Extreme Heat and Mental Health-Related Outcomes in Adolescent Populations: A Machine Learning Approach

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Extreme Heat and Mental Health-Related Outcomes in Adolescent Populations: A Machine Learning Approach

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Key Points:

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

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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 adolescent populations. The objective of this study was to apply a machine learning approach to identify key environmental conditions that predicted MBD-related emergency room (ER) visits in adolescents in select cities (i.e., Asheville, Charlotte, Greenville, Hickory, Raleigh, Wilingminton) in North Carolina. Daily MBD-related ER visits, which totaled over 42,000 records were paired with daily environmental conditions, including hot ambient temperatures, as well as sociodemographic variables to determine if certain conditions lead to higher vulnerability to exacerbated mental health conditions. Four machine learning models (i.e., generalized linear model, generalized additive model, extreme gradient boosting, random forest) and a distributed lag non-linear model (DLNM) were used to assess the impact of multiple environmental and sociodemographic variables had on MBD-related ER visits. The best-performing machine learning model and a DLNM was then applied to each of the six individual cities. 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-hour difference in the maximum temperature, and two of the cities had a 24-hour difference in the minimum temperature, maximum temperature, or NDVI as a leading predictor of MBD emergency department visits. Results can inform the use of machine learning models for predicting MBD during high-temperature events and identify variables that affect youth mental and behavioral responses during these events.

Plain Language Summary

There is new evidence showing that really hot weather during the summer might make it harder for people with mental and behavioral disorders to cope. But not much research has been done on adolescents. This study used machine learning to look at data from over 42,000 visits to the emergency room for mental and behavioral issues in adolescents in North Carolina. We examined the association between adolescent mental and behavioral disorders and environmental conditions using different types of computer models. The research found that in some cities, environmental factors like the temperature,had a big 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 mental and behavioral disorders to cope, but this might not be the case everywhere. And things like where people live and their backgrounds also play a big role in their mental health.

1 Introduction

The burden of mental illness in the United States is substantial; 1 in 5 individuals experience a diagnosable mental illness each year [1]. Instances of mental health are the highest among young adults aged 18-25, with 1 in 3 reporting having a mental illness [50]. 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 seven years [52][50]. Additionally, nearly $300 billion is estimated to be lost to the cost of disability payments and workers' productivity [46].

Environmental conditions such as air temperature have been associated with mental health disorders [38][35][5][59], but the majority of this work has been focused on adults rather than youth populations [56]. 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 seven days and a strong increase (26-29%) in mental and behavioral disease emergency visits compared to days below this threshold [59][47]. Research has also observed a positive association between increased hospital admissions for MBDs (7.3%) and heat-wave days [23]. Additionally, 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) [58][64][63]. Despite many studies investigating the mental health susceptibility to extreme heat events, the lack of defined metrics of how environmental (e.g., vegetation amount, ambient temperature, humidity) and socioeconomic factors (e.g., income and race) contribute to susceptibility means that there is still a need to better understand this relationship [45][58].

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 [57]. However, there has been little research on how different geographical and climatological regions respond to high-temperature extremes and the susceptibility of geographical differences, particularly in the southeastern US, a region regularly impacted by high temperature and humidity [45]. The extreme heat and health associations are typically assessed by looking at a select individual area [23][51] or multiple urban cities spread across a single country [43]. There is limited research across a large geographic area to understand how place-based disparities in access to greenspaces or other mental health-promoting resources influence the heat-health relationship [38]. As a result, there is limited information about how neighboring cities differ in their response behavior and what contributes to this differing response.

It would be useful to capture the driving risk factors in predicting the occurrence of MBDs for determining interventions to address climate change's implications of 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 in a more effective manner to improve response rates, decrease mortality, and reduce medical costs [50]. Due to the distribution of environmental stressors, simple models (i.e., linear regression, additive model) are used for their ease of interpretation, but at the expense of accuracy [4][7][2]. Additionally, it can be troublesome to handle the problems of less accurate predictions and collinearity of multiple stressors in a data-driven problem. State-of-the-art machine learning approaches (e.g., random forest and XGBoost), can create useful predictions when handling multicollinearity within the data [65][3][28][48]. However, the lack of interoperability has impacted their application in medical decision support [33]. Recently, the SHapely Additive exPlanations (SHAP) has been used to allocate contribution values for model outputs among the explanatory variables [33].

