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# Characterizing Populations Living Near Concentrated Animal Feeding Operations: Implications For Health Equity And Environmental Justice

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## *Abstract*

Current literature has highlighted that concentrated animal feeding operations (CAFOS) are associated with adverse health outcomes among populations living in close proximity to the farms and that, in certain states, vulnerable populations may be disproportionately exposed to CAFOs. However, none of the existing studies have assessed the sociodemographic makeup of areas highly exposed to CAFOs across a diverse geographic range. Using locations of CAFOs across six states with robust operations, we conducted logistic regression models assessing the likelihood of high exposure vs. low exposure at the census tract level for each 10% increase in sociodemographic variables (percent unemployed, percent minority, percent no high school diploma, percent living below 150% of the poverty line, percent uninsured, and percent disabled). Findings support that, across the full population, the odds of living in a high CAFO exposure census tract significantly increased for each 10% increase in the percent of the population with no high school diploma and the percent of the population living below 150% of the poverty line. Beyond overall patterns, each state's analyses showed varying interactions between high exposure and sociodemographic variables that were not uniform across all states, highlighting the complexity of relationships across varying geographies and demographic makeups. These findings have important implications for the future of research and policies addressing environmental justice and health equity, as they demonstrate the unique demographic differences between states and draw attention to the ways in which populations may differ in their vulnerabilities.

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## *Introduction*

Throughout most of our agricultural history, humans raised livestock in subsistence farming systems or on small, family-owned farms where the animals grazed in large open pastures. However, in the late 1960s, the United States transitioned to what researchers call the "livestock revolution," where meat, dairy, and eggs were now being procured in high efficiency, low-cost industrial farms housing thousands of animals in one building. These types of large-scale animal farms are referred to as Animal Feeding Operations (AFOs); in these facilities, animals are raised and fed for a minimum of 45 days in a year (US EPA, 2015). Concentrated AFOs, or CAFOs, are those that meet certain regulatory definitions based on the number of animal units on the farm and if animal waste is discharged onto surrounding land where it may come into contact with water systems (US EPA, 2015).

Concentrating animals in high-density settings is known to have detrimental effects on both the environment and the health of communities living near these facilities. Unlike human waste, which is processed and treated at sanitation plants before being re-circulated into the environment, raw animal waste is often collected in earthen manure lagoons outside of the facilities and may be sprayed on surrounding farmland as fertilizer, polluting both the groundwater via leaching and surface water via runoff (Nicole, 2013). CAFOs are also known to emit air pollutants that can cause serious health effects, such as respiratory irritation, asthma, chronic bronchitis, and lung disease (Hribar, 2010).

While the U.S. Environmental Protection Agency (EPA) is formally charged with permitting and regulating CAFOs under the Clean Water Act to ensure they have proper waste management systems, policy experts at the National Resources Defense Council have reported that, rather than a uniform, country-wide database, the availability of information on CAFOs is highly variable from state to state. In fact, because information submitted in applications for national pollution discharge elimination system (NPDES) permits are self-reported, the data reported to the EPA – such as the number of animals per farm, amount of waste produced, and how the waste is disposed – may not be complete or accurate, reducing their ability to ensure that CAFOs are not releasing harmful pollutants into surrounding populations and watersheds (Miller & Muren, 2019). This lack of transparency on CAFO operations, coupled with low-frequency inspection visits and reliance on farms to self-report information, raises concerns that communities with high exposure to animal agriculture may also be exposed to resultant air and water pollution from CAFOs and suffer from reduced quality of life (QOL); (GAO, 2008; Chugg et al. 2021).

Several resources exist that quantify the vulnerability of communities to disease outbreaks and harmful environmental exposures, such as the Centers for Disease Control and Prevention/Agency for Toxic Substances Disease Registry's Social Vulnerability Index (CDC/ATSDR SVI) and the Environmental Protection Agency's Environmental Justice Screening and Mapping Tool (EJScreen); however, these resources do not take into account exposure or proximity to CAFOs in their vulnerability calculations (Quist et al., 2022). Additionally, existing literature assessing population characteristics and health outcomes near CAFOs has often been limited to evaluations within a single state or region and a specific type of CAFO, e.g., hogs or cattle. Thus, in contrast to the vast majority of published research on CAFOs, this thesis will look at sociodemographic characteristics across six different states with robust CAFO operations and across all four major animal agriculture industries (i.e., pork, beef, dairy, and poultry). The goal of this analysis is to describe the population characteristics, such as race/ethnicity, poverty status, education, disability, and access to healthcare, of census tracts that have high exposure to CAFOs, which we define as the top 25% of tracts based on the number of operations. We hypothesize that census tracts with high exposure to CAFOs are more likely to have greater proportions of vulnerable populations versus those with low exposure.

