**Assessing the Impact of Extreme Heat on Poor Mental Health Outcomes in the U.S. in 2024**

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## ABSTRACT

Rising temperatures driven by anthropogenic climate change are accelerating the frequency of extreme heat events across the U.S. (*Climate Change Indicators: U.S. and Global Temperature | US EPA*, 2025). This study investigates the relationship between extreme heat days and mental health outcomes in 2024. Utilizing data from the CDC HeatTracker tool, we applied a logistic regression model, accounting for key sociodemographic and environmental factors. We then employed a random forest machine learning model to pinpoint the most significant predictors of poor mental health outcomes, comparing extreme health, social factors, and environmental variables. Results revealed a significant relationship between extreme heat and poor mental health prevalence, with each additional extreme heat day corresponding to a decreased odds of poor mental health by 6.3%. Among all predictors, poverty and high school education status were found to be the most significant in predicting mental health outcomes, with extreme heat being a less important factor. This study highlights the need for further research on the role of sociodemographic indictors in shaping mental health outcomes and emphasize the need for continued research using a more accurate extreme heat variable.

## INTRODUCTION

Global temperatures are increasing due to anthropogenic climate change, with an average increase of 0.32 to 0.51°F every decade since 1979 (*Climate Change Indicators: U.S. and Global Temperature | US EPA*, 2025). Within the U.S., temperatures have risen at a rate 60% faster than the global average, intensifying the risk of extreme heat events (*Extreme Heat | US EPA*, 2025). As a result, extremely hot days are projected to become more frequent, and heat waves are expected to worsen in the coming years (*Extreme Heat | US EPA*, 2025). Meanwhile, mental

illness in the United States is a significant concern as well. It is estimated that 23.1% of the U.S. adult population lives with a mental illness, equating to about 59.2 million people (*Mental Illness*, n.d.). Various studies have attempted to understand if a relationship exists between extreme heat and mental health outcomes in the United States. A systematic review by Thompson et al. (2018) found strong evidence spanning 15 studies of a relationship between extreme heat and suicide risk in the U.S. Similarly, higher temperatures were found to coincide with increased risk of mental health-related hospital admissions. Despite these findings, significant knowledge gaps remain in the understanding of the heat-mental health relationship.

In this study, we hope to examine the relationship between extreme heat and poor mental health at the zip code level for the entire U.S. Specifically, we will aim to address the following two research questions:

1. What is the relationship between number of extreme days and poor mental health outcomes at the zip code level in the U.S. for 2024?

2. What is the most important predictor of poor mental health in 2024, comparing extreme heat days to other environmental and sociodemographic factors?

## METHODS

### *Data Collection and Preparation*

Data was collected from the CDC HeatTracker, a tool developed by the Centers for Disease Control and Prevention to monitor heat-related risks and trends across the U.S. (Centers for Disease Control and Prevention, n.d.). The data are annual and provided at the Zip Code Tabulation Area (ZCTA) level for the year 2024.

The outcome variable for this study is mental health status, which is defined by a binary variable for the logistic regression analysis indicating whether a ZCTA has a high prevalence of poor mental health (defined as reporting "not good" mental health for at least 14 days). It is coded as 1 (indicating high levels of poor mental health) if the ZCTA's mental health percentile rank is at or above the 66.6th percentile rank (as defined by the CDC), and 0 if the percentile rank is below this threshold (indicating not high prevalence of poor mental health). For the random forest machine learning model, a continuous outcome variable for mental health status was used: percentile rank of crude prevalence of persons (age 18+) reporting "not good" mental health for at least 14 days at the zip code level. The main predictor for this study is number of extreme heat days, a continuous variable defined as the number of days above the 95% historical average temperature per ZCTA.

Missing values accounted for 3.51% of the data and, as a result, were removed from the dataset, resulting in a remaining 31,057 total observations.

*Logistic Regression Analysis*

Covariates for the logistic regression model were selected using a Directed Acrylic Graph (DAG) to account for confounding and causal relationships (**Figure 1**); green arrows in the figure indicate the hypothesized causal pathway. Poor physical health (gray) was identified as a mediator and therefore was dropped as a covariate from the model. Covariates kept in the model included sociodemographic score, which is a continuous summary indicator averaging the percentile ranks of various specific sociodemographic indicators, with higher scores indicating worse sociodemographic conditions for each ZCTA. Other continuous covariates in the model include the % of ZCTA with impervious surface coverage, % of ZCTA with tree canopy

coverage, % of ZCTA with mobile homes, % of ZCTA with households without vehicle access, and annual mean days above the PM2.5 regulatory standard (3-year average per ZCTA).

