible - Able to capture nonlinearity in the dependence structure

2.2.4. Model Selection and Validation

We used the remaining randomly split 20% of the data from the original data set for model testing and validation. Predictive accuracies of the four different prediction models were evaluated using RMSE and MAE. RMSE is the mean difference between observed and predicted values and shows an average predictive error; thus, the smaller the RMSE, the better the model. MAE is the mean of the absolute value of the difference between the predicted and observed values, a smaller MAE indicates a better prediction. The model with the lowest RMSE and MAE was selected as the best fit and used to identify which variables contribute to an individual's susceptibility to being admitted to the ER for MBDs.

2.3. Evaluation of Developed Prediction Model Variables

We examined the impact that the most important variables had on the prediction of MBD cases for the best-performing model by using SHapley Additive exPlanations (SHAP) values. The goal of SHAP is to explain why the model predicts a certain outcome based on the variable values that are provided and the contribution that those values contribute to the final prediction (Lundberg & Lee, 2017; Molnar, 2022). The SHAP value shows how much an individual variable contributes (either negatively or positively) to the difference between the mean and the actual prediction in the context of the other variables in the data. The mean absolute contribution value is the SHAP value, which indicates the average absolute contribution value that variable makes to the overall predicted outcome. Analysis was conducted using gam (Hastie, 2022), caret (Kuhn, 2022), tidymodels (Kuhn & Wickham, 2020), iBreakDown (Gosiewska & Biecek, 2019), and vip (Greenwell & Boehmke, 2020) packages in R version 4.2.0.

10.1029/2023GH000839

Table 5
Characteristics of Train and Test Data Sets in Six North Carolina Cities Between June and August From 2016 to 2019

Variable	Train	Test
Mental and behavior disorders	31,656	7,976
Median Age	37.15 (33.68–40.82)	36.79 (33.33–40.24)
Male to female ratio	92.4 (90.54–94.29)	92.43 (90.51–94.34)
ICE Income	−0.075 (−0.26–0.11)	−0.072 (−0.26–0.12)
ICE race	0.53 (0.29–0.77)	0.51 (0.27–0.75)
Percent Unemployment	5.24 (4.13–6.35)	5.33 (4.21–6.45)
NDVI	0.39 (0.34–0.45)	0.4 (0.35–0.44)
TMAX, °C	30.67 (27.85–33.49)	30.68 (27.80–33.56)
TAVG, °C	25.37 (22.67–28.07)	25.4 (22.82–27.99)
TMIN, °C	20.07 (17.02–23.12)	20.13 (17.32–22.94)
TMAX 24 hr difference, °C	−0.002 (−2.17–2.16)	0.065 (−2.07–2.20)
TMIN 24 hr difference, °C	−0.02 (−1.71–1.67)	0.024 (−1.66–1.71)
Relative Humidity, %	71.53 (63.81–79.25)	71.81 (64.05–79.57)
Excessive Heat Factor	0.0052 (−0.046–0.0565)	0.0037 (−0.036–0.043)

2.4. Sensitivity Analysis: Distributed Lag Non-Linear Model

Relying on a standard approach typically used in environmental health studies, the distributed lag nonlinear model (DLNM) was employed to confirm the machine learning results. We investigated the association between daily average temperature and any MBD-related ER visit to confirm our machine-learning ambient temperature findings in the individual city models.

Prior literature has demonstrated a non-linear and delayed (e.g., typically 3 to 7-day lag) relationship between temperature and MBD-related ER visits; therefore, we performed the DLNM combined with a GLM as a sensitivity analysis to further confirm the temperature-related results from our top-performing ML approach (Crank et al., 2022; Gasparrini, 2011; Peng et al., 2017; Yoo, Eum, Gao, & Chen, 2021). In each city, a DLNM was applied as a quasi-Poisson distribution with a lag period of 0 days in order to establish the associations between temperature and the relative risk (RR) of increased ER visits. DLNM can characterize the non-linear exposure-response relationship at varying delayed exposure times (Gasparrini, 2011). For this analysis, the region-specific temperature-ER visit association for MBDs was calculated. In this study, DLNM was employed to investigate the relationship between exposure to varying temperatures in the summer months for each individual city and the corresponding mental and behavioral ER visits. The model is written as:

$$\log E(Y_t) = \alpha + \mathrm{cb}\left(\mathrm{Temp}_t, \mathrm{df}_1\right) + \mathrm{ns}(\mathrm{RH}_t, \mathrm{df}_2) + \mathrm{ns}(\mathrm{Time}_t, \mathrm{df}_3) + \beta \mathrm{DOW}_t \tag{1}$$

where $E(Y_t)$ is the expected ER visits related to MBDs on day t as a logarithmic function of an intercept (α); cb() denotes the cross basis function for temperature (daily average temperature); ns() denotes the natural cubic spline applied to RH and time trend. Three knots in the lag space of the cross basis-function were set equally spaced values in the log scale of lags for more flexible lag effects at shorter delays (Gasparrini, 2011; Yoo, Eum, Gao, & Chen, 2021). The day of the week (DOW_t) and Time were used as controls for the temperature and RH variables (Dominici, 2004). The degrees of freedom (df) for the predictors were set; $\mathrm{df}_1 = 4$ for the temperature in the crossbasis function, $\mathrm{df}_2 = 2$ for RH, and $\mathrm{df}_3 = 7 \times$ number of years for the time trend to model for the season and long-term time trends. These parameters were identified based on previous studies (Crank et al., 2022; Gasparrini, 2011; Peng et al., 2017; Yoo, Eum, Gao, & Chen, 2021) and then tested for the best fitting model based on qAIC (Guo et al., 2011). Analysis was conducted using glm to analyze a quasi-Poisson generalized linear regression model and dlnm (Gasparrini, 2011) and mixmeta (Sera et al., 2019) packages for distributed lag models and meta-analyses, respectively in R version 4.2.0.

Table 6				
RMSE and Mean Absolute Error of the Models for Train and Test Performance for All Machine Learning Approaches				
	GLM	GAM	RF ranger	XGBoost
Train RMSE	4.71	4.71	4.01	4.35
Test RMSE	4.97	4.96	4.96	5.00
Train MAE	3.45	3.45	2.94	3.20
Test MAE	3.59	3.59	3.62	3.68

Note. RMSE, Root Mean Squared Error; MAE, Mean Absolute Error.

3. Results

3.1. Prediction for Mental Health Aggregated Approach Across All Cities

The variables used in the training and testing data sets are located in Table 5. The total number of MBDs reported from June–August of 2016 to 2019 is summarized as 31,656 and 7,976 cases for training and testing, respectively.