## *Review of Relevant Studies*

### *Air Pollution and Respiratory Health*

Several epidemiological studies have found that exposure to CAFOs is associated with an increased risk of acute and chronic respiratory issues (May et al., 2012; van Dijk et al., 2016). For example, Wing et al. found that swine farms emit harmful air pollutants such as particulate matter (e.g., $PM_{2.5}$, $PM_{10}$), ammonia, and hydrogen sulfide, which were associated with increased blood pressure and asthma rates among residents in North Carolina (Schinasi et al., 2011; Wing et al., 2013). Similar findings were reported in Wisconsin, where residents living within 1.5 miles of a CAFO had significantly increased odds of self-reported nasal allergies, lung allergies, and uncontrolled asthma (Schultz et al., 2019). A cross-sectional study in Norway found that livestock farmers had an increased risk of chronic bronchitis and chronic obstructive pulmonary disease compared to crop farmers (Eduard et al., 2009). In rural Iowa, Merchant et al. found significant increased odds of asthma among children raised on swine farms and children raised on farms with an antibiotic additive in the feed compared to children who did not live on farms or who lived on farms that did not raise swine (Merchant et al., 2005).

### *Water Pollution, Bacterial Illnesses, and Antibiotic Resistance*

CAFOs are also sources of contaminants that make their way into surrounding water sources and are harmful to human health, especially for those that rely on well water. One such substance is nitrate, which forms as the nitrogen in animal waste decomposes (Hribar, 2010). A research study in Wake County, North Carolina found that 44% of drinking water wells located near a hotspot of dairy farms had nitrate levels well above the maximum contaminant level (Showers et al., 2008). In California's San Joaquin Valley, ZIP codes with higher concentrations of dairy farms and higher dairy cow densities were also found to have higher levels of nitrate contamination in the water (Blake, 2014). In this study, no correlation was detected between low birthweight and unsafe nitrate levels; however, high nitrate levels in drinking water can cause nitrate poisoning and lead to serious health issues, such as blue baby syndrome, birth defects, and colon, bladder, and thyroid cancers (Blake, 2014; Hribar, 2010; Ward et al., 2018).

Additionally, animal waste contains pathogenic bacteria that can cause serious illnesses (Hribar, 2010). In 2014, Carrel et al. found that hospital patients living within one mile of a highly populated swine CAFOs in rural Iowa was associated with nearly double the risk of methicillin-resistant Staphylococcus aureus (MRSA) infections at the time of admission (Carrel et al., 2014). One cohort study across 10 states found that ZIP codes with broiler chicken operations in Georgia, Tennessee, and Maryland had significantly higher incidence rates of campylobacteriosis than ZIP codes without broiler farms; similarly, campylobacteriosis incidence rates were significantly higher among ZIP codes with dairy operations in both Minnesota and New York (Rosenberg Goldstein et al., 2016). Looking across socioeconomic factors, the same study found an overall increased incidence of campylobacteriosis among ZIP codes with higher percentages of the population that were of Hispanic ethnicity and living below the poverty level (Rosenberg Goldstein et al., 2016). While proving that CAFOs are the point source of bacterial contamination in drinking water is challenging, there have been several outbreaks of bacterial diseases across the country that have been linked to CAFO manure runoff (Bowman, 2009; Flynn, 2017).

***Cancer***

Several ecological studies have been published assessing CAFO exposure and cancer incidence in both children and adults. Looking at the county level across nine states, Booth et al. found significant positive associations between density of chickens and childhood acute myeloid leukemia incidence as well as density of hogs and acute lymphoblastic leukemia incidence (Booth et al., 2017). A recent publication in Iowa observed that residential proximity to CAFOs was positively associated with risk of leukemia and non-Hodgkin lymphoma in farmers, even after controlling for potential occupational exposures (Fisher et al., 2020). In South Korea, a population-based cohort study revealed that childhood leukemia mortality was significantly elevated in counties with the highest percentages of populations working on farms; however, this study did not differentiate between livestock and crop farming (Cha et al., 2014).

### *Mental Health and Quality of Life*

Beyond the physical health impacts of living near a CAFO, many studies have addressed the potential reduced QOL and negative mental health effects of exposure. One of the driving forces affecting QOL and mental health is the noxious odors that are known to emanate from CAFOs, particularly swine and cattle CAFOs. For example, in North Carolina, a matched case-control study found that persons living near swine CAFOs who experienced odors reported significantly more tension, depression, anger, fatigue, and confusion as well as higher total mood disturbance than control subjects who did not live near swine CAFOs (Schiffman et al., 1995). Several years later, Wing and Wolf also found that North Carolina residents living in close proximity to swine CAFOs had increased occurrences of headaches, runny nose, sore throat, excessive coughing, diarrhea, and burning eyes compared to those who resided farther away. These residents also had a significantly higher incidence of days where they could not open their windows or go outside due to foul smells (Wing & Wolf, 2000). Given the age of these studies, updated research is needed on the mental health and QOL effects of CAFO exposure on surrounding communities to provide a more contemporary understanding of these impacts.