**Figure 1:** Directed Acrylic Graph (DAG) of Extreme Heat Predictor, Poor Mental Health Outcome, and Potential Environmental Exposure, Poor Physical Health, and Sociodemographic Covariates.
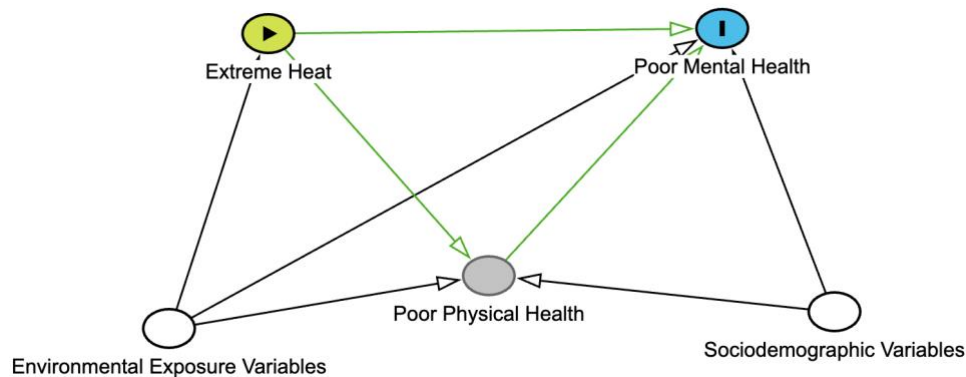


Though multiple linear regression was initially attempted, heteroscedascity and non-linear assumptions were continuously violated due to the nature of the outcome variable (percentile rank of poor mental health), and therefore, logistic regression was selected as the analysis method of choice with a binarized mental health variable.

Logistic multivariate regression was applied to assess the association between extreme heat days and high prevalence of poor mental health. Covariates that were selected in the DAG analysis were included. The CDC-provided summary environmental exposure variable had calculation issues; therefore, a univariate analysis was conducted for each individual environmental exposure variable, and all significant variables were included in the model. Likelihood ratio tests were used to identify the most parsimonious multivariate model and assess interaction terms; ultimately, significant interaction terms were removed due to multicollinearity concerns (as indicated by VIF analysis). The resulting final model is below, where controls

selected included sociodemographic risk index, % of ZCTA with impervious surface coverage, % of ZCTA with tree canopy coverage, % of ZCTA with mobile homes, % of ZCTA with no vehicle households, and annual mean days above PM2.5 regulatory standards.

$$\log\left(\frac{P(Y=Poor\ Mental\ Health)}{1-P(Y=Poor\ Mental\ Helath)}\right) = \beta_0 + \beta_1 Extreme\_Heat + \beta_2 Controls \tag{1}$$