The aim of this study is to identify what regional differences in environmental and socio-demographic conditions predict ER visits for MBD in adolescents living within six metropolitan cities in the warm season. We hypothesize that there is an association between hot ambient temperatures and youth mental health (ages 5 to 24) but that socioeconomic and regional differences are the most influential factors involved in explaining mental health disparities. A secondary aim of this analysis is to identify the leading environmental factors, with a focus on ambient temperature and greenspace, that predict adolescent mental health responses at the city level. We will explore multiple machine learning approaches (i.e., generalized linear model, generalized additive model, random forest, and extreme gradient boosting), with the best-performing model being selected to identify the leading contributors to the mental health outcome. These top contributing variables will then be explored via SHAP analysis. Machine learning models offer more precise and robust results than traditional linear regression and additive models. SHAP values are able to quantify variable contribution, removing the previous lack of interoperability in non-linear model results. Interpretability will enable us to identify high-impact non-linear environmental risk factors for ER visits related to MBDs in North Carolina adolescents. Results from this study can provide new guidance on the application of ma-

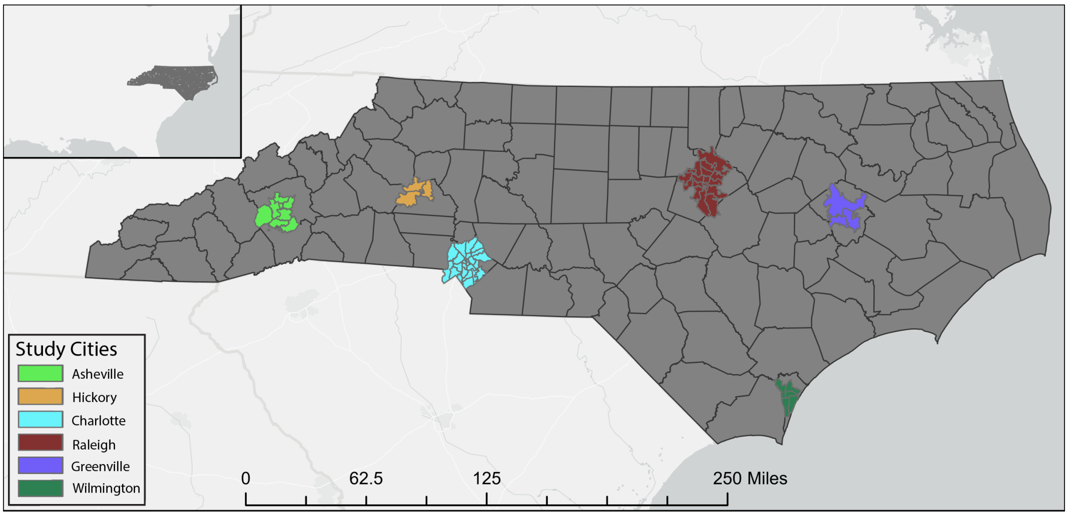

Figure 1: Study area with the ZIP Codes that comprise the six cities in North Carolina that are part of the study highlighted in a unique color and the ZIP Codes not in the study are shaded gray.

chine 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.

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 dataset, which contains all ER visits across North Carolina [40]. 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 to 2019 of individuals between the ages of 5 and 24, which was used as the outcome variable. 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 2020, this was determined based on the change from ICD-9 to ICD-10 codes in 2016, leading to a classification change in several mental health-related codes. Additional, 2019 was chosen as to not include data during the COVID-19 pandemic, as hospital visits decreased for mental health due to a lack of hospital space. The cities were treated as a categorical variable in the model analysis.