### *Health Equity and Environmental Justice*

Many of the foundational studies highlighting the environmental injustices of living near CAFOs were pioneered by Dr. Steve Wing. Wing's career focused heavily on researching swine farms and environmental justice in North Carolina, and in 2000 he published a study finding that those who live close to swine farms are more likely to be nonwhite, live in poverty, and rely on private wells, raising concerns that these populations were at greater risk of exposure to contaminated drinking water (Wing et al., 2000). Wing and his colleagues expanded their research efforts to Mississippi's hog industry, similarly finding that swine farms were significantly more likely to be located in census block groups with higher percentages of African Americans and those living in poverty (Wilson et al., 2002). In Ohio, Lenhardt and Ogneva-Himmelberger found that black and Hispanic populations, as well as low income populations, were disproportionately exposed to census tracts with a high density of CAFOs (i.e., greater number of CAFOs per square kilometer) compared to other demographics (Lenhardt & Ogneva-Himmelberger, 2013). More recently, researchers in Iowa found that areas with high exposure to AFOs had higher percentages of minority and low socioeconomic status (i.e., educational attainment) populations than areas with low exposure (Son & Bell, 2022).

This high-level review of relevant literature demonstrates that many studies focus on the same states with the greatest number or intensity of CAFO operations (e.g., North Carolina, and Iowa), and often limit their scope to a single region. These studies provide a valuable foundation and important framing for the goals of the following analysis, which will broaden the scope of environmental justice impacts of CAFO exposure.

# *Methods*

## *Data Acquisition*

Locations of CAFOs in Mississippi, North Carolina, South Carolina, and Texas as of 2019 were obtained from cafomaps.org, a research portfolio developed by the Department of Geographical and Sustainability Sciences at the University of Iowa (2020). Locations of California CAFOs were obtained from the California Integrated Water Quality System website, which provides a dynamic registry of state-regulated CAFOs; data as of the time of download included currently operating facilities through January 1st, 2023 (*CIWQS Regulated Facility Report*, 2023). Locations of currently operating and historical CAFOs in Iowa through 2020 were obtained from the Iowa Department of Natural Resources (*Animal Feeding Operations*, 2020; Fisher et al., 2020), and additional facilities compiled by the Environmental Working Group (Rundquist & Carr, 2019; Konopacky, 2020). Across all facilities in all locations, the earliest time reference for CAFOs went as far back as 1975 in California, 1991 in Iowa, 1979 in South Carolina, 1998 in North Carolina, and 2004 in Texas; however, information on facilities in Mississippi had only been collected since 2014. Though exposure based on the number of animals per census tract was also of interest, this data was inconsistently available for all states; thus, we focused on the number of farms as the main characterization of CAFO exposure.

Data on social vulnerability and various population demographics at the census tract level for all six states were downloaded from the 2020 CDC/ATSDR Social Vulnerability Index (SVI) (*CDC/ATSDR SVI Data and Documentation Download*, 2022). This index is comprised of 16 different census variables at the tract level to identify communities that are in need of supplemental support (e.g., supplies, personnel, shelter) during emergency events, such as disease outbreaks, environmental exposures, or natural disasters. All data sources are described in Table 1.

### ***Data Processing***

The CAFO datasets were uploaded and cleaned in RStudio (version 2022.12.0). This process included identifying and removing duplicate entries (i.e., an exact match on CAFO name and geographic coordinates) and evaluating distributions of numbers of CAFOs and ancillary characteristics to identify unrealistic values. To ensure consistency in the information across states, inactive farms in Iowa were removed (n=1,265) since all other state data files contained only farms with active permits. After cleaning, a total of 1,579 CAFOs were excluded. CAFO locations were geocoded in ArcGIS Pro (version 3.0.0) and mapped for visualization. Next, shapefiles of the 2020 census tract boundaries were overlaid on the CAFO locations. The SVI data was joined to the census tract boundary layers. For the purposes of this study, the six variables chosen for analysis included percent unemployed, percent minority (defined as all individuals who reported any race/ethnicity other than White/non-Hispanic), percent with no high school diploma, percent uninsured, percent living below 150% of the poverty line, and percent living with a disability (*CDC,* 2022). CAFO locations were spatially joined to the census tract boundaries in ArcGIS, and we enumerated the farms in each tract. The final dataset for each state contained census tract IDs, total population of each tract, the selected CDC SVI demographic variables, and the number of farms in each tract.