### *Random Forest Analysis*

To understand how extreme heat compares to other environmental exposure and sociodemographic variables in explaining poor mental health status in the U.S., a random forest machine learning model was selected as a favorable model to use considering its excellent predictive ability (Fernandez-Delgado et al., 2014). This analysis used the percentile rank of self-rated "not good" mental health days as the outcome variable. To run the random forest model, the R package ranger was used in R software to run a random forest regression.
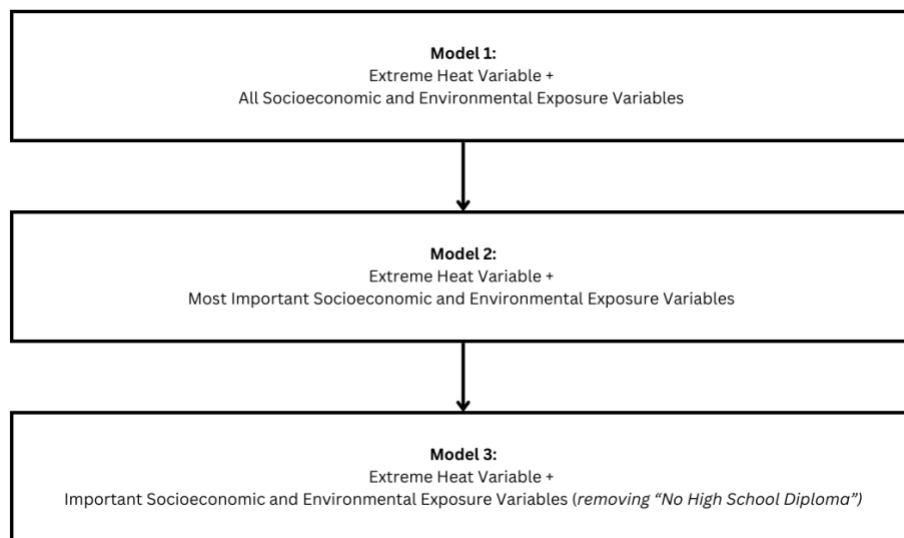
The full dataset was randomly divided into two subsets: 80% was allocated for training the model and 20% was reserved for testing. The split ensured that the evaluating the model performance was possible. A random forest model was then run using the training data. Within our model, we chose to use 500 trees, as this was appropriate for our sample size and was large enough to minimize error in the model. Mtry, the number of predictors that are randomly selected at each split in random forest decision trees, was set to number of predictors divided by 3, as this is the standard for regression forests with continuous outputs (López et al., 2022).

After assessing for out-of-bag error and r-squared, variance importance plots were created using the ggplot2 package in R. To identify which variables are most important, the methodology

shown in Figure 2 was used, in which "not good" mental health percentile rank was regressed onto Model 1, 2, and 3.

To ensure model accuracy, after the initial most important variables were identified, the "No High School Diploma" variable was dropped due to its high correlation with the Poverty variable (as shown in **Figure 3**) and its lesser importance compared to the Poverty variable. As a result, all variables included in the final model (Model 3) are uncorrelated with each other. Extreme heat was kept as a variable in all models, due to its relevance in our study.

**Figure 2**: Process towards identification and selection of final Random Forest Regression model.



**Model 1:**
Extreme Heat Variable +
All Socioeconomic and Environmental Exposure Variables

**Model 2:**
Extreme Heat Variable +
Most Important Socioeconomic and Environmental Exposure Variables

**Model 3:**
Extreme Heat Variable +
Important Socioeconomic and Environmental Exposure Variables (*removing "No High School Diploma"*)

**Figure 3**: Correlation plot of all variables: extreme heat, mental health, environmental exposure, and sociodemographic variables.
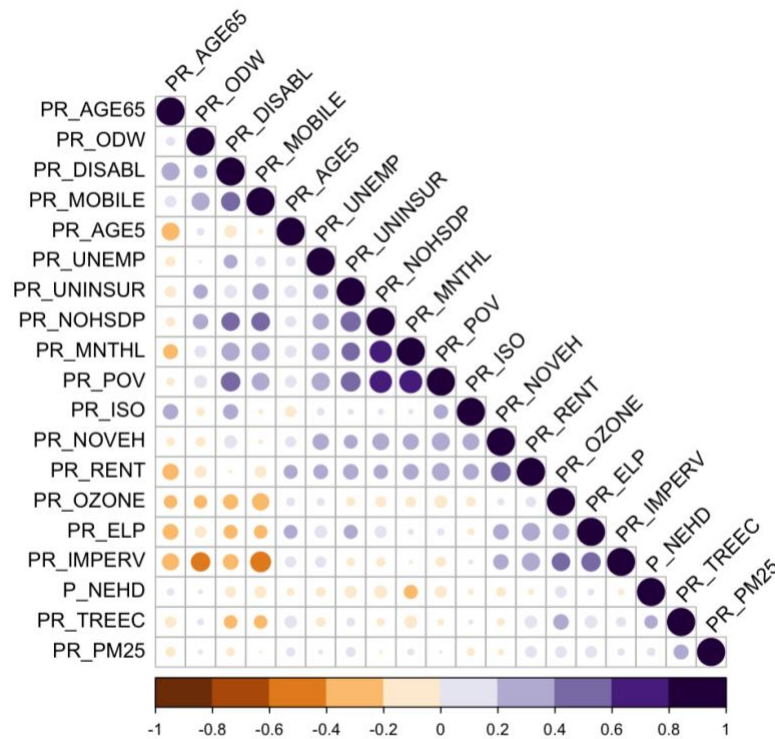


All analysis were conducted in R version 4.4.1 utilizing the following packages: dplyr, ggplot2, readr, lmtest, broom, tidyverse, gridExtra, car, flextable, officer, and ranger.