2.1.2 Sociodemographic Data

Additional sociodemographic information was obtained 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 [29] (Table 2). The ICE income ratio is the number of persons in

Table 1: Sociodemographic information for each of the six cities in the dataset 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[1]	-0.14	-0.27	0.06	0.28	-0.21	-0.16
ICE Race[1]	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, %	3.78	5.50	5.80	3.97	7.03	5.48

ICE metrics range from -1 (least privilege) to 1 (most privileged)

the 80th percentile of income subtracted from the 20th percentile, divided by the total population with a known income. The ICE race metric is derived from the ratio of white to black individuals [29]. The ICE metrics range from -1 (least privilege) to 1 (most privileged) [29]. Variables were from the American Community Survey (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, micropolitan, small-town, and rural commuting areas based on the size and direction of the primary (largest) commuting flows [12], for the ZIP Codes comprising the area within the chosen cities, city limits.

Table 2: Variables considered as predictors of adolescent mental and behavioral disorders in North Carolina, 2016-2019.

Category	**Variable & Operational definitions**	**Association with Mental Health Outcomes**	**Citation**

Socioeconomic Status	• **% Unemployment -** the number 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 education attainment, studies suggest that individuals without access to more resources have a greater risk of temperature-related shocks to mental health.	[38][60]
Green Space	• **NDVI -** Method of quantifying vegetation greenness	• In urban environments green space has been shown to lower temperatures and provide protection to pedestrians.	[53][27]

Climate Conditions	• **TMAX** - The daily maximum temperature. • **TMIN** - The daily minimum temperature. • **TAVG** - The mean value of the daily maximum and minimum temperature. • **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. • **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-hour 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.	[38][60][43]
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.	[9][29]

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	[44][16]

2.1.3 Weather data

Daily gridded raster temperature data at 4 km resolution was obtained from the PRISM Climate Group [49] 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 in order to calculate the mean value within the grid. In addition to the metrics obtained by PRISM, several other metrics were derived; the TMAX 24-hour difference (°C), TMIN 24-hour difference (°C), and TAVG 24-hour 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 relative humidity. Lastly, excess heat factor (EHF) was calculated using TAVG and following the methodology from Nairn et al., 2014[39]. 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 [26]. 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 [41]. The spatial resolution of the data set was 5km with a temporal resolution of 24 hours. 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.

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 was notated in the data set and incorporated into the final models.

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

Table 3: Variable Inflation Factor of the chosen variables for GLM, GAM, Random Forest, and XGBoost models.

Variable	**GLM and GAM**	**Random Forest and XGBoost**
Total Population	-	6.12
Median Age of City	3.55	3.15
Male to Female Ratio	8.31	-
Population 5-24 per 1000	6.62	-
City	3.71	2.79
ICE Income[1]	-	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-hour difference[2]	1.71	1.70
TMAX 24-hour difference[2]	1.62	1.63
EHF[3]	1.28	1.28
Relative Humidity	3.48	3.43
Above 95th	1.38	1.38

[1] ICE metrics range from -1 (least privilege) to 1 (most privileged).
[2] 24 hour difference, current days temperature subtracted by previous days temperature, values range from negative to positive.
[3] EHF (Excess Heat Factor) values begin at 0.

2.2 Model Establish

2.2.1 Preprocessing

Prior research has documted a strong association between exposure to high temperatures and increased risk of MBD-related ER visits [55][58][60][43]. Therefore, this study focused on the warmer period (June through August). Multicollinearity among the sociodemographic and environmental variables was assessed against the outcome variable, mental and behavioral health conditions, using the variable inflation factor [20][42][15]. Independent variables were removed when they had a Variable Inflation Factor (VIF) value greater than 10, an indication of multicollinearity [36][34]. 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 [10] (Table 3).

2.2.2 Procedure of Prediction Models

Four kinds of machine learning models were assessed including (1) generalized linear model (GLM) assuming Poisson distribution with multivariable predictors and log of population size as the offset; (2) generalized additive model (GAM) assuming Poisson distribution with multivariable predictors and log of population size as the offset; (3) random forest models with multivariable predictors; and (4) 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-

Table 4: Summary characteristics of machine learning algorithms, packages, and optimized hyperparameters for the training dataset.