We combined the state data into a single dataset for the overall analyses by aligning the time periods across states and limiting the farms included to only those with permits issued through 2019. This process excluded a total of 120 farms from the Iowa registry and 145 farms from the California registry. Prior to statistical analysis, unpopulated census tracts were removed (n=145).

### ***Statistical Analysis***

We computed quantiles of counts of CAFOs within tracts and defined “high” exposure as tracts in the top quartile of these counts (Q4; ≥75$^{th}$ percentile). We generated descriptive statistics (mean, SD) of CAFO counts overall (full population) and by state for binary categorizations of exposure (tracts with and without CAFOs) and high exposure (tracts in the top quartile) versus low exposure (tracts in Q1-Q3). Due to the large variations in the number and relative densities of CAFOs between states, these quartile cut points were determined on a state-by-state basis. We evaluated the statistical significance of categorical comparisons of means using Welch's two-sample t-tests. We used multivariable logistic regression models to estimate odds ratios (ORs) and 95% confidence intervals (95%CI) evaluating the change in population characteristics comparing high to low CAFO exposure overall and by state. The vast majority of census tracts in the six states (with the exception of Iowa) do not have CAFOs, therefore we conducted our multivariable analyses only among exposed tracts. The dependent variable for each regression was whether a census tract was considered high exposure (Q4) or low exposure (Q1-3, reference group). The independent variables of interest were percent unemployed, percent minority, percent disabled, percent under 150% of the poverty line, percent uninsured, and percent with no high school diploma. Additionally, all models included a natural-log transformed term for the population density of each census tract. We expressed all resulting ORs for each 10% increase in the dependent variable (i.e., the population demographics). A threshold of $p<0.05$ was used as the criterion for statistical significance. All analyses were conducted in RStudio (version 2022.12.0).

Correlation matrices and variance inflation factors were used to assess multicollinearity of the independent variables (Figure 1). Variance inflation factors for all covariates in all states were under 5. Correlation analyses by state generally revealed weak to moderate positive correlations between most variables ranging from Spearman's $\rho=0.04$ to 0.66, with percent minority and percent disabled having negative correlations from $\rho=-0.07$ to -0.26 in several states. We observed a high positive correlation for percent minority and percent no diploma in California ($\rho=0.72$) and Texas ($\rho=0.70$). To address these strong correlations, we ran sensitivity analyses excluding these variables one at a time for these states for comparison to our overall results. To evaluate potential effect modification by poverty on the relationship between high CAFO exposure and the other covariates of interest, we separately ran analyses stratified by poverty, splitting each state's census tracts at the median (≥ and <50$^{th}$ percentile) of the 150%-of-poverty variable and running models overall and by state. We generated tabular outputs for all analyses and figures for selected multivariable analyses by state to aid in visual comparison of the resulting odds ratios.

## *Results*

### *Descriptive Statistics*

The locations of CAFOs across the six states is depicted in Figure 2; their numbers, density, and spread varied considerably with each state. For instance, in Iowa the CAFOs were widely distributed statewide whereas in California they were largely concentrated in the central valley of the state. Likewise, the spatial distribution in Texas was diffuse and in Mississippi, North and South Carolina were more regionalized. The proportion of exposed census tracts also varied greatly; for example, only 2.3% of census tracts in Texas contained CAFOs, compared to 46.0% in Iowa (Table 2). Table 2 shows that many of the differences between means of tracts with CAFOs vs. without CAFOs are insignificant ($p>0.05$). Among tracts with CAFOs, Mississippi had the highest mean percent of the population living with a disability, at 19.1% (SD: 6.1), while Iowa had the lowest (mean: 12.0, SD: 3.5). Overall, the percentages of the population with no diploma and with a disability both had significantly higher means ($p<0.05$) in census tracts with CAFOs compared to census tracts without.

Table 3 contains sociodemographic comparisons among census tracts with high exposure (Q4) and low exposure (Q1-3) to CAFOs. The number of farms in a census tract that constituted high exposure varied greatly from state to state; for example, in California, tracts with seven or more CAFOs were in the top 25th percentile of exposure, whereas in Iowa tracts with 42 or more farms were in the top 25th percentile (Table 3). Across all states, the mean proportions of the population living below 150% of the poverty line (ranging from a low of 16.7% in Iowa to a high of 33.7% in South Carolina) and with no high school diploma (from 7.6% in Iowa to 27.5% in California) are greater in high versus low exposure tracts. The average percent minority varied greatly from state to state among high exposure tracts, with a high of 58% (SD: 20.2) in California to a low of 6.9% (SD: 5.6) in Iowa. In all states besides North Carolina and Texas and in the overall comparison, the mean percent uninsured was significantly greater in high exposure census tracts versus low exposure tracts.