## RESULTS

### *Descriptive Analysis*

A total of 31,057 zip codes were included in this study taken from the entire continental U.S. **Table 1** shows number of extreme heat days averaged at 12.5 days (SD = 4.77), highest in the West at 16.8 (SD: 3.66) and lowest in the South at 9.85 (SD: 5.36). 'Not Good' self-rated mental health also varies by region, with the South having the highest percentage (56.2%) and

Northeast having the lowest (15.1%); the overall average 'Not Good' self-rated mental health is 32.6%. **Figure 4** is consistent with these conclusions.

Sociodemographic factors differ across regions. Instances of poverty below 150% was highest in the South, with a county average of 26.5%; poverty was least prevalent in the Northeast at 15.9%. The proportion of individuals with no high school diploma was also highest in the South (14.5%) and lowest in the Northeast (7.7%). The sociodemographic risk index followed a similar pattern, with the highest value in the South (0.546, SD = 0.130) and the lowest in the Northeast (0.441, SD = 0.124).

Environmental exposures also varied considerably by region. Impervious surface coverage and tree canopy coverage were highest in the Northeast (4.47% of ZCTA & 45.9% of ZCTA) and lowest in the West (1.44% of ZCTA & 15.2% of ZCTA). The prevalence of mobile homes was highest in the South (15.4% of ZCTA) and lowest in the Northeast (2.2% of ZCTA)

**Figure 4:** Spatial distribution of extreme heat days and 'not good' self-rated mental health
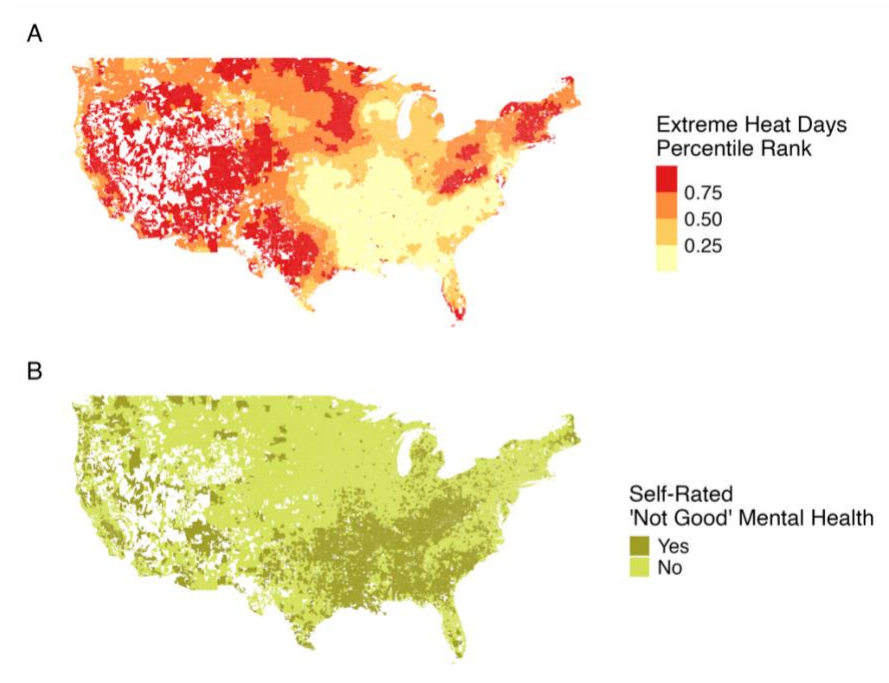
**Table 1:** Descriptive characteristics of U.S. zip codes