We developed machine learning models to predict the number of MBDs using a GLM, GAM, random forest, and extreme gradient boosting (XGBoost) using multivariable predictors in the training data set. Amongst these models, GAM was chosen based on having the lowest root-mean-squared error (RMSE), 4.96, and lowest MAE, 3.59, when applied to the testing data (Table 6). The performance across the entire test data set is graphically represented in Figure 2. The observed number of MBDs was found to be strongly correlated with the predicted values from all four machine-learning approaches. In the GAM, 12 of the predictor variables that had variable inflation factor values below 10 were selected (Median age, the population of our study age, male-to-female ratio, the city location, day of the week, TMAX 24-hr difference (°C), TMIN 24 hr difference (°C), RH, TMAX, TMIN, month of the year, and NDVI of the city) as the top contributors to the predictive outcome of the model set by the RFE method.

The GAM model had all twelve top-performing variables' SHAP values calculated, which are summarized in Figure 3 and show the importance of its predictors. The SHAP summary model illustrates the leading variables in identifying what leads youths in a city to be more prone to MBDs. The variables that lead to higher predictions

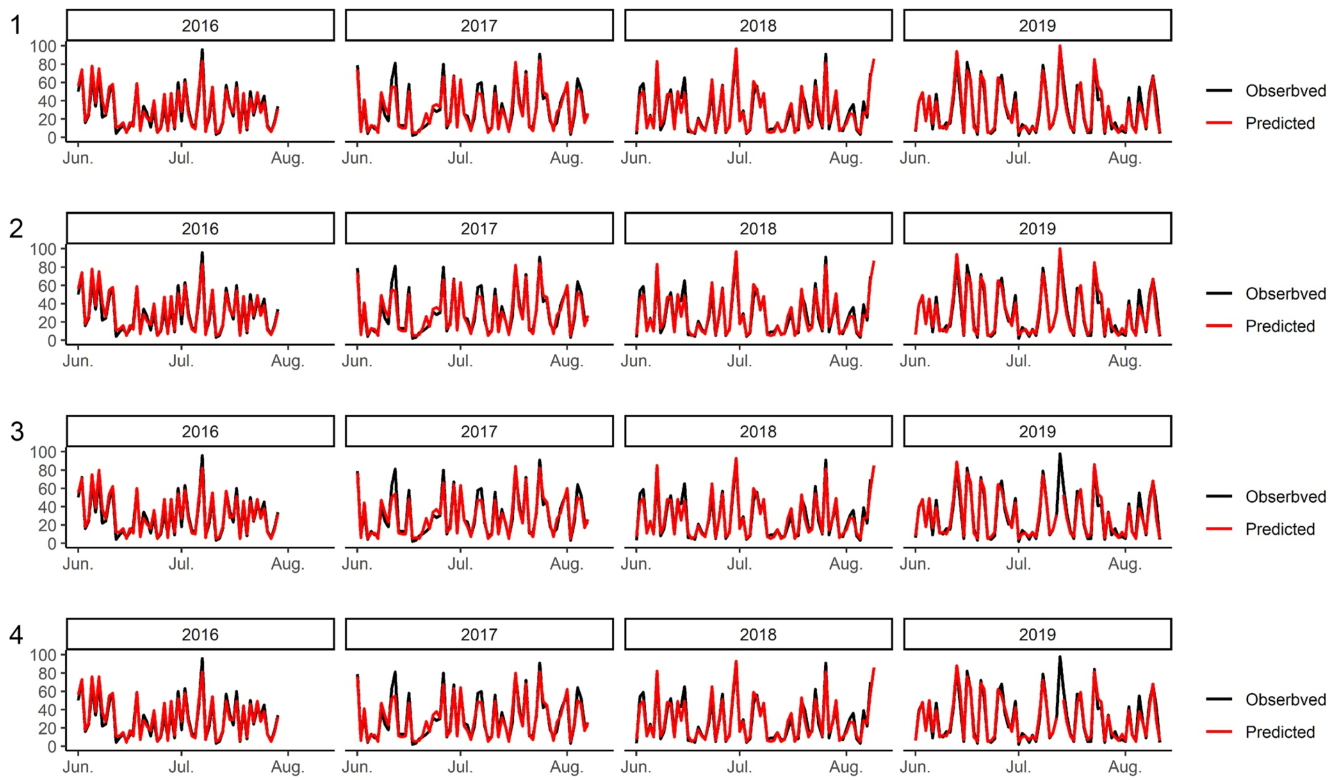

Figure 2. Comparison between observed and the predicted number of mental and behavioral disorder-related emergency department visits across six North Carolina cities from June to August 2016 to 2019 by generalized linear model (GLM), generalized additive model (GAM), RF, and XGBoost. The black line indicates the observed totals of MBD-related emergency department visits per day across six North Carolina cities and the red line indicates the predicted total number of mental and behavioral-related emergency department visits per day in the six North Carolina cities. These predictions were obtained from the following models from top to bottom: (1) GLM using multivariable predictors, (2) GAM using multivariable predictors, (3) RF using multivariable predictors, and (4) XGBoost using multivariable predictors.