***Multivariable Logistic Regressions***

In multivariable analyses, we found that the odds of living in the tracts with the highest exposure burden (Q4) compared to low exposure (Q1-3) were greater as the proportions of several socioeconomic indicators increased (Table 4). Specifically, the proportion of population with no high school education was associated with significantly increased odds of high exposure overall (OR=1.32, CI=1.28-1.35) and in each state, from a low of OR=1.14, 95%CI=1.07-1.21 in Mississippi to a high of OR=1.96, 95%CI=1.76-2.19 in Iowa (Figure 3). Likewise, the odds significantly increased up to 2.06-fold as the proportion of uninsured population increased, with the exception of no association observed in Mississippi (OR: 0.95, 95%CI=0.87-1.02) and Texas (OR: 0.94, 95%CI=0.89-1.00; Figure 4). Mississippi, North Carolina, South Carolina, and Texas all showed statistically significant increases in odds of high exposure as the proportion of the population living below 150% of the poverty line increased (ORs: 1.35, 1.11, 1.73, and 1.13, respectively); however, inverse associations between high CAFO exposure and poverty were found in California (OR: 0.85, 95%CI=0.82-0.88) and Iowa (OR: 0.91, 95%CI=0.87-0.96); Figure 5. Percent minority was positively associated with high exposure in Iowa (OR: 1.91, 95% CI=1.81-2.02) and North Carolina (OR: 1.05, 95% CI=1.04-1.06); results overall and in all other states showed inverse associations ranging from ORs of 0.77-0.92 (Table 4). North Carolina was the only state in which the proportion of the population with a disability was positively associated with high exposure (OR: 1.25, 95% CI=1.18-1.31).

Table 5 shows the results of the sensitivity analyses for the highly correlated variables in California and Texas. In both states, the removal of percent minority from the model only marginally changed the magnitude of the ORs compared to the full models. However, removing percent no diploma from the California model resulted in large changes in the associations with percent minority and percent below 150% of the poverty line, and for percent uninsured in Texas. In the California model, the odds of being in a highly exposed tract decreased for each 10% increase in percent minority (OR=0.92, 95% CI=0.90-0.94) and percent below 150% of the poverty line (OR=0.85, 95% CI=0.82-0.88), whereas when the variable is removed, we observed positive associations (OR: 1.10, 95%CI=1.08-1.12 for % minority and OR: 1.04, 95% CI=1.01-1.07 for population experiencing poverty). Similarly, in Texas, the percent uninsured was not associated with high exposure in the full model (OR: 0.94, 95% CI=0.89-1.00) and became positively associated once the no diploma was removed (OR: 1.09, 95% CI=1.04-1.14).

Analyses stratified by high vs. low poverty showed somewhat different patterns from the main analysis in state-specific models (Table 6). For example, the odds of high exposure for each 10% increase in percent disability have a negative association among low poverty census tracts and a positive association among high poverty tracts in Iowa, Mississippi, and South Carolina, whereas in the unstratified analysis we found no association with poverty in these three states. As the percent of population with no high school diploma increased, the odds of being in a high exposure tract were increased among census tracts experiencing high poverty in Mississippi (OR: 1.36, 95% CI=1.25-1.49), South Carolina (OR: 2.02, 95% CI=1.89-2.15), and Texas (OR: 2.33, 95% CI=2.12-2.56), whereas these associations were inverse or null among tracts considered low poverty in these states. In North Carolina and Texas, the percent minority population was associated with high exposure to CAFOs in low poverty tracts (North Carolina, OR: 1.56, 95% CI=1.51-1.61; Texas, OR: 1.20, 95% CI=1.16-1.25) whereas the relationship was inverse in the high poverty census tracts. While an association between percent unemployed and high exposure in Mississippi was not evident in the main analyses, they were significantly and positively related among high poverty census tracts (OR: 1.28, 95% CI=1.15-1.43). In the overall model, patterns were similar to the unstratified analyses, with a positive association observed between high exposure and percent with no high school in both the low and high poverty strata.

## *Discussion*

As mentioned in the review of relevant literature, many studies have already shown that there are disparities in sociodemographics within states or regions in which industrial animal agriculture is common. However, the nature of CAFO operations and associated characteristics can vary considerably across states, including in the type of animals, the topographical and other geographic characteristics that influence population exposures, and the characteristics of the populations. The purpose of this analysis, therefore, was to explore if these disparities can be generalized across a variety of geographic locations with high CAFO exposure. In the overall analysis combining data from all six states, the proportions of the population with no high school diploma and living below 150% of the poverty line were positively associated with high CAFO exposure, further supporting that these census tracts have populations that are vulnerable to social and health-related disparities. However, looking at just the odds of high exposure overall provides an incomplete picture of how these sociodemographic variables are differently associated with high exposure on a state-by-state basis. Importantly, we observed positive associations in several states for variables that were shown to have inverse associations in the overall model, and we also found that some patterns of association varied between individual states. By comparing state-specific and overall patterns, this analysis elucidated important differences in associations between high CAFO exposure and demographic characteristics and highlights the ways in which populations in each state may differ in their vulnerabilities to these facilities.