Model	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.
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 metrological and socioeconomic variables.
Extreme Gradient Boosting	XGBoost	$nrounds = 51$ $max_d epth = 3$ $eta = 0.1$ $gamma = 0.3$ $colsample_b ytree = 0.8$ $min_c hild_w eight = 5$ $subsample = 0.4$	• Able to handle missing data, can be optimized on different loss functions and provides several hyper parameter tuning options that make the function fit very flexible. • Able to capture nonlinearity in the dependence structure.

square error (RMSE) and mean absolute error (MAE) [43]. 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 [25]. 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 dataset and combining their predictions for a more accurate result [6]. XGBoost is an optimized distributed gradient-boosting decision tree model [61]. 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

For each model, 5-fold cross-validation (CV), which is a resampling procedure that randomly selects hold-out test data for every fold to test the performance of the training model. This procedure is repeated based on the number of folds selected and leads to a more robust model, was used to identify the optimal predictors (i.e., feature selection) by using recursive feature selection (RFE) and to identify optimal hyperparameters (i.e., hyperparameter tuning) using grid-search [8]. The optimal model and hyperparameters were chosen based on having the lowest RMSE. This was performed using a randomly selected 80% of the data from the original data set.

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 [30].

In the final models, city-level socioeconomic information included median age, population per 1000 of 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-hour difference (°C), TMAX 24-hour difference (°C), EHF, and RH (%). The total population was modeled into a log of population per 1000 as the offset term in GLM and GAM but was excluded from the random forest and XGBoost.

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 [37][33]. 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 [24], caret [31], tidymodels [32], iBreakDown [19], and vip [21] packages in R version 4.2.0.

2.4 Sensitivity Analysis: Distributed Lag Non-Linear Model

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 generalized linear model as a sensitivity analysis to further confirm the temperature-related results from our top-performing ML approach. 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 of increased ER visits. DLNM can characterize the non-linear exposure-response relationship at varying delayed exposure times [18]. 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:

$$logE(Y_t) = \alpha + cb(Temp_t, df1) + ns(RH_t, df2) + ns(Time_t, df3) + \beta DOW_t \ (1)$$

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 relative humidity 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 ([63][18]. The day of the week ($DOWt$) and Time were used as controls for the temperature and relative humidity variables [14]. The degrees of freedom (df) for the predictors were set; df1= 4 for the temperature in the crossbasis function, df2= 2 for relative humidity, and df3= 7*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 [63][18][11][47][62] and then tested for the best fitting model based on qAIC [22]. Analysis was conducted using glm to analyze a quasi-Poisson generalized linear regression model and dlnm [17] and mixmeta ([54] packages for distributed lag models and meta-analyses, respectively in R version 4.2.0.

3 Results

3.1 Prediction for Mental Health across all cities

We developed machine learning models to predict the number of MBDs using a generalized linear model (GLM), generalized additive model (GAM), random forest, and extreme gradient boosting (XGBoost) using multivariable predictors in the training dataset. Amongst these models, GAM was chosen based on having the lowest root-mean-squared error (RMSE), 4.96, and lowest mean absolute error (MAE), 3.59, when applied to the testing data (Table 6). The performance across the entire test data set is graphically represented in Fig. 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, twelve 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-hour difference (°C), TMIN 24 hour difference (°C), relative humidity, 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 recursive feature elimination (RFE) method.