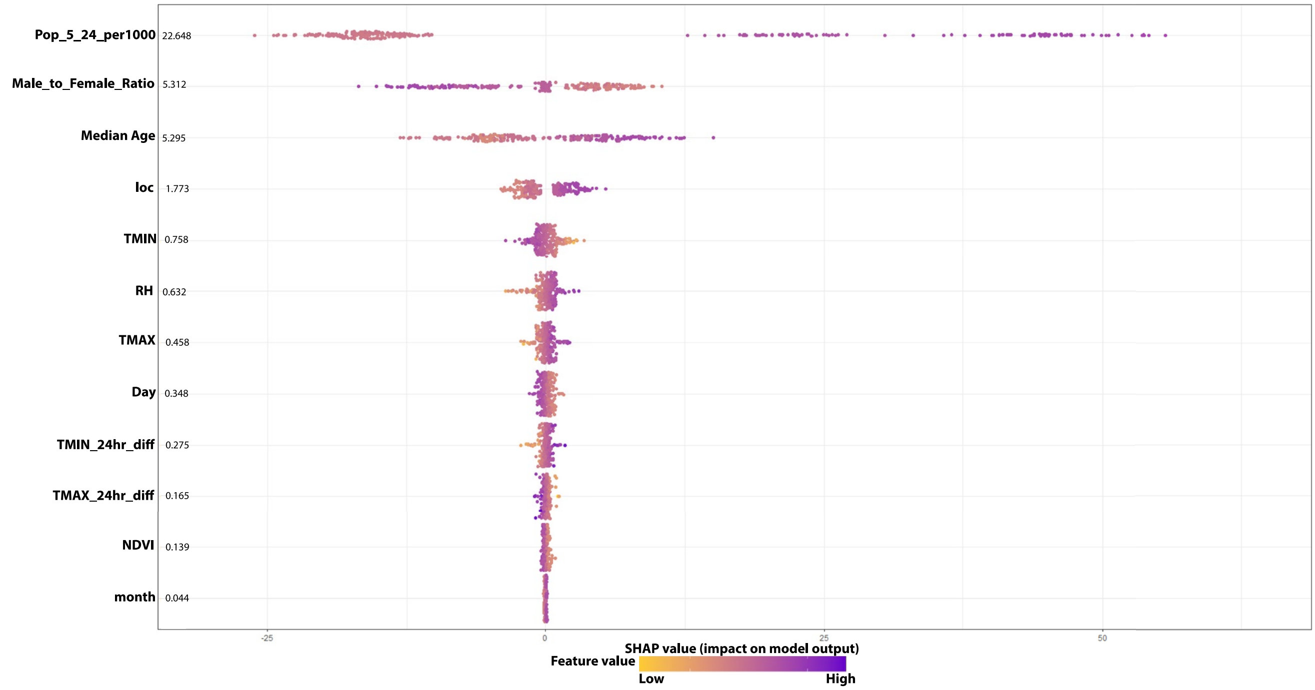

Figure 3. SHapely Additive exPlanations (SHAP) (SHapley Additive exPlanations) values and contributions of the best-performing variables in the best model (generalized additive model). The plot shows the importance of the predictors, with the most important at the top, of the best-performing model using SHAP values. The effect of the contribution is notated as a positive or negative point-level contribution; the given variables' value is represented with a sliding scale from yellow, representing a low variable value to purple, representing a high variable value for each. The x-axis SHAP value illustrates the contribution of every variable to the predicted number of mental and behavioral disorders emergency department visits, with positive values leading to a higher number of predicted emergency room (ER) visits and a negative value leading to a lower number of predicted ER visits.

of MBDs were a larger population between the ages of 5 and 24 per 1,000, a smaller male-to-female ratio, higher median age, being located on the eastern side of the state, lower minimum temperature, higher RH, being in the first half of the week, higher 24-hr minimum temperature difference, lower 24-hr maximum temperature difference, and lower NDVI all lead to higher rates of MBDs.

3.2. Prediction for Mental Health in Each City

Individual GAM models were developed for each of the six cities in this analysis to identify leading environmental contributors to an individual's risk of an MBD; building this model took into account land cover and temperature data and used temporal information as controls for the model (Table 7).

The RMSE and MAE were summarized across all six cities (Table 8), the individual city approach had a smaller mean RMSE (4.43 vs. 4.96) and a smaller mean MAE (3.53 vs. 3.59) than the all cities approach.

To better understand the difference in the influence of ambient temperature and land cover on MBD-related ER visits, SHAP values were calculated for each city. The top-performing variables that were identified within the GAM model were chosen to be represented in the SHAP model (Lundberg & Lee, 2017). The SHAP value model can be seen in Figure 4, and shows the feature importance for the models with respect to the mental health case count prediction. The features are listed top-down with decreasing importance. The overall SHAP value of the contribution, found on the left side of the plot for each category gives the total contribution value and shows the average impact of the individual features on the models' output. Each dot represents an individual SHAP value for individual patients instead of the average absolute value. The further away a point is from $x = 0$, the larger the impact on the output prediction. Values to the left of $x = 0$ are contributing to decreased MBD-related ER visits, while values to the right are contributing to the prediction of increased MBD-related ER visits. Each of the colored dots for each category represents an individual

Table 7
Temperature and Land Cover Information Averaged Across the Study Period for Each of the Six Cities in the Data Set Between June and August From 2016 to 2019, North Carolina

City	Ashville	Hickory	Charlotte	Raleigh	Greenville	Wilmington
Mental and behavioral disorders	3,773	1,877	17,533	9,811	2,462	4,176
TMAX	28.05 (25.69–30.41)	30.32 (27.71–32.93)	31.76 (29.17–34.35)	30.86 (28.21–33.51)	31.56 (28.9–34.22)	31.49 (29.17–34.81)
Tmean	22.36 (20.35–24.37)	24.76 (22.59–26.93)	26.24 (24.05–28.43)	25.63 (23.27–27.99)	26.35 (23.94–28.76)	26.93 (24.82–29.04)
Tmin	16.67 (14.28–19.57)	19.21 (16.89–21.53)	20.72 (18.43–23.01)	20.4 (17.91–22.89)	21.14 (18.5–23.78)	22.36 (19.98–24.74)
Tmax 24 hr diff	0.0088 (−1.820–1.8378)	0.0127 (−2.278–2.304)	0.0164 (−2.245–2.277)	0.0191 (−2.268–2.306)	0.0057 (−2.320–2.3317)	0.0048 (−1.921–1.931)
Tmin 24 hr diff	0.0004 (−1.509–1.511)	−0.0037 (−1.573–1.566)	−0.0089 (1.601–1.583)	−0.0116 (−1.693–1.678)	−0.0181 (−2.055–2.026)	−0.0213 (−1.736–1.694)
EHF	0.0026 (−0.022–0.030)	0.0016 (−0.018–0.021)	0.0069 (−0.048–0.062)	0.001 (0.012–0.010)	0.0097 (−0.064–0.083)	0.0076 (−0.061–0.078)
Above 95th	0.0287 (−0.125–0.183)	0.0254 (−0.127–0.177)	0.0467 (−0.159–0.252)	0.0177 (−0.099–0.029)	0.0462 (−0.161–0.253)	0.0354 (−0.127–0.198)
NDVI	0.41 (0.16–0.66)	0.43 (0.22–0.62)	0.38 (0.16–0.60)	0.4 (0.18–0.62)	0.41 (0.16–0.66)	0.34 (0.20–0.48)

day. The color of a dot signifies the feature value for that patient. A purple dot represents a high value, while a yellow dot represents a low value; the gradients represent a value in between these two points. These plots visualize how different feature values contribute to either higher or lower MBD-related ER visits.

From these models, we can see that in Asheville, a higher RH, lower minimum temperature, higher 24-hr maximum temperature difference, and higher 24-hr minimum temperature difference all lead to a higher incidence of MBD. In Hickory, a lower 24-hr maximum temperature difference leads to higher incidences of MBD. A lower maximum temperature leads to higher incidences of MBD in Charlotte. A lower 24-hr maximum temperature difference, higher NDVI value, a lower maximum temperature, and a higher 24-hr minimum temperature difference all lead to higher incidences of MBD in Raleigh. In Greenville, a higher NDVI and in Wilmington, and higher 24-hr maximum temperature difference leads to higher incidences of MBD.

3.3. Sensitivity Analysis

Figure 5 shows the change in RR of ER visits associated with MBD for each of the individual six cities at the 2.5th and 97.5th percentile of temperature.

The results indicate that in the all-cities model, there is not a significant association between ER visits related to MBD and extreme daily average air temperature. For the 97.5th percentile of temperature across the all-cities model, there was a significant decrease in the risk associated with emergency department visits (RR = 0.97; 95% CI: 0.93–0.99).