California, Mississippi, South Carolina and Texas all had inverse associations between high exposure and percent minority population. While the analysis controlled for population density, this result could be due to the fact that CAFOs are often located in rural areas, which have a significantly higher proportion of non-Hispanic white populations than urban areas (Castillo & Cromartie, 2020). We observed that there is no significant difference in the mean percent minority between low exposure and high exposure areas besides in North Carolina, further reinforcing that these rural areas have similar percentages of white populations. Additionally, the strong inverse association between CAFO exposure and percent unemployment in California, Iowa, and Texas may be explained by the substantial number of jobs that CAFOs provide to the communities they are located within. An economic analysis of the U.S. animal agriculture industry estimated that the sector provided over 2.3 million jobs in 2014, with state-level employment estimates ranging from approximately 20,000 animal agricultural workers in South Carolina to over 287,000 in Texas (*Economic Analysis,* 2015); in Iowa, it is estimated that 57% of all agricultural workers in the state work in animal production (*Iowa Workforce Development,* 2017).

We evaluated a number of different sociodemographic variables in this analysis with the expectation that each might capture different components of the multi-dimensional factors that comprise socio-structural vulnerabilities; however, several of these factors are (perhaps understandably) related. The sensitivity analyses of percent minority and percent no diploma to address strong correlations between these variables in California and Texas confirmed that both of these variables are important predictors of high CAFO exposure, and that their contributions to the overall models of California and Texas differ. When percent minority was removed, the associations between high exposure and other sociodemographic factors did not materially change in direction or magnitude in either state. However, the patterns of association changed more substantially in the models where percent no diploma was removed, suggesting it is a more influential variable in these particular states. These findings further underscore that the relationships between these factors and CAFO exposure are far more nuanced than described in the existing literature.

Our findings in analyses stratified by high versus low poverty point towards poverty as an effect modifier, where the magnitude of the association between other sociodemographic variables of interest and high CAFO exposure differs based on the relative rate of poverty in a census tract. Our results confirmed that poverty is positively associated with high exposure to CAFOs in all states we evaluated, except for in California and Iowa. For instance, we observed that some associations not apparent or inverse in the unstratified model became positively associated with high exposure in areas of high poverty. This furthers the point that high poverty may have a compounding effect on the vulnerability of a population, and that patterns that were not seen in general analyses are uncovered when focusing on areas that are disproportionately experiencing poverty. We see confirmation of this in other studies, such as in North Carolina, where census block groups in the top quintile of poverty had 7.2 times as many hog CAFOs as those in the bottom quintile of poverty (Wing et al., 2000). Wing (2002) had similar findings in Mississippi, where block groups in the top four quartiles of poverty had 2.68 times as many hog CAFOs as block groups in the bottom quartile. Our analysis adds to this picture by not only showing that poverty is related to CAFO exposure, but that it may interact with other socioeconomic factors at varying poverty levels.

In the poverty-stratified analysis, we also observed the opposite pattern; in some instances, associations were positive in the low poverty group. One reason for these different patterns of association may be due to the use of the statewide median in determining poverty status rather than the median percent of only census tracts that contain CAFOs. We did this because poverty status was associated with high vs. low CAFO exposure among exposed tracts, which were less than 50% of all tracts across the states; this approach allowed us to separately evaluate the influence of state-level poverty status on these relationships. Taken together with our main analyses, these results demonstrate that both state-level poverty status and poverty of the tract of residence are associated with high CAFO exposure.

Similar to other known point source pollutants, such as power plants, oil and gas extraction sites, and landfills, CAFOs generally tend to be concentrated in areas with vulnerable populations (i.e., more people in poverty, less health insurance coverage, and less education) (Johnston & Cushing, 2020). Our findings of associations between high exposure and the percentage of the population without health insurance in four of the six states are consistent with this existing literature. Considering the plethora of research showing that CAFO exposure is associated with both acute and chronic health issues, these findings also suggest that populations who may be suffering from adverse health outcomes from CAFO exposure are also more likely to be lacking access to preventive and primary health care. There are few studies directly assessing these relationships with CAFOs specifically, but evidence is available from studies of other adverse environmental exposures. For example, one study evaluating the burden of air pollution among racial minorities in New York found higher relative risks of respiratory hospitalizations among the Medicaid and uninsured populations compared those who were the privately insured (Gwynn & Thurston, 2001).