The GAM model had all twelve top-performing variables' SHAP values calculated which are summarized in Fig 3. and show the importance of its predictors. The SHAP summary model illustrates the leading variables in identifying what leads a city to be more prone to MBDs. The variables that lead to higher predictions of MBDs were a larger population between the ages of 5 and 24 per 1000, a smaller male-to-female ratio, higher median age, being located on the eastern side of the state, lower minimum temperature,

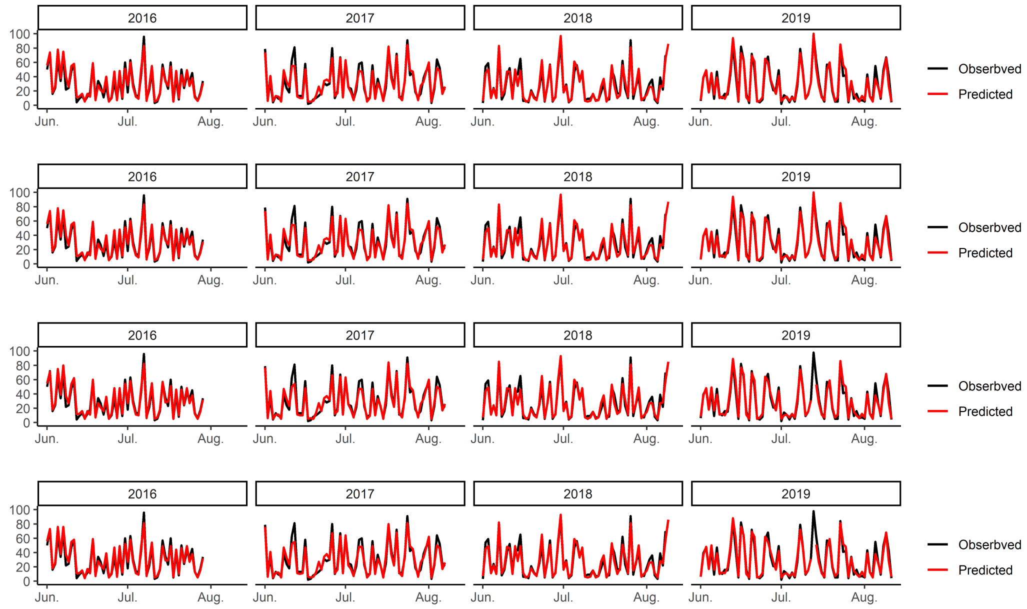

Figure 2: Comparison between observed and the predicted number of mental and behavioral disorder-related emergency department visits across six North Carolina cities from June to August 2016 to 2019 by GLM, GAM, RF, and XGBoost. The black line indicates the observed totals of MBD-related emergency department 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: (1) GLM using multivariable predictors, (2) GAM using multivariable predictors, (3) RF using multivariable predictors, and (4) XGBoost using multivariable predictors.

Table 5: Summary characteristics of machine learning algorithms, packages, and optimized hyperparameters for the training dataset.

Variable	Train	Test
Mental and behavior disorders	31656	7976
Median Age of City	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)	0.40 (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 hour difference, °C	-0.002 (-2.17 - 2.16)	0.065 (-2.07 - 2.20)
TMIN 24 hour 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)
EHF, %	0.0052 (-0.046 - 0.0565)	0.0037 (-0.036 - 0.043)

higher relative humidity, being in the first half of the week, higher 24-hour minimum tem-

Table 6: Summary characteristics of machine learning algorithms, packages, and optimized hyperparameters for the training dataset.

	GLM	GAM	Random Forest	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	4.62	3.68

perature difference, lower 24-hour 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 versus 4.96) and a smaller mean MAE (3.53 versus 3.59) than the all cities approach.

Table 7: Temperature and land cover information averaged across the study period for each of the six cities in the dataset between June and August from 2016 to 2019, North Carolina.