Similar to the results found in the pooled cumulative effects model, no significant increase was observed at the 97.5th percentile of temperature; the results can be seen in Table 9. A significant decrease in risk associated with the temperature at the 97.5th percentile was observed for Asheville (RR = 0.91; 95% CI: 0.86–0.96) and Charlotte (RR = 0.96; 95% CI: 0.93–0.99). The results from the DLNM for Asheville confirm the results seen in the SHAP model where the hottest temperatures corresponded with a decrease in the MBD-related outcomes. In the DLNM model for Charlotte, we see that extreme heat contributes to a significant decrease in the RR of MBD-related ER visits, which confirms the findings in the SHAP model, which indicates that at the highest temperatures, we see fewer predicted case counts. Lastly, in the DLNM for Raleigh, while not significant, we see that the coldest and hottest temperatures are associated with a lower RR, which mirrors the results of the SHAP model. In the SHAP model, both the lowest and highest temperature values are associated with a decrease in case counts.

4. Discussion

The objective of this study was to apply a machine learning approach to identify key environmental conditions that predicted MBD-related ER visits in youths. Our findings from the all-cities model indicate that socio-demographic variables contribute a greater impact on youths' mental health compared to environmental variables. Important sociodemographic factors that contributed the most to the predictive outcome included the population between 5 and 24, male to female ratio, and the median age of the city; followed by the following environmental: included minimum temperature, RH, and maximum temperature. These findings are consistent with previous studies of extreme heat, which have demonstrated that the socio-demographic makeup of a city contributes to the overall MBD health of its youth population more than environmental drivers of mental health disparities (Dessai, 2003; Y. Wang et al., 2019). Further, The increase in hospital admissions on days of higher maximum temperature and higher RH, found in the all-cities machine-learning model, is consistent with multiple studies, which identified an increased RR at higher maximum temperatures, even after adjusting for RH as a covariate (Crank et al., 2022; Mullins & White, 2019; Peng et al., 2017). In the individual city models, we found no clear environmental variable contributing to an increased risk of MBD-related ER visits. However, the GAM model, with the use of the SHAP model to quantify the results, indicated that the traditional "higher exposure yields higher

Table 8
RMSE and Mean Absolute Error of the Models for Train and Test Performance of the Generalized Additive Model for All Six Cities Individually

	Ashville	Hickory	Charlotte	Raleigh	Greenville	Wilmington	Overall
Train RMSE	3.36	2.31	7.88	6.06	2.67	3.4	4.28
Test RMSE	3.39	2.51	8.24	6.05	2.87	3.5	4.43
Train MAE	2.69	1.82	6.56	4.85	2.17	2.75	3.47
Test MAE	2.81	1.98	6.6	4.83	2.24	2.73	3.53
Normalized Test RMSE	0.331	0.486	0.173	0.227	0.416	0.303	0.32
Normalized Test MAE	0.275	0.384	0.138	0.181	0.324	0.236	0.26

Note. Normalized RMSE and normalized MAE for the test data set to better illustrate how the models performed on different data sets.

risk" association between temperature and MBD-related ER visits was not consistent within our study area, with lower minimum temperatures associated with increasing counts of MBD-related ER visits.

The secondary aim of this analysis was to identify the leading environmental factors of mental health responses at the city level for six cities in North Carolina in the summer months between 2016 and 2019. The results of this analysis illustrate how environmental factors affect the mental health response across varying geographic locations within North Carolina. All but two cities had different environmental metrics as their leading predictors (i.e., Hickory and Willmington). However, there were some shared commonalities, with four cities having the 24-hr difference in the maximum temperature and two of the cities having the 24-hr difference in the minimum temperature, maximum temperature, or NDVI as a leading predictor of MBD emergency department visits. Our work highlights the importance of local-level understanding when trying to understand how temperature may influence MDB.

Our results indicate that when the city comprises a higher ratio of females to males, we see an increase in the predicted number of MBD ER visits. Previous research has indicated that females are more likely to display help-seeking behaviors compared to males (Oliver et al., 2005). Results also showed that cities with a larger youth population, a strong predictor in our study, showcased higher instances of MBD-related ER visits.

In contrast to previous studies showing a corresponding increase in ER visits for mental disorders as minimum nighttime temperatures increase, our results in the aggregated all-cities model indicate that as the minimum temperature decreases, we see a rise in MBD ER visits. These results contrast with previous research, which has indicated that minimum temperature plays a stronger role than maximum temperature (Mullins & White, 2019). A potential explanation for this finding is that there is a large daily swing in temperature between night and day and that this dramatic increase in temperature contributes to additional heat stress on individuals.

Our study contrasts with previous studies examining individual cities demonstrating that as temperature increases, the risk for MBD increases, with studies finding that at the 99th percentile of temperature, an individual is over 25% more likely to suffer from a mental or behavioral disorder than at the 50th percentile of temperature (Peng et al., 2017; X. Wang et al., 2014; Yoo, Eum, Gao, & Chen, 2021). More specifically for youths, Niu et al. (2023) found that high summer temperatures were associated with a significant increase in MBD-related ER visits. However, in our analysis, we found that not only was maximum temperature normally not the most predictive variable, but a high maximum temperature resulted in lower MBD-related hospital visits when it was a top contributing variable. We confirmed our results by conducting a sensitivity analysis using a DLNM and pooling our results across all cities.

More specifically, the maximum temperature was a top contributing variable for Charlotte and Raleigh in the individual city models. The SHAP values indicate that neither the highest nor lowest maximum temperature values contributed to higher predicted ER visits. Still, temperatures near the median contributed to higher predicted MBD emergency department visits. These results are consistent with the results from the DLNM,