There were several limitations to this study. First, data on CAFO locations was gathered from three different sources, meaning that there are potential differences in the way the data was collected and cleaned by the original researchers. One of the most apparent differences is the time periods covered by each state's registry of CAFO locations; data from Mississippi only included farm locations from 2014-2019, while California's registry spanned back as far as 1975 and is dynamically updated as new facilities are created. This is likely due to the fact that these data are not mandated to be compiled and, therefore, earliest permit dates can be unclear. Thus, some states' analyses captured decades of CAFO data, while others only contained several years of information. Also, while CAFOs are the largest types of animal facilities and therefore are more likely to have larger contamination potential than small farms, there are likely many census tracts with farms that do not meet the regulatory definitions of CAFOs, yet still pose exposure risks to their communities; these smaller farms were not captured in our analysis.

We had no way to confirm that the data sources contained all CAFOs within the state or whether an included farm was still active outside of the Iowa dataset, which distinguished active versus inactive farms. However, given that most of these states have long histories of animal farming, new CAFOs are not frequently built, and by including all CAFOs through 2019, we hope our analyses reflect a reasonable cross-sectional evaluation of these relationships of contemporary data. This analysis would have benefitted from evaluation of the differences in population characteristics stratified by different types of animal farms (e.g., pig farms vs. cattle dairy farms vs. chicken farms) or by higher exposure to animal units, rather than number of farms. However, not all of the state CAFO data files contained this additional information, limiting our ability to conduct uniform analyses across all states. Last, we conducted data analysis at the population level, raising concerns of ecological fallacy in any results and conclusions. While we can say that these results show significant exposure trends at the census tract level, we cannot extrapolate this to mean that the individuals living close to CAFOs are more likely to be uninsured, less educated, etc. In the future, researchers may consider ways in which they can assess these variables on an individual or household level across multiple states of differing geographies and demographic makeups.

There were also notable strengths of this analysis. We included states with some of the largest numbers and geographic densities of CAFOs in the country, and that also represented all major CAFO industries (pork, beef, dairy, and poultry) and were geographically spread throughout the U.S. Additionally, each state differs in their respective population densities, demographics, and spatial distribution and proximity of CAFOs to populations, enabling us to evaluate how sociodemographic patterns of CAFO exposure differ across the U.S. The large number of CAFOs in these states ensured that our analyses had sufficient statistical power and allowed us to conduct state-specific analyses and to further stratify by poverty status. Finally, the data were all collected from reliable sources, such as university research centers, state and federal government databases, and well-regarded non-profit institutions, with available metadata describing data sources and quality control efforts.

## *Conclusions*

The significant disparities in CAFO exposure by sociodemographic factors that we observed in this analysis have important implications for health equity and environmental justice. In all six states, the odds of living in a census tract with high CAFO exposure increased significantly with the proportion of population with no high school diploma, and in each state, at least two sociodemographic variables were positively associated with high CAFO exposure. Existing studies on CAFO exposure and sociodemographic disparities have overwhelmingly focused on a single state and have not assessed patterns across multiple, diverse geographic settings with CAFOs, which reinforces that these findings are unique and important in the study of environmental justice and industrial animal agriculture. While we observed some overarching trends in the association between high CAFO exposure and sociodemographics overall and across states, these are obviously complex relationships that cannot be generalized to all areas and thus require a more nuanced comparison. This thesis also highlights that there are opportunities for future research to expand beyond the most common indicators of environmental injustice, such as race/ethnicity and household income, and look at lesser studied demographic variables like percent disabled, percent uninsured, and percent unemployed, as well as their interaction.

Health disparities described in the background of this thesis underscore the need for further regulation and policies that promote the safety and wellbeing of those who live in close proximity to CAFOs. Given the EPA's lack of action to ensure that CAFOs are not disproportionately polluting vulnerable populations, the most promising solutions likely will stem from strengthening state oversight, and mandating more frequent environmental quality testing. In June 2023, New York's new law requiring waste facility permit applications to consider their potential for disproportionate impacts and pollution burden on disadvantaged communities will go into effect, which sets an important foundation for future laws to consider the same regulations for CAFO permits as well (S8830, 2022). Recently, the EPA announced that they will undertake a detailed study of the current effluent limitation guidelines for CAFOs to determine if the regulatory standards for wastewater discharge should be revised (EPA, 2023). Several bills have been proposed in recent years that would place a moratorium on new large-scale animal farming operations at both the state and federal level, including most recently the Farm System Reform Act (2023). The improvement of regulations, in addition to policies that lessen the environmental and human health impacts of CAFOs, will have downstream effects in lessening health disparities among vulnerable populations, and thus should be recognized by policymakers and public health professionals as actions that advance environmental and social justice.