City	Ashville	Hickory	Charlotte	Raleigh	Greenville	Wilmington
Mental and Behavioral Disorders	3773	1877	17533	9811	2462	4176
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 (28.90 - 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)	20.40 (17.91 - 22.89)	21.14 (18.5 - 23.78)	22.36 (19.98 - 24.74)
Tmax 24hr diff	0.009 (-1.820 - 1.838)	0.012 (-2.278 - 2.304)	0.016 (-2.245 - 2.277)	0.019 (-2.268 - 2.306)	0.006 (-2.320 - 2.332)	0.005 (-1.921 - 1.931)
Tmin 24hr diff	0.0004 (-1.509 - 1.511)	-0.004 (-1.573 - 1.566)	-0.009 (1.601 - 1.583)	-0.012 (-1.693 - 1.678)	-0.018 (-2.055 - 2.026)	-0.021 (-1.736 - 1.694)
EHF	0.003 (-0.022 - 0.030)	0.002 (-0.018 - 0.021)	0.007 (-0.048 - 0.062)	0.001 (0.012 - 0.010)	0.010 (-0.064 - 0.083)	0.008 (-0.061 - 0.078)
Above 95th	0.029 (-0.125 - 0.183)	0.025 (-0.127 - 0.177)	0.047 (-0.159 - 0.252)	0.018 (-0.099 - 0.029)	0.046 (-0.161 - 0.253)	0.035 (-0.127 - 0.198)
NDVI	0.41 (0.16 - 0.66)	0.43 (0.22 - 0.62)	0.38 (0.16 - 0.60)	0.40 (0.18 - 0.62)	0.41 (0.16 - 0.66)	0.34 (0.20 - 0.48)

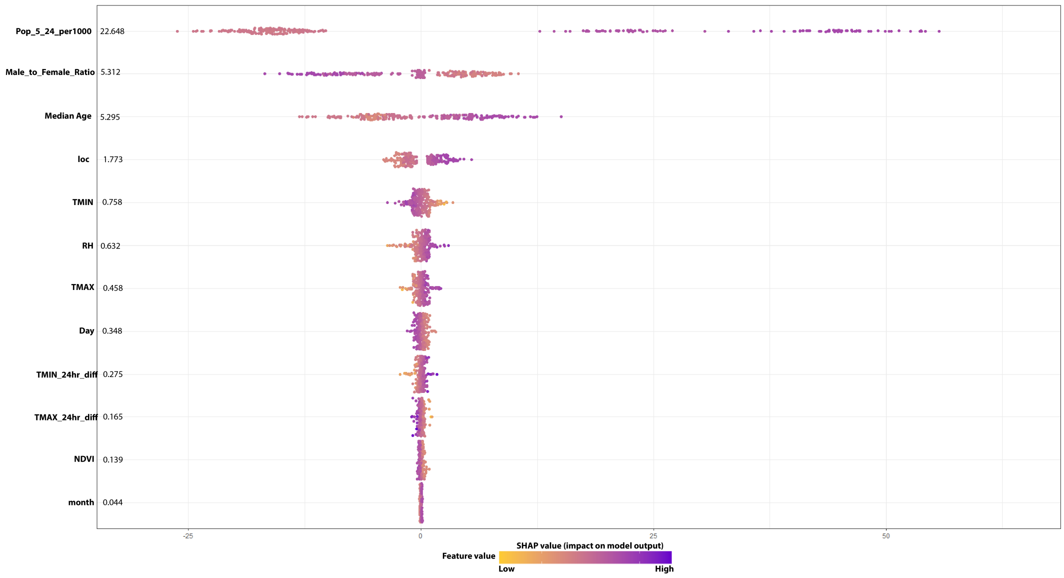

Figure 3: SHAP (SHapley Additive exPlanations) values and contributions of the best-performing variables in the best model (GAM model). The plot shows the importance of the predictors, with the most important at the top, of the best-performing model using SHAP values. The effect of the contribution is 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 MBD emergency department visits, with positive values leading to a higher number of predicted emergency room visits and a negative value leading to a lower number of predicted emergency room visits.

Table 8: RMSE and MAE of the models for train and test performance of the GAM model for all six cities individually. Normalized RMSE and normalized MAE for the test dataset to better illustrate how the models performed on different datasets.

