Contextualizing Depression Hotspots in North Carolina

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Abstract

Discussions about depression often focus on individual experiences, such as one's isolation from their environment, but this lens can overlook how broader environmental and structural factors, like income, education, poverty, or geography, may also shape depression rates. Recognizing these contextual factors is essential for identifying community-level patterns and determining which areas could benefit from additional mental health support. To help policymakers make more informed decisions about resource allocation, we developed an interactive dashboard that visualizes North Carolina county depression rates in relation to demographic factors, allowing users to identify patterns across regions and within individual counties. We also designed an adjustable "needs index" that provides a value for a county's mental health vulnerability based on these demographic variables, giving users a customizable way to highlight potential priority areas for intervention. Our final dashboard provided valuable insights by revealing that there are clear geographic and demographic patterns that support our initial prediction that environmental context plays a meaningful role in where depression rates are highest.

1 Introduction

The discussion surrounding depression is often limited to the individual level. We tend to focus on how isolation from one's environment contributes to depression. However, this view can overlook an important contrasting question, how the characteristics of one's environment, including geographic patterns, might also influence where depression rates are higher or lower. This motivated our solution, as we explored the geography of depression in North Carolina and examined how certain regions become "depression hot-spots," where higher depression rates seem to cluster. To identify these hot-spots and understand why they emerge, we need to look at broader structural factors like income, education, poverty, and regional context.

This is a significant problem, especially in North Carolina. In recent years, there has been increasing concern for mental health in North Carolina, with NAMI even reporting that "North Carolina is facing a mental health crisis," especially with over 3,500,000 residents living in communities without enough mental health specialists [13]. This urgency has caused an increase in funding; in 2023, NCDPI awarded approximately $17 million for mental health support in public schools [11], and in 2024, NCDHHS invested around $5 million to create a "Collaborative Care Model" for behavioral health services [12]. Despite these efforts, 2025 NAMI data reports that 1 in 5 adults in NC still experience a mental illness every year [13], highlighting that there is a persistent need statewide in the way we distribute resources.

This data raised an important question for us, how can we better analyze depression in a way that helps guide where and how mental health resources should go to meet the needs of underserved communities. If depression rates cluster geographically or vary with environmental factors, such as income, education, or poverty, recognizing these patterns can help policy makers to target assistance more effectively and better understand the type of support different regions need. This motivated our project and the creation of tools that are designed to explore these structural and geographic influences.

2 Related Work

Socioeconomic, geographic, and community-level factors all combine to produce disparities in mental health. Studies confirm a bidirectional causal relationship between poverty and common mental illnesses, including anxiety and depression [7]. Negative economic events-from job loss to income instability linked to climate change-exacerbate mental health problems, while interventions such as cash transfers and antipoverty programs consistently reduce symptoms of anxiety and depression [7]. These studies suggest chronic stress, environmental exposure, trauma, and reduced cognitive capacity are candidate mechanisms that link material deprivation to psychological distress. Long-term evidence also suggests that early-life economic hardship confers enduring deficits in cognitive function and adult mental health, perpetuating intergenerational cycles of disadvantage [7].

Community-level characteristics also play a role in the spatial distribution of mental health burden. Built environment factors, such as air and noise pollution, green space availability, walkability, and housing quality, are strongly associated with spatial variation in rates of depression and anxiety at the neighborhood level [5], [6]. Geographically weighted regression analyses have also validated that associations are not constant and, therefore, that the impact of social and environmental risk factors on mental health is different in magnitude and direction for different contexts [8]. Furthermore, economic segregation, sociodemographic composition, and availability of local services are found to predict a higher prevalence of depressive symptoms across different regions within the United States [5], [6] [8]. The findings emphasize the need to consider local contextual features when constructing models of risk for mental health or when designing populationlevel interventions.

Schools are important points of access for youth mental health services, but significant geographic disparities exist. Rural and town schools are far less likely to provide diagnostic mental health evaluations and commonly report severe shortages of qualified mental health professionals [9]. Inadequate funding, workforce shortage, and physical isolation tend to be the main obstacles in these settings, while city schools more often report barriers related to parental concern and community disagreement. This disparity is particularly worrisome, as rural youth have a higher risk for major depression, anxiety disorders, and suicidal behaviors. The aggregation of these studies demonstrates that mental health service ecologies vary dramatically along the rural–urban continuum, with profound implications for how mental health needs are identified and treated. A common thread in these studies [5]–[9] has been that mental health outcomes are strongly related to social determinants, environmental context, and geographic access to care. Previous studies have established that what is needed are models and systems that are capable of: (1) grasping these context-sensitive drivers of depression and anxiety, (2) determining spatial inequities, and (3) supporting targeted interventions for high-risk communities. Given this foundation, our work builds on it by using those empirically validated determinants to inform the design of our predictive framework, enabling more localized, context-aware assessments of mental health risk.