| | Total[1] (N=30121) | Midwest[1] (N=9572) | Northeast[1] (N=5623) | South[1] (N=10392) | West[1] (N=4534) |
|---|---|---|---|---|---|
| ***Main Predictor and Outcome Variables*** | | | | | |
| Number of extreme heat days | 12.5 (4.77) | 12.2 (3.25) | 14.5 (2.89) | 9.85 (5.36) | 16.8 (3.66) |
| 'Not Good' Self-Rated Mental Health | | | | | |
|   Yes | 9823 (32.6%) | 1810 (18.9%) | 851 (15.1%) | 5845 (56.2%) | 1317 (29.0%) |
|   No | 20298 (67.4%) | 7762 (81.1%) | 4772 (84.9%) | 4547 (43.8%) | 3217 (71.0%) |
| ***Sociodemographic Variables*** | | | | | |
| Below 150% poverty estimate[2] | 20.9 [0, 100] | 18.7 [0, 100] | 15.9 [0, 100] | 26.4 [0, 100] | 21.0 [0, 100] |
| Persons living alone[2] | 13.6 [0, 100] | 14.3 [0, 100] | 13.4 [0, 100] | 13.5 [0, 100] | 12.6 [0, 100] |
| Persons who speak English less than well[2] | 0.357 [0, 100] | 0.119 [0, 54.6] | 0.413 [0, 41.5] | 0.495 [0, 48.9] | 1.23 [0, 100] |
| Persons with no high school diploma (age 25+)[2] | 9.80 [0, 100] | 8.10 [0, 86.6] | 7.70 [0, 94.5] | 14.5 [0, 100] | 8.80 [0, 100] |
| Persons aged 65 and older[2] | 17.9 [0, 100] | 18.2 [0, 76.4] | 18.5 [0, 100] | 17.3 [0, 100] | 17.3 [0, 100] |
| Sociodemographic risk index3 | 0.493 (0.135) | 0.463 (0.122) | 0.441 (0.124) | 0.546 (0.130) | 0.501 (0.138) |
| ***Environmental Exposure Variables*** | | | | | |
| Impervious surface coverage[2] | 1.91 [0.032, 93.8] | 1.57 [0.066, 93.0] | 4.47 [0.065, 93.8] | 1.83 [0.049, 91.5] | 1.44 [0.032, 93.0] |
| Tree canopy coverage[2] | 29.5 (24.0) | 17.4 (17.2) | 45.9 (20.4) | 38.0 (24.0) | 15.2 (18.4) |
| No vehicle availability[2] | 4.10 [0, 100] | 3.60 [0, 100] | 4.90 [0, 100] | 4.70 [0, 100] | 3.50 [0, 85.7] |
| Mobile homes[2] | 7.20 [0, 100] | 5.00 [0, 100] | 2.20 [0, 100] | 15.4 [0, 100] | 8.50 [0, 100] |

[1] Median [Min, Max]; n (%); Mean (SD)
[2] Percent of ZCTA (Zip Code Tabulation Area)
[3] Average of percentile ranks for various sociodemographic indicators, with higher scores indicating worse sociodemographic conditions for each ZCTA.

*Logistic Regression Analysis*

  The final selected logistic regression model met assumptions of no perfect multicollinearity, linearity of the log odds for continuous predictors, and binary outcome variable were met. There were also no influential outliers in the dataset, as no observations had externally studentized residuals above 3 and a cook's d value above 1.

  **Table 2** shows the multivariate logistic regression analysis for the relationship between extreme heat days and prevalence poor mental health outcomes, accounting for relevant controls. Extreme heat days is found to be significantly associated with prevalence of poor mental health at the zip code level ($p < 0.001$). Specifically, for each additional extreme heat day, the odds of experiencing poor mental health decrease by 6.3% (OR: 0.937 [0.931, 0.942]). In addition, the socioeconomic risk index has an especially strong relationship with poor mental health prevalence; every additional 0.1 increase in socioeconomic risk index, the odds of poor mental health approximately doubles (OR: 2.048, $p < 0.001$).