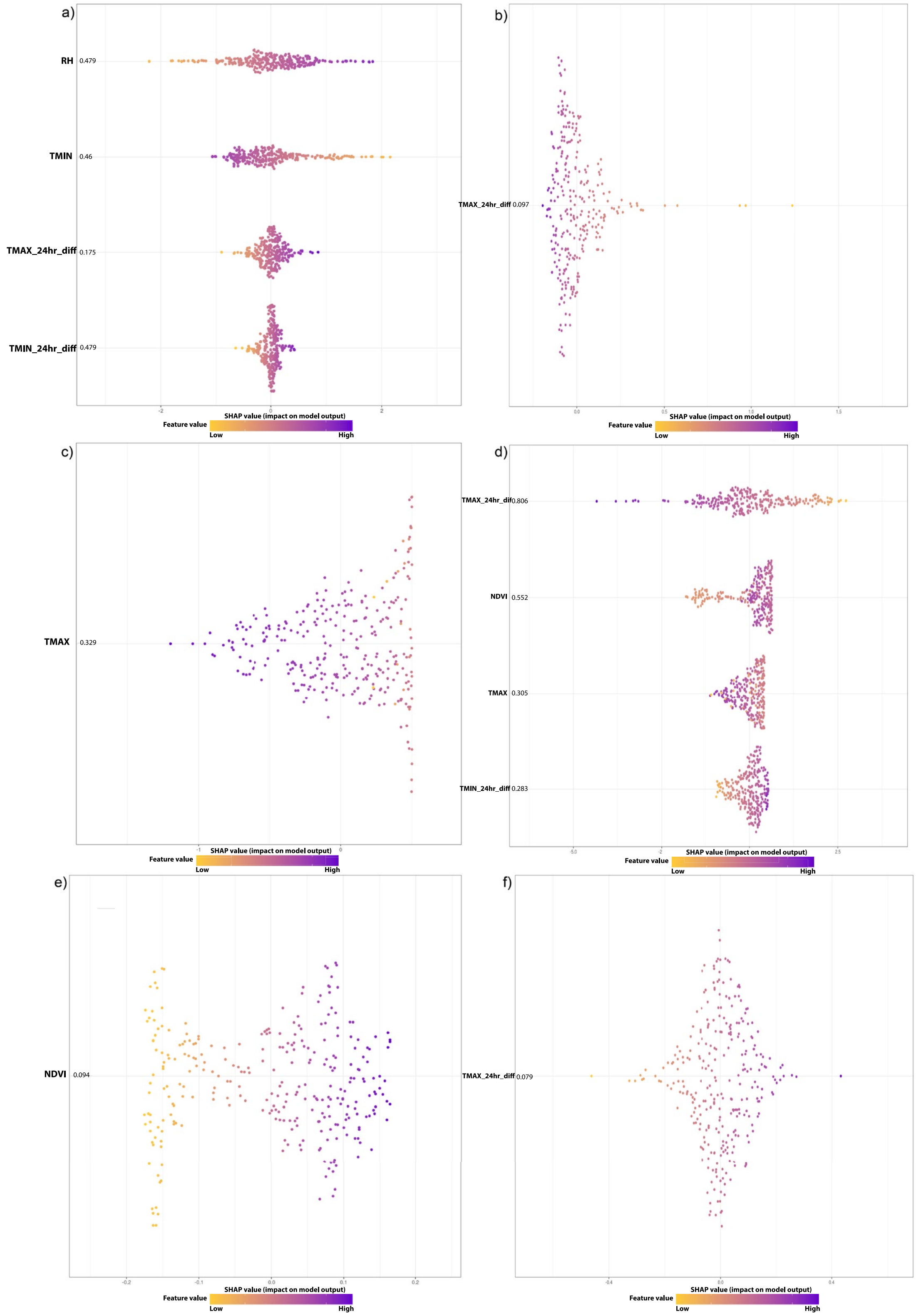
a)
RH 0.479
TMIN 0.46
TMAX_24hr_diff 0.175
TMIN_24hr_diff 0.479
SHAP value (impact on model output)
Feature value
Low
High
b)
TMAX_24hr_diff 0.097
c)
TMAX 0.329
d)
TMAX_24hr_diff 0.806
NDVI 0.552
TMAX 0.305
TMIN_24hr_diff 0.283
e)
NDVI 0.094
f)
TMAX_24hr_diff 0.079

Figure 4.

which had a significant decrease in ER visits in Charlotte at the highest average temperatures and no significant correlation between high average temperature and ER visits in Raleigh.

The reason for this temperature-mental health difference could be based on the location of the study. Previous studies have focused further north and therefore have cooler summers, with extreme temperatures falling between 23 and 27°C for the 75th to 97.5th percentile of temperature, whereas in the Southeast US, where North Carolina is located, the 75th and 97.5th percentile of maximum temperature being 33–37°C (Peng et al., 2017; X. Wang et al., 2014; Yoo, Eum, Gao, & Chen, 2021). Due to the temperature reaching much higher levels, individuals might be more inclined to seek shelter during these events, leading to fewer extreme heat exposures for youths in North Carolina and mitigation of the environmental risk factors of heat-related MBD.

4.1. Strengths and Limitations

This study had several notable strengths. First, we evaluated the association between summer environmental data, sociodemographic information, and ER visits for any MBD in multiple cities across North Carolina, which allowed for a more general state-wide analysis as well as a secondary analysis looking at each city individually. We included variables that were not related to temperature to assess if the MBD-related hospital visits were primarily affected by the climate or by sociodemographic factors. Second, unlike most nonlinear model results that only indicate the top contributing predictive variables (Y. Wang et al., 2019), through the use of SHAP, we provided precisely how each variable contributes to the outcome of the model. Unlike previous studies that have used traditional additive models or DLNM, machine learning was employed to identify the top predictive variables, and SHAP models were used to quantify the contribution that each of the top variables made in the overall prediction of the model. Lastly, we tested multiple machine learning approaches to ensure our results were robust (e.g., random forest).

This study had a few limitations. First, a longer study period could increase the robustness of results and better identify trends. Second, an analysis of specific MBD would be more informative. Lastly, air pollution, such as ozone, generally has a high correlation with temperature and has been shown to impact mental health (X. Wang et al., 2014), and future studies should include $PM_{2.5}$ as a covariate in the model to better understand the temperature-mental health relationship. However, our analysis was conducted at the ZCTA scale, and $PM_{2.5}$ or ozone data are not readily available at this scale. Lastly, our results highlighted several notable trends, including increased NDVI and high temperatures, corresponding to lower MBDs, and are worthy of further exploration.

5. Conclusion

This study is among the first to examine the driving factors behind MBD ER visits in youth in North Carolina, USA. Our study leveraged a daily ER inpatient data set for the entire state of North Carolina, allowing us to leverage a suite of machine learning models to examine the daily MBD response in youth to varying environmental conditions and socioeconomic changes in distinct geographic regions. This study suggests that at the aggregated city level, socioeconomic factors contribute more to an individual's mental and behavioral well-being during the summer than environmental factors. At the city level, this study indicates that no clear environmental factor contributes to the greatest risk of MBDs. Results from this study can provide new guidance on the application of machine learning models for predicting mental health conditions and help inform what variables contribute to youth mental and behavioral responses during high-temperature events.

Figure 4. Shows the SHapely Additive exPlanations (SHAP) values for (a) Asheville, (b) Hickory, (c) Charlotte, (d) Raleigh, (e) Greenville, (f) Wilmington. SHAP values and contributions of the best-performing variables in the best model (generalized additive model). The plot shows the importance of the predictors, with the most important at the top, of the best-performing model using SHAP values. The effect of the contribution is notated as a positive or negative point-level contribution; the given variables' value is represented with a sliding scale from yellow, representing a low variable value to purple, representing a high variable value for each. The *x*-axis SHAP value illustrates the contribution of every variable to the predicted number of mental and behavioral disorders emergency department visits, with positive values leading to a higher number of predicted emergency room (ER) visits and a negative value leading to a lower number of predicted ER visits.