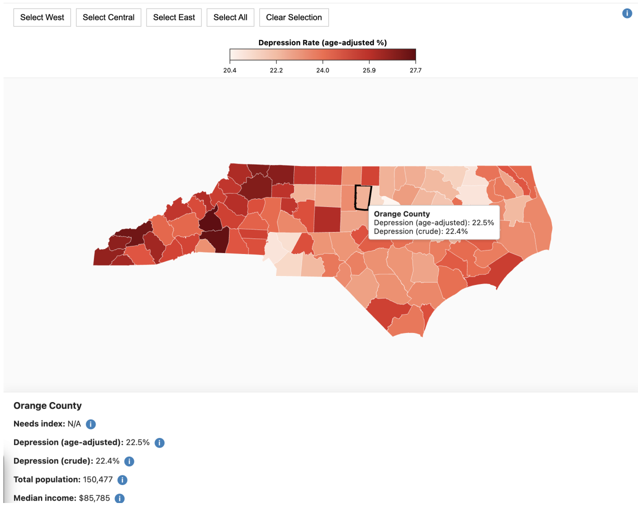

Figure 1: Interactive Choropleth Map showing hover tooltip feature and sequential color ramp according to depression rate.

3 Project Description

We developed an interactive visualization dashboard encompassing four key features to allow users to analyze the correlation between depression rates and demographic factors in North Carolina. These features include a choropleth map, scatter plots visualizing the correlation between depression rates and county demographics, a county-detail panel, and an adjustable "needs index" formula. In addition to each feature displaying a unique view of the data, the components connect with each other to help contextualize geographical patterns. In addition to the visualization features, the dashboard includes information icons that reveal brief tooltips upon hover. These icons offer concise explanations of each interactive feature, allowing users to learn how to navigate the dashboard without cluttering the interface or distracting from the data.

3.1 Choropleth Map

Our main feature is the choropleth map (see Fig.1), which is the center point of our dashboard and provides an overview of the spatial patterns of depression rates across NC counties. We used a sequential luminance color scale using darker shades of red to highlight counties with higher depression rates, which we describe as "hot spots." We determined that luminance was the best channel for this visualization because it clearly indicated the intensity of the depression rates. One of our design challenges was choosing between using size and circles to create bubbles to represent "hot spots" and using a continuous color ramp. After testing both ideas, the color ramp proved to be the design choice that resonated most with our goal because it clearly highlighted the difference between county depression rates.

Another crucial design choice for this part of the visualization was the color legend and scale, which we decided to set the range from the lowest depression rate to the highest (20.4 - 27.7) rather than a fixed range to more accurately represent the distance between the data points on the map.

Although the collected Census data for county depression rate held different types of values, such as crude depression rate and age-adjusted depression rate, we chose to include the age-adjusted data for the map. This data reflects what the raw data would look like if all sources had the same standard age distribution, which we felt would show a more accurate comparison between counties when visualizing the depression rates on the map.