**Table 2:** Logistic regression model of high prevalence of poor mental health

| Covariate | OR | 95% CI Lower | 95% CI Upper | P Value |
|---|---|---|---|---|
| (Intercept) | 0.008 | 0.007 | 0.010 | 0.000e+00 |
| Number of Extreme Heat Days | 0.937 | 0.931 | 0.942 | 1.229e-99 |
| Sociodemographic Risk Index[1] | 2.048 | 1.994 | 2.104 | 0.000e+00 |
| Impervious Surface Coverage[2] | 1.014 | 1.012 | 1.016 | 4.639e-47 |
| Tree Canopy Coverage[2] | 1.014 | 1.013 | 1.016 | 2.347e-106 |
| Mobile Homes[2] | 1.037 | 1.034 | 1.039 | 2.126e-188 |
| No Vehicle Households[2] | 1.032 | 1.028 | 1.036 | 7.784e-56 |
| Annual Mean Days Above PM2.5 Regulatory Standard[3] | 1.045 | 1.035 | 1.055 | 7.388e-20 |

Statistically significant P-values < 0.05, OR: odds ratio, 95% CI: 95% confidence interval.
[1] Average of percentile ranks for various sociodemographic indicators, with higher scores indicating worse sociodemographic conditions for each ZCTA.
[2] Percent of ZCTA
[3] 3-year average

## *Random Forest Analysis*

As shown in **Table 3,** all three random forest regression models demonstrated similar performance, with out-of-bag (OOB) mean-squared error (MSE) equal to 0.02 in Model 1 and 0.03 in Model 2 and 3; the indicated error rate is very low, so we can assume our models are highly accurate. R-squared values indicate that Models 1, 2, and 3 explain 73%, 68%, and 70% of variance in poor mental health outcomes, respectively.

**Table 3:** Evaluation of Random Forest Model Performance

| Metric | Model 1 | Model 2 | Model 3 |
|---|---|---|---|
| Number of Trees | 500 | 500 | 500 |
| Mtry | 6 | 3 | 3 |
| OOB Error (MSE) | 0.02 | 0.03 | 0.03 |
| R-squared (OOB) | 0.73 | 0.68 | 0.70 |

**Figure 5:** Random Forest Variable Importance Plots for Poor Mental Health Outcomes
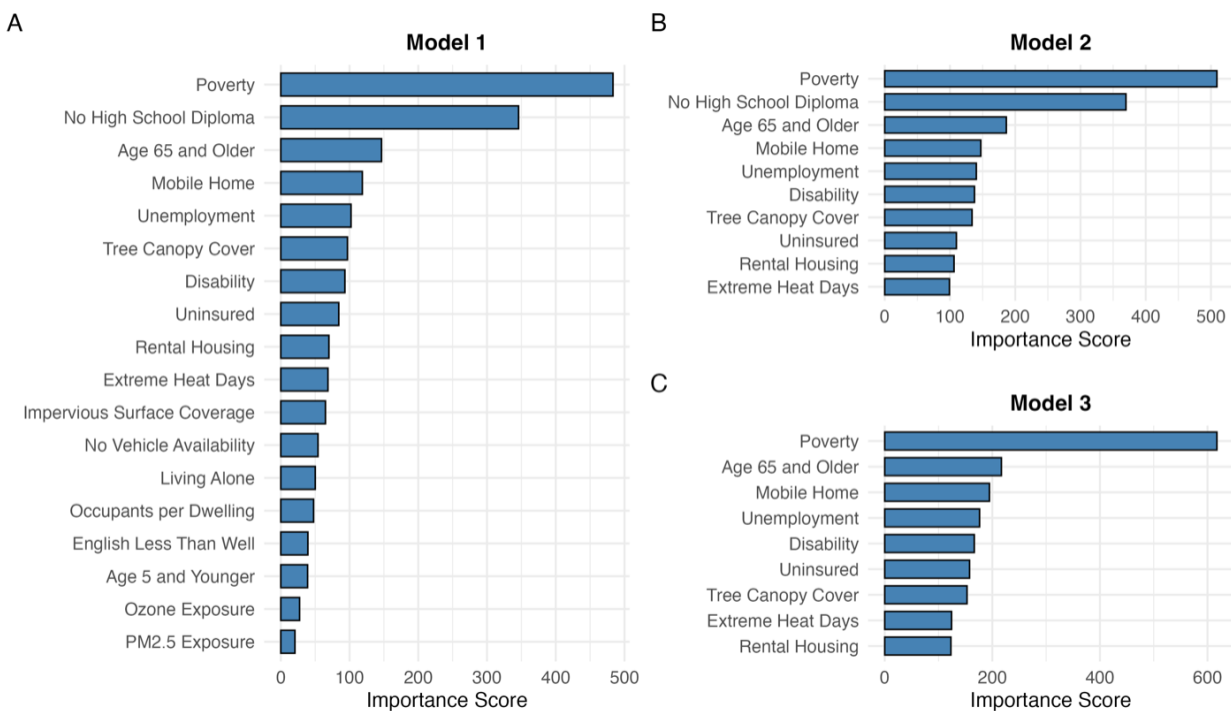


**Figure 5A** highlights that poverty rate and no-high-school-diploma rate are the most important predictors of poor mental health outcomes at the zip code level. Other important predictors include rate of age 65 and older, mobile home use, unemployment, tree canopy cover,

disability, uninsured, and rental housing. Extreme heat falls, though a marginally important predictor, is less important than the variables mentioned previously.