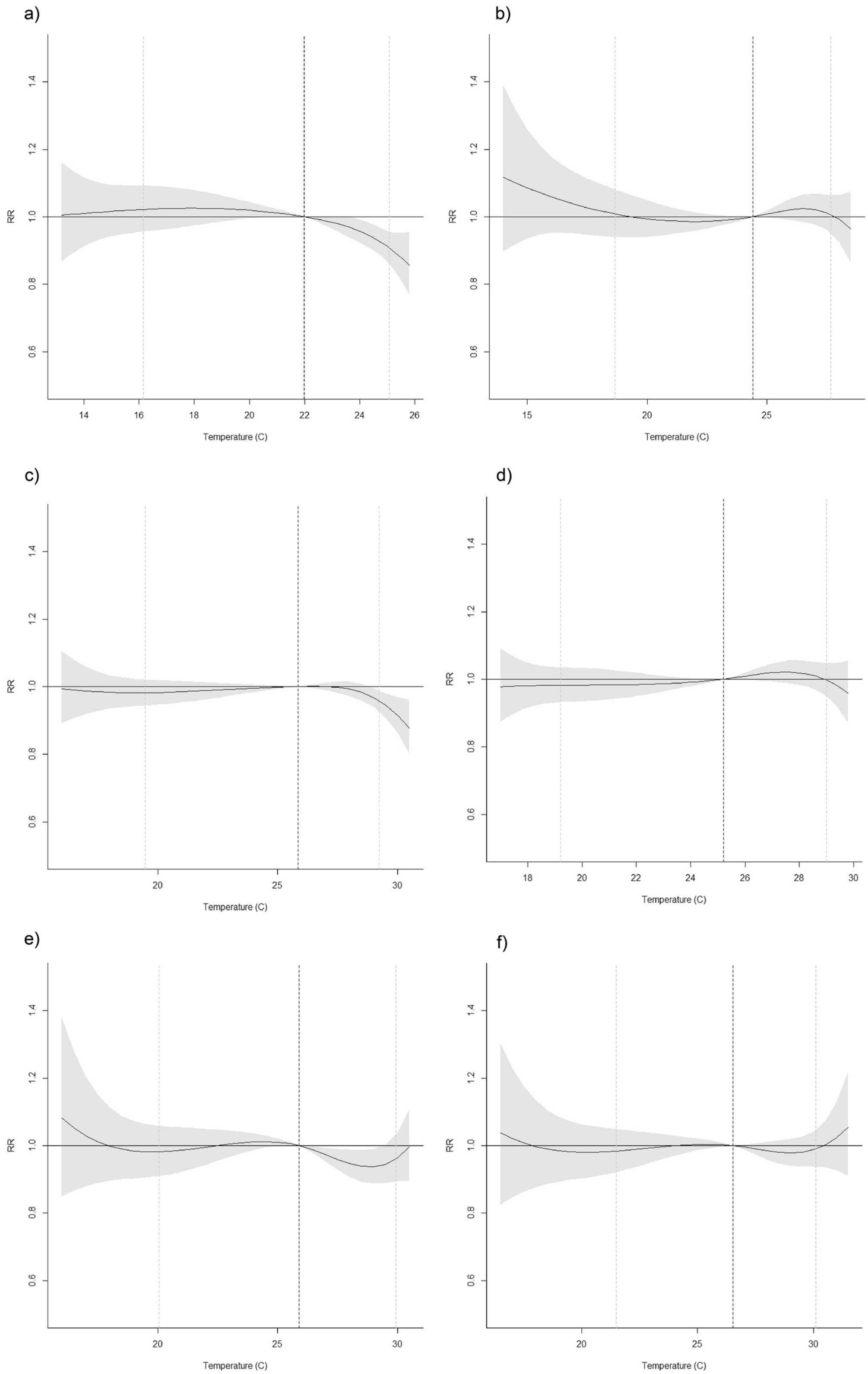

Figure 5. The individual effect of daily average temperature for all MBD-related emergency room (ER) visits for (a) Asheville, (b) Hickory, (c) Charlotte, (d) Raleigh, (e) Greenville, (f) Wilmington. The optimal ER visit temperature was defined as the temperature that corresponded with the minimum risk of emergency department visits. The black line indicated the relative risk, with the shaded area representing the 95% confidence intervals, dotted lines representing the 2.5th and 97.5th temperature percentile, and the gray dashed line representing the optimal ER visit temperature.

Table 9
Relative Risk at the 2.5th and 97.5th Percentile of Temperature in the Summer Months Between 2016 and 2019

Location	Low (2.5th percentile)	High (97.5th percentile)
North Carolina	0.99 (0.96–1.02)	0.97 (0.93–0.99)
Asheville	1.02 (0.96–1.09)	0.91 (0.86–0.96)
Hickory	1.00 (0.94–1.08)	1.01 (0.95–1.06)
Charlotte	0.98 (0.94–1.02)	0.96 (0.93–0.99)
Raleigh	0.98 (0.93–1.03)	0.99 (0.95–1.05)
Greenville	0.98 (0.91–1.06)	0.96 (0.89–1.03)
Wilmington	0.98 (0.92–1.05)	0.99 (0.94–1.05)

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

Sheps Center data is available for academic/public health research via an application process, found at https://www.shepscenter.unc.edu/data/nc-hospital-discharge-data/. The R scripts used for this article for machine learning are available at https://github.com/wertisml/Temperature_Socioeconomic_Health_Response.

Acknowledgments
We thank our external funders and collaborators for supporting this work. This work is made possible through the funded support of the National Institute of Environmental Health Sciences (NIEHS)'s R15 grant (Grant 1R15ES033817-01), "A Causal Analysis of the Complex Mental Health Impacts of the Climate Crisis in Young People" (2021–2024), National Science Foundation CAREER grant (Grant 2044839), the National Oceanic and Atmospheric Administration (NOAA) Climate Program Office Climate Adaptation Partnerships program (Grant NA210AR4310312), and through the Cooperative Institute for Satellite Earth Systems under Cooperative Agreement (Grant NA19NES4320002) The content is solely the authors' responsibility and does not represent the official views of the National Institute of Environmental Health Sciences, the National Oceanic and Atmospheric Administration, and the National Science Foundation.