	Ashville	Hickory	Charlotte	Raleigh	Greenville	Wilmington	
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

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 which were identified within the GAM model were chosen to be represented in the SHAP model [33]. The SHAP value model can be seen in Fig 4. From these models, we can see that in Asheville, a higher relative humidity, lower minimum temperature, higher 24-hour maximum temperature difference, and higher 24-hour minimum temperature difference all lead to a higher incidence of MBD. In Hickory, a lower 24-hour maximum temperature difference leads to higher incidences of MBD. A lower maximum temperature leads to higher incidences of MBD in Charlotte. A lower 24-hour maximum temperature difference, higher NDVI value, a lower maximum temperature, and higher 24-hour minimum temperature difference all lead to higher incidences of MBD in Raleigh. In Greenville a higher NDVI and in Wilmington and higher 24-hour maximum temperature difference leads to higher incidences of MBD.

3.3 Sensitivity Analysis

Relying on a standard approach typically used in environmental health studies, the DLNM was employed. 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. Figure 5 shows the change in relative risk (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 that there is not a significant association between ER visits related to mental and behavioral disorders 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).

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 adolescents. Our

Figure 4: Shows the 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 (GAM 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 MBD emergency department visits, with positive values leading to a higher number of predicted emergency room visits and a negative value leading to a lower number of predicted emergency room visits.