The main interactions we added for this feature was a tooltip

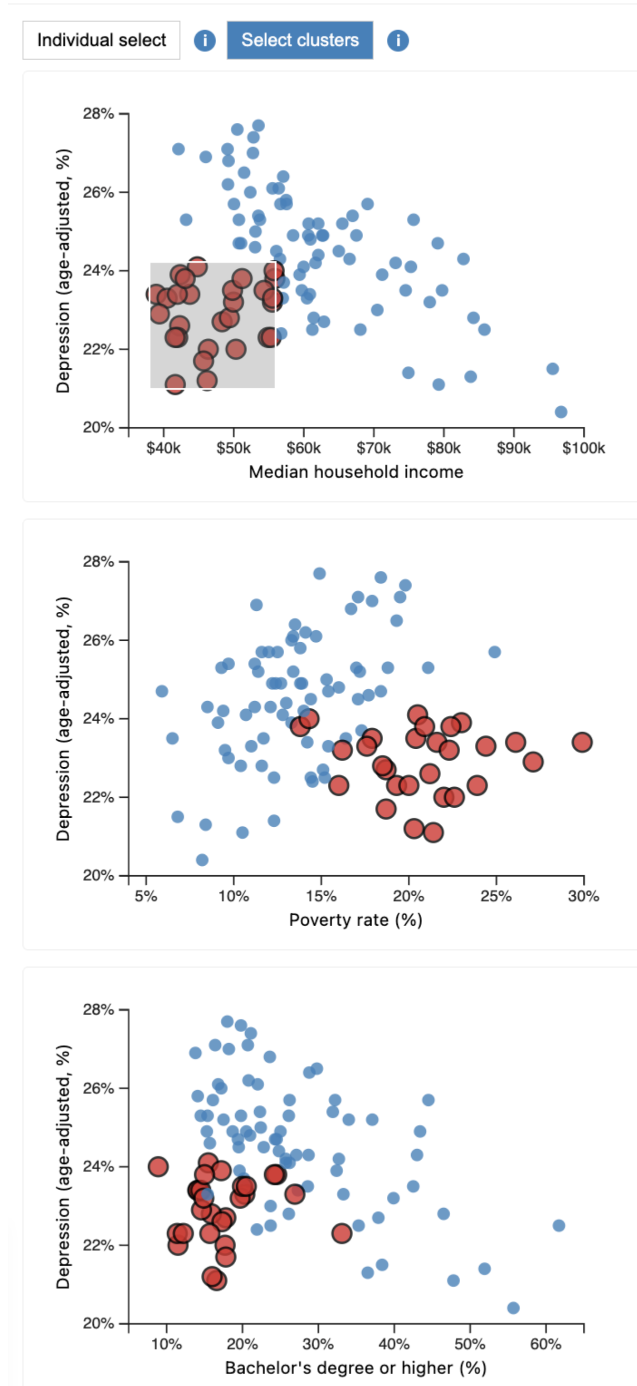

Figure 2: Three scatterplots show how the selected county compares to all others for poverty, income, and education relative to the depression rate. In addition, outlier cluster is selected to show discrepency in trend.

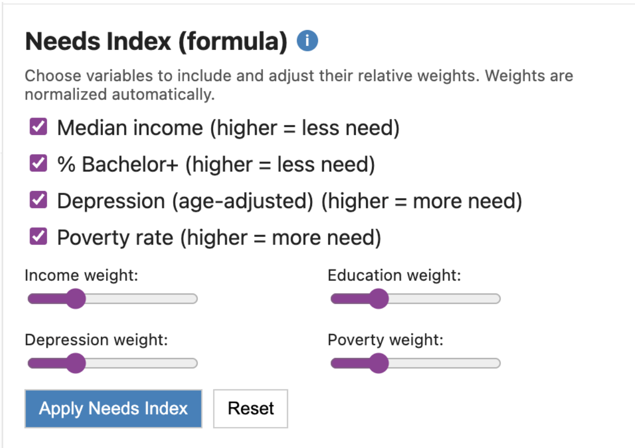

Figure 3: Needs-based index Formula simulator in which users are able to customize the weights and inclusion of different factors to tailor their output.

(a) Main Index Formula

$$\mathrm{NeedsIndex}_i = 10(w_I \tilde{I}_i + w_E \tilde{E}_i + w_D \tilde{D}_i + w_P \tilde{P}_i).$$

(b) Normalization Function

$$n(X_i) = \frac{X_i - \min_j X_j}{\max_j X_j - \min_j X_j}.$$

(c) Inversion Rules

$$\tilde{I}_i = 1 - n(I_i),$$
$$\tilde{E}_i = 1 - n(E_i).$$

(d) Weight Rescaling

$$w_k = \frac{w_k^{\mathrm{raw}}}{\sum_m w_m^{\mathrm{raw}}}.$$

Figure 4: Formulas used for the adjustable needs index. For each county i, the index combines normalized indicators for income ($\tilde{I}_i$), education ($\tilde{E}_i$), age-adjusted depression rate ($\tilde{D}_i$), and poverty rate ($\tilde{P}_i$), using weights defined by the user w_I, w_E, w_D, and w_P that are rescaled to sum to 1. Income and education are inverted so that lower values correspond to higher need, and the final score is mapped to a scale from 0 to 10.

on hover, which gave context to the map data by providing a pop-up box with the county name and depression rate (both crude and age-adjusted). We also included an interaction for users to select individual counties on click, which would reveal county data on the county detail panel including county name, needs index value, depression rate (age-adjusted), depression rate (crude), total population, median income, poverty rate percentage, and percent of people who have a bachelor's degree or higher in the county. In addition to individually selecting counties, we included region filter buttons above the map for users to select between West, Central, East, and all Counties in North Carolina. By selecting these region buttons, we allowed users to highlight these data clusters on our scatterplots.