Figure 5B, which shows only the most important predictors from Model 1, indicates poverty and high school education status (both sociodemographic variables) again as the most powerful predictors of poor mental health outcomes. The percentile rank of persons aged 65 and older closely follows as an important predictor. Other relevant sociodemographic variables include percentile rank of unemployment, disability, and uninsured. Important environmental exposure indicators include tree canopy cover and percentile rank of mobile homes estimate and rental housing. Extreme heat remains the least important indicator.

Figure 5C shows the same model as Model 2, yet the following variable was dropped due to its high correlation with poverty: No High School Diploma. Here, results remain highly similar, with poverty being by far the most important predictor and extreme heat days becoming slightly more important than it was in previous models.

## DISCUSSION

### *Comparing Logistic Regression and Random Forest Findings*

To evaluate the relationship between number of extreme heat days and poor mental health outcomes at the zip code level across the U.S., logistic regression was used. Our logistic regression model found an inverse relationship between extreme heat days and poor mental health outcomes, while controlling for relevant sociodemographic and environmental exposure variables. Additionally, it revealed a highly significant positive relationship—with an exceptionally large effect size—between the sociodemographic risk index and poor mental health prevalence.

While logistic regression identified significant associations, it did not indicate which predictors were most important. To address this, we applied a random forest model to assess the relative importance of extreme heat days compared to other sociodemographic and environmental exposure factors. Results showed that poverty rate was by far the strongest predictor of poor mental health outcomes, followed by high school education status; extreme heat days showed much lower importance in comparison.

Together, these findings suggest that while extreme heat days are significantly associated with poor mental health outcomes, it is a much less important indicator than other variables such as poverty and high school education status.

### Strengths and Limitations of Analysis

Our analysis has several notable strengths. First, the large, nationwide dataset used in our analysis ensures reliability of the results and generalizability of our conclusions across the U.S. Furthermore, the use of Directed Acyclic Graph (DAG) model to effectively identify confounders reinforced the accuracy of our findings. Finally, employment of multiple, diverse analytical methods provides a multifaceted understanding of the relationship between extreme heat and mental health outcomes.

It is important to acknowledge limitations in our study due to constraints in our methodology. First, the extreme heat variable is defined based on historical temperatures for specific zip codes, which could introduce measurement error. For example, in colder regions, a day classified as an "extreme heat day" might actually feel pleasant, while in hotter regions, temperatures may be high but still within the historical norm, potentially missing true extreme heat events. Additionally, the assessment of mental health using self-reported ratings, rather than

an objective measurement tool, introduces the potential for biases related to stigma or differences in mental health awareness. Another limitation is that our analysis did not account for the spatial nature of the data, and that due to the ecological design of this study, complex dynamics within zip codes are not detected or accounted for.

It is important to acknowledge that our findings contradict the existing literature establishing a connection between extreme heat days and poor mental health outcomes (Thompson et al., 2018). This discrepancy may be explained by the previously mentioned limitations in our study. As a result, future research is needed to investigate whether our findings are representative of reality.

### *Future Directions and Conclusions*

Future studies should continue to explore the relationship among extreme heat, social factors, and mental health outcomes using spatial models to account for inherent spatial dynamics of climate and health variables. We also recommend using a different, more absolute extreme heat indicator, such as wet-bulb globe temperature (Writer, 2024), to better capture the temperature actually experienced by populations.

To summarize, our analysis offers valuable insights into the relationship between extreme heat days, sociodemographic and environmental factors, and mental health across the United States in 2024. Our findings underscore the importance of sociodemographic indicators, such as poverty and high school education status, in shaping mental health outcomes and emphasize the need for continued research using a more accurate extreme heat variable.

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