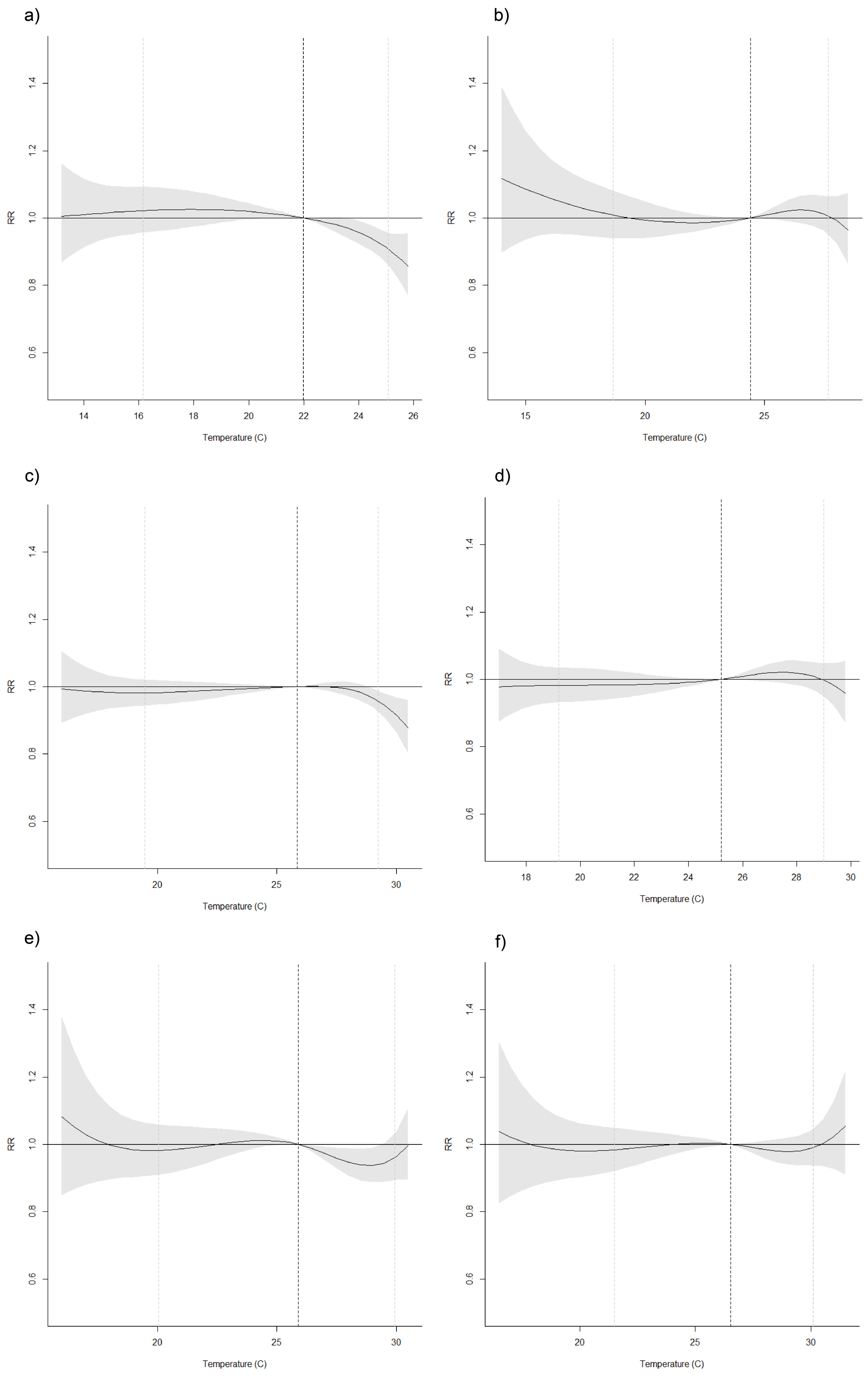

Figure 5: The individual effect of daily average temperature for all MBD-related emergency room visits for (a) Asheville, (b) Hickory, (c) Charlotte, (d) Raleigh, (e) Greenville, (f) Wilmington. The optimal emergency room visit temperature was defined as the temperature that corresponded with the minimum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

findings from the all-cities model indicate that socio-demographic variables contribute a greater impact on adolescents' mental health compared to environmental variables. Important sociodemographic factors that contributed the greatest to the predictive outcome included population between 5 and 24, male to female ratio, and the median age of the city; while important environmental variables included minimum temperature, relative humidity, 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 adolescent population more than the environmental variables [13][60]. Further, the increase in hospital admissions on days of higher maximum temperature and higher relative humidity, found in the all-cities machine-learning model, is consistent with multiple studies, which identified an increased relative risk at higher maximum temperatures, even after adjusting for relative humidity as a covariate [47] [38][11]. 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 association between temperature and MBD-related ER visits was not consistent within our study area, with lower minimum temperatures increasing 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 a 24-hour difference in the maximum temperature, and two of the cities having a 24-hour 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 emergency room visits. Previous research has indicated that females are more likely to display help-seeking behaviors compared to males [44]. We also see that the population of our study age is a strong predictor, which indicates in cities with a larger youth population, there are higher instances of MBD ER visits for that age group.

In contrast to previous studies, our minimum temperature results in the 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, which we see in our study, but that an increase in minimum temperature corresponds with an increase in MBD ER visits rather than our observed decrease [38].

Our study contrasts with previous work focusing on an individual city's response during the summer. Studies have found 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 [63][59][47]. 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 distributed lag non-linear model (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, rather temperatures near the median contributed to higher predicted MBD emergency department visits. These results are consistent with the results from the DLNM, 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°C 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°C to 37°C[59][47] [63]. 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 adolescents 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 statewide 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 if sociodemographic factors. Second, unlike most nonlinear model results that will indicate the top contributing variables to the prediction [60], through the use of SHAP, we provide 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, ozone pollution generally has a high correlation with temperature and has been shown to impact mental health [59], and should have been tested as a possible effect modifier in the temperature-mental health relationship. However, our analysis was conducted at the ZCTA scale, and ozone data was not readily available for this scale.

5 Conclusion

This study is among the first to examine the driving factors behind MBD ER visits in North Carolina, USA. Our study leveraged a daily ER inpatient dataset for the entire state of North Carolina, allowing us to examine the daily MBD response in youth to varying environmental conditions and socioeconomic changes. This study suggests that at the state 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 response during high-temperature events.

CRediT authorship contribution statement

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

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data Availability

Sheps center data is available for academic/public health research via application process, found at `https://www.shepscenter.unc.edu/data/nc-hospital-discharge-data/`. The R scripts used for this article for machine learning is avaliable at `https://github.com/wertisml/temperature-Health_Response`, for DLNM models at `https://github.`

com/wertisml/Statistical_methods/tree/main/DLNM, for PRISM data at https://github.com/wertisml/Heatwave.

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