To emphasize user priorities, lastly, we decided to adjust the color ramp/ legend of the map when users set the needs index formula. Once the formula is set, the color scale used on the map and the legend changes to reflect the needs index score (out of 10) rather than the depression rate. We made this design choice to cater the visualization to a user's priorities.

3.2 Graphs Tab

Another one of our main features is our graphs tab, which appears as a sidebar next to the map to act as an analytical tool that lets users explore the data through a different view. The graphs tab includes three different scatter plots showing correlations between age-adjusted depression rates for all counties and median household income, poverty rate, and percent of people with a Bachelor's degree or higher (see Fig. 2). This tab also has two interaction options users can choose between: individual selection and cluster selection. We included the select clusters option to allow users to interact with the visualizations in a different way and isolate clusters to see the relationships of certain clusters given different variables. Using either of the select buttons also highlights the selected counties on the map and vice versa, which also helps users make comparisons and connect demographic factors with the county's geography.

One of the key design choices we made when designing the graphs tab was layout and deciding to vertically align the graphs. By putting all of the scatter plots next to each other instead of separate tabs, the layout allows users to visually see how the same data points compare with different correlations. With the select features we designed, this also lets users see how counties compare with each other, given different factors. This also isolates the data points on the map panel to the side, which allows for a direct comparison for connecting geography with the demographic factors as well.

3.3 Formula Tab

Our final feature works alongside the needs index by allowing users to adjust the formula that calculates this value. The needs index was a feature we decided to include that calculates a county's potential vulnerability. The index combines demographic variables, including income, education, poverty, and depression rate (see Fig. 4). The formulas tab is a feature that users can use to decide which of these variables they want to factor into the index, and includes sliders for users to decide the weight of the given variables to configure to the situation they are analyzing (see Fig.3).

This feature was motivated by the understanding that policymakers consider both perceived resource scarcity and community needs when deciding how to allocate funding [1]. So rather than creating a fixed definition of "need", we designed the index to be transparent and user-controlled to avoid adding our personal bias into the analysis. By adjusting the weights, users can observe how county vulnerability scores shift, which also reiterates how depression rates are influenced by contextual factors using color.

4 Discussion

Our work highlights how geography and local context strongly influence depression rates across North Carolina. By combining county-level demographic, socioeconomic, and geographic data in an interactive visualization, we were able to explore associations that go beyond individual-level factors. One of the clearest findings from our visualization is that depression rates are unevenly distributed across the state. We can see distinct patterns when comparing western, central, and eastern counties, suggesting that regional factors influence a substantial portion of the variation in mental health.

One of the key takeaways is the generally negative relationship between income and depression rates: counties with higher median incomes tend to have lower rates of depression. This aligns with prior research linking economic stability to mental well-being. However, we also observed outlier clusters, particularly in Eastern North

Carolina, that deviate from this trend. These exceptions show that income alone does not fully explain regional differences in mental health and highlight the need to consider other contextual factors, such as population density, access to services, and social isolation.

Our findings show that location-based disparities in mental health are significant and something that would provoke action from policymakers. For example, some counties in Eastern North Carolina have relatively high depression rates despite moderate income levels, suggesting that interventions may need to focus on improving access to care, addressing social isolation, and mitigating environmental stressors rather than solely targeting economic conditions. This insight is particularly useful for policymakers and public health officials, as it emphasizes the importance of tailored, region-specific strategies instead of one-size-fits-all approaches.

Overall, our study highlights the value of linking geographic context with demographic and socioeconomic data when examining mental health outcomes. By highlighting regional patterns and identifying outlier clusters in North Carolina, we are laying the groundwork for more informed allocation of resources to counties that need it the most and also tailoring it to each county based on specific needs.

Since there is a persistent need for mental health resources across North Carolina, identifying geographic patterns and external factors that contribute to depression is crucial for guiding effective solutions.

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