References

Aragones, E., Gilboa, I., Postlewaite, A., & Schmeidler, D. (2002). Accuracy vs. simplicity: A complex trade-off. *SSRN Electronic Journal*, 51. https://doi.org/10.2139/ssrn.332382

Benka-Coker, W., Hoskovec, L., Severson, R., Balmes, J., Wilson, A., & Magzamen, S. (2020). The joint effect of ambient air pollution and agricultural pesticide exposures on lung function among children with asthma. *Environmental Research*, *190*, 109903. https://doi.org/10.1016/j.envres.2020.109903

Berry, H. L., Bowen, K., & Kjellstrom, T. (2009). Climate change and mental health: A causal pathways framework. *International Journal of Public Health*, *55*(2), 123–132. https://doi.org/10.1007/s00038-009-0112-0

Breiman, L. (2001). Random forests. *Machine Learning*, *45*(1), 5–32. https://doi.org/10.1023/a:1010933404324

Centers for Disease Control and Prevention. (2021). *About mental health*. Centers for Disease Control and Prevention. Retrieved from https://www.cdc.gov/mentalhealth/learn/index.htm#:~:text=1%20in%205%20Americans%20will,illness%20in%20a%20given%20year.&%20text=1%20in%205%20children%2C%20either,a%20seriously%20debilitating%20mental%20illness.&text=1%20in%2025%20Americans%20lives,bipolar%20disorder%2C%20or%20major%20depression

Chen, Q., Meng, Z., Liu, X., Jin, Q., & Su, R. (2018). Decision variants for the automatic determination of optimal feature subset in RF-RFE. *Genes*, *9*(6), 301. https://doi.org/10.3390/genes9060301

Conner, K. O., Copeland, V. C., Grote, N. K., Koeske, G., Rosen, D., Reynolds, C. F., & Brown, C. (2010). Mental health treatment seeking among older adults with depression: The impact of stigma and Race. *American Journal of Geriatric Psychiatry*, *18*(6), 531–543. https://doi.org/10.1097/jgp.0b013e3181cc0366

Craney, T. A., & Surles, J. G. (2002). Model-dependent variance inflation factor cutoff values. *Quality Engineering*, *14*(3), 391–403. https://doi.org/10.1081/qen-120001878

Crank, P. J., Hondula, D. M., & Sailor, D. J. (2022). Mental health and air temperature: Attributable risk analysis for schizophrenia hospital admissions in arid urban climates. *SSRN Electronic Journal*, 20. https://doi.org/10.2139/ssrn.4225400

Dessai, S. (2003). Heat stress and mortality in Lisbon Part II. An assessment of the potential impacts of climate change. *International Journal of Biometeorology*, *48*(1), 37–44. https://doi.org/10.1007/s00484-003-0180-4

Dominici, F. (2004). *Time-series analysis of air pollution and mortality: A statistical review*, *Research Report* (Vol. 123). Health Effects Institute.

Dormann, C. F., Elith, J., Bacher, S., Buchmann, C., Carl, G., Carré, G., et al. (2012). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography*, *36*(1), 27–46. https://doi.org/10.1111/j.1600-0587.2012.07348.x

EPA. (2022). *Climate impacts in the Southeast*, *Climate Change Impacts*. US EPA.

Gasparrini, A. (2011). Distributed lag linear and non-linear models in R: The package dlnm. *Journal of Statistical Software*, *43*(8), 1–20. https://doi.org/10.18637/jss.v043.i08

Gosiewska, A., & Biecek, P. (2019). Do not trust additive explanations arXiv:1903.11420. Retrieved from https://arxiv.org/abs/1903.11420

Graham, M. H. (2003). Confronting multicollinearity in ecological multiple regression. *Ecology*, *84*(11), 2809–2815. https://doi.org/10.1890/02-3114

Greenwell, B. M., & Boehmke, B. C. (2020). Variable importance plots—An introduction to the vip package. *The R Journal*, *12*(1), 343–366. https://doi.org/10.32614/RJ-2020-013

Guo, Y., Barnett, A. G., Pan, X., Yu, W., & Tong, S. (2011). The impact of temperature on mortality in Tianjin, China: A case-crossover design with a distributed lag nonlinear model. *Environmental Health Perspectives*, *119*(12), 1719–1725. https://doi.org/10.1289/ehp.1103598

Hansen, A., Bi, P., Nitschke, M., Ryan, P., Pisaniello, D., & Tucker, G. (2008). The effect of heat waves on mental health in a temperate Australian city. *Environmental Health Perspectives*, *116*(10), 1369–1375. https://doi.org/10.1289/ehp.11339

Hastie, T. (2022). _gam: Generalized Additive Models_. R package version 1.22. Retrieved from https://CRAN.R-project.org/package=gam
IBM. (2011). Generalized linear models. Retrieved from https://www.ibm.com/docs/en/spss-statistics/28.0.0?topic=SSLVMB_28.0.0%2Fstatistics_mainhelp_ddita%2Fspss%2Fadvanced%2Fidh_idd_genlin_typeofmodel.html
Kianmehr, A., & Lim, T. C. (2022). Quantifying interactive cooling effects of morphological parameters and vegetation-related landscape features during an extreme heat event. *Climate*, *10*(4), 60. https://doi.org/10.3390/cli10040060
Krieger, N., Waterman, P. D., Spasojevic, J., Li, W., Maduro, G., & Van Wye, G. (2016). Public health monitoring of privilege and deprivation with the index of concentration at the extremes. *American Journal of Public Health*, *106*(2), 256–263. https://doi.org/10.2105/ajph.2015.302955
Kuhn, M. (2019). The caret package. 20 recursive feature elimination. Retrieved from https://topepo.github.io/caret/recursive-feature-elimination.html
Kuhn, M. (2022). _caret: Classification and Regression Training_. R package version 6.0-93. Retrieved from https://CRAN.R-project.org/package=caret
Kuhn, M., & Wickham, H. (2020). Tidymodels: A collection of packages for modeling and machine learning using tidyverse principles. Retrieved from https://www.tidymodels.org
Lundberg, S. (2018). An introduction to explainable AI with Shapley values - SHAP latest documentation. Retrieved from https://shap.readthedocs.io/en/latest/example_notebooks/overviews/An%20introduction%20to%20explainable%20AI%20with%20Shapley%20values.html
Lundberg, S. M., & Lee, S.-I. (2017). In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, & R. Garnett (Eds.), *Advances in Neural Information Processing Systems* (Vol. 30, pp. 4765–4774). Curran Associates, Inc.
Mason, R. L., Gunst, R. F., & Hess, J. L. (2003). *Statistical design and analysis of experiments: With applications to engineering and science*. John Wiley & Sons.
McMichael, A. J., Woodruff, R. E., & Hales, S. (2006). Climate change and human health: Present and future risks. *The Lancet*, *367*(9513), 859–869. https://doi.org/10.1016/s0140-6736(06)68079-3
Menard, S. (1995). *Applied logistic regression analysis: Sage university series on quantitative applications in the social sciences*. Sage.
Molnar, C. (2022). Interpretable machine learning. 9.6 SHAP (SHapley Additive exPlanations). Retrieved from https://christophm.github.io/interpretable-ml-book/shap.html
Mullins, J., & White, C. (2019). Temperature and mental health: Evidence from the spectrum of mental health outcomes. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3457647
Nairn, J., & Fawcett, R. (2014). The excess heat factor: A metric for heatwave intensity and its use in classifying heatwave severity. *International Journal of Environmental Research and Public Health*, *12*(1), 227–253. https://doi.org/10.3390/ijerph120100227
Neter, J., Wasserman, W., & Kutner, M. H. (1989). *Applied linear regression models*. Richard D. Irwin, Inc.
Niu, L., Girma, B., Liu, B., Schinasi, L. H., Clougherty, J. E., & Sheffield, P. (2023). Temperature and mental health–related emergency department and hospital encounters among children, adolescents and young adults. *Epidemiology and Psychiatric Sciences*, *32*, e22. https://doi.org/10.1017/s2045796023000161
NOAA. (2022). Index of /data/land-normalized-difference-vegetation-index/access. Retrieved from https://www.ncei.noaa.gov/data/land-normalized-difference-vegetation-index/access/
O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality and Quantity*, *41*(5), 673–690. https://doi.org/10.1007/s11135-006-9018-6
Ogata, S., Takegami, M., Ozaki, T., Nakashima, T., Onozuka, D., Murata, S., et al. (2021). Heatstroke predictions by machine learning, weather information, and an all-population registry for 12-hour heatstroke alerts. *Nature Communications*, *12*(1), 4575. https://doi.org/10.1038/s41467-021-24823-0
Oliver, M. I., Pearson, N., Coe, N., & Gunnell, D. (2005). Help-seeking behaviour in men and women with common mental health problems: Cross-sectional study. *British Journal of Psychiatry*, *186*(4), 297–301. https://doi.org/10.1192/bjp.186.4.297
Park, J., & Kim, J. (2018). Defining heatwave thresholds using an inductive machine learning approach. *PLoS One*, *13*(11), e0206872. https://doi.org/10.1371/journal.pone.0206872
Peng, Z., Wang, Q., Kan, H., Chen, R., & Wang, W. (2017). Effects of ambient temperature on daily hospital admissions for mental disorders in Shanghai, China: A time-series analysis. *Science of the Total Environment*, *590*, 281–286. https://doi.org/10.1016/j.scitotenv.2017.02.237
Prism Climate Group. (2022). *PRISM climate data*. PRISM Climate Group. Retrieved from https://prism.oregonstate.edu/
Reiss, F. (2013). Socioeconomic inequalities and mental health problems in children and adolescents: A systematic review. *Social Science & Medicine*, *90*, 24–31. https://doi.org/10.1016/j.socscimed.2013.04.026
Rocklöv, J., Forsberg, B., Ebi, K., & Bellander, T. (2014). Susceptibility to mortality related to temperature and heat and cold wave duration in the population of Stockholm County, Sweden. *Global Health Action*, *7*(1), 22737. https://doi.org/10.3402/gha.v7.22737
Roehrig, C. (2016). Mental disorders top the list of the most costly conditions in the United States: $201 billion. *Health Affairs*, *35*(6), 1130–1135. https://doi.org/10.1377/hlthaff.2015.1659
Schatz, J., & Kucharik, C. J. (2015). Urban climate effects on extreme temperatures in Madison, Wisconsin, USA. *Environmental Research Letters*, *10*(9), 094024. https://doi.org/10.1088/1748-9326/10/9/094024
Sera, F., Armstrong, B., Blangiardo, M., & Gasparrini, A. (2019). An extended mixed-effects framework for meta-analysis. *Statistics in Medicine*, *38*(29), 5429–5444. https://doi.org/10.1002/sim.8362
Sheps Center. (2022). NC hospital discharge data. Retrieved from https://www.shepscenter.unc.edu/data/nc-hospital-discharge-data/
Son, J.-Y., Lane, K. J., Lee, J.-T., & Bell, M. L. (2016). Urban vegetation and heat-related mortality in Seoul, Korea. *Environmental Research*, *151*, 728–733. https://doi.org/10.1016/j.envres.2016.09.001
Sugg, M. M., Fuhrmann, C. M., & Runkle, J. D. (2018). Temporal and spatial variation in personal ambient temperatures for outdoor working populations in the southeastern USA. *International Journal of Biometeorology*, *62*(8), 1–14. https://doi.org/10.1007/s00484-018-1553-z
The Government Office for Science. (2019). *Future of an ageing population*. GOV.UK. Retrieved from https://www.gov.uk/government/publications/future-of-an-ageing-population
U. S. Census Bureau. (2023). Explore census data. Retrieved from https://data.census.gov/
USDA. (2020). *Rural-urban commuting area codes*. USDA ERS - Rural-Urban Commuting Area Codes. Retrieved from https://www.ers.usda.gov/data-products/rural-urban-commuting-area-codes/
U.S. Department of Health and Human Services Substance Abuse and Mental Health Services Administration. (2014). Projections of National Expenditures for treatment of mental and substance use disorders, 2010–2020. Retrieved from https://store.samhsa.gov/sites/default/files/d7/priv/sma14-4883.pdf
U.S. Department of Health and Human Services Substance Abuse and Mental Health Services Administration. (2021). Key substance use and mental health indicators in the United States: Results from the 2020 National Survey on drug use and health. Retrieved from https://www.samhsa.gov/data/sites/default/files/reports/rpt35325/NSDUHFFRPDFWHTMLFiles2020/2020NSDUHFFR1PDFW102121.pdf

USGS. (2018). *NDVI, the Foundation for Remote sensing Phenology*. U.S. Geological Survey. Retrieved from https://www.usgs.gov/special-topics/remote-sensing-phenology/science/ndvi-foundation-remote-sensing-phenology#:~:text=NDVI%20values%20range%20from%20%2B1.0

Wang, C., Zhang, Z., Zhou, M., Wang, P., Yin, P., Ye, W., & Zhang, L. (2018). Different response of human mortality to extreme temperatures (MOET) between rural and urban areas: A multi-scale study across China. *Health & Place*, *50*, 119–129. https://doi.org/10.1016/j.healthplace.2018.01.011

Wang, X., Lavigne, E., Ouellette-kuntz, H., & Chen, B. E. (2014). Acute impacts of extreme temperature exposure on emergency room admissions related to mental and behavior disorders in Toronto, Canada. *Journal of Affective Disorders*, *155*, 154–161. https://doi.org/10.1016/j.jad.2013.10.042

Wang, Y., Song, Q., Du, Y., Wang, J., Zhou, J., Du, Z., & Li, T. (2019). A random forest model to predict heatstroke occurrence for heatwave in China. *Science of the Total Environment*, *650*, 3048–3053. https://doi.org/10.1016/j.scitotenv.2018.09.369

XGBoost documentation. (2022). XGBoost Documentation - xgboost 2.0.0-dev documentation. Retrieved from https://xgboost.readthedocs.io/en/latest/

Yoo, E., Eum, Y., Gao, Q., & Chen, K. (2021). Effect of extreme temperatures on daily emergency room visits for mental disorders. *Environmental Science and Pollution Research*, *28*(29), 39243–39256. https://doi.org/10.1007/s11356-021-12887-w

Yoo, E., Eum, Y., Roberts, J. E., Gao, Q., & Chen, K. (2021). Association between extreme temperatures and emergency room visits related to mental disorders: A multi-region time-series study in New York, USA. *Science of the Total Environment*, *792*, 148246. https://doi.org/10.1016/j.scitotenv.2021.148246