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## *Appendix*

Table 1: Data Sources

| Variable | Data Source (Years) |
|---|---|
| **California CAFO Locations** | California Integrated Water Quality System Regulated Facility Report (1975-2023) |
| **Iowa CAFO Locations** | Iowa Department of Natural Resources (1991-2020); Fisher et al. (2020); Rundquist & Carr (2019); Konopacky (2020) |
| **Mississippi CAFO Locations** | CAFOMaps, Department of Geographical and Sustainability Sciences at the University of Iowa (2014-2019) |
| **North Carolina CAFO Locations** | CAFOMaps, Department of Geographical and Sustainability Sciences at the University of Iowa (1998-2019) |
| **South Carolina CAFO Locations** | CAFOMaps, Department of Geographical and Sustainability Sciences at the University of Iowa (1979-2019) |
| **Texas CAFO Locations** | CAFOMaps, Department of Geographical and Sustainability Sciences at the University of Iowa (2004-2019) |
| **Census Tract Boundaries (All States)** | TIGER/Line Shapefiles, United States Census Bureau (2020) |
| **% Unemployed (All States)** | CDC/ATSDR SVI Data and Documentation Download (2020) |
| **% Minority (All States)** | CDC/ATSDR SVI Data and Documentation Download (2020) |
| **% No High School Diploma (All States)** | CDC/ATSDR SVI Data and Documentation Download (2020) |
| **% Uninsured (All States)** | CDC/ATSDR SVI Data and Documentation Download (2020) |
| **% Below 150% of the Poverty Line (All States)** | CDC/ATSDR SVI Data and Documentation Download (2020) |
| **% Living with a Disability (All States)** | CDC/ATSDR SVI Data and Documentation Download (2020) |

Table 2: Sociodemographic Characteristics in Census Tracts with and Without CAFOs, Overall and By State

| | **California (n=2,095)^** | **Iowa (n=12,541)^** | **Mississippi (n=1,469)^** | **North Carolina (n=2,280)^** | **South Carolina (n=997)^** | **Texas (n=642)^** | **Overall (n=20,024)^** |
|---|---|---|---|---|---|---|---|
| **Predominant CAFO Industry** | Dairy Cattle | Hogs | Chickens | Hogs | Chickens | Beef Cattle | |
| | **N (%)** | **N (%)** | **N (%)** | **N (%)** | **N (%)** | **N (%)** | **N (%)** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Tracts with CAFOs** | 268 (3.0) | 411 (46.0) | 160 (18.4) | 398 (15.1) | 221 (16.9) | 158 (2.3) | 1,616 (7.5) |
| **Tracts without CAFOs** | 8,780 (97.0) | 483 (54.0) | 709 (81.6) | 2,244 (84.9) | 1,086 (83.1) | 6,679 (97.7) | 19,981 (92.5) |
| | **Mean (SD)** | **Mean (SD)** | **Mean (SD)** | **Mean (SD)** | **Mean (SD)** | **Mean (SD)** | **Overall Mean** |
| **% Unemployed** | | | | | | | |
| Tracts with CAFOs | 8.3 (7.5)* | 3.2 (2.2)* | 6.4 (5.5)* | 6.0 (4.0) | 6.8 (5.4)* | 4.1 (3.8)* | 5.8 |
| Tracts without CAFOs | 6.3 (4.2)* | 4.7 (4.0)* | 8.0 (6.4)* | 5.6 (4.4) | 5.8 (4.7)* | 5.5 (4.4)* | 6.0 |
| **% Minority** | | | | | | | |
| Tracts with CAFOs | 55.1 (23.8)* | 7.5 (8.0)* | 36.4 (22.7)* | 36.4 (21.4) | 38.2 (22.0) | 41.1 (25.6)* | 35.8 |
| Tracts without CAFOs | 61.9 (25.7)* | 20.7 (15.6)* | 46.7 (28.7)* | 36.8 (25.7) | 37.4 (24.2) | 57.9 (27.7)* | 43.6 |
| **% with No High School Diploma** | | | | | | | |
| Tracts with CAFOs | 21.9 (14.8)* | 7.1 (4.3)* | 17.1 (6.4)* | 16.1 (7.0)* | 16.9 (6.6)* | 18.3 (10.2)* | 16.2 |
| Tracts without CAFOs | 16.4 (14.3)* | 8.7 (7.8)* | 14.6 (8.7)* | 11.2 (8.3)* | 11.9 (8.6)* | 16.6 (14.1)* | 13.2 |
| **% Uninsured** | | | | | | | |
| Tracts with CAFOs | 7.5 (4.5) | 4.6 (3.9) | 12.2 (5.2) | 12.2 (5.3)* | 10.9 (5.2) | 17.0 (8.0) | 10.7 |
| Tracts without CAFOs | 7.2 (5.5) | 5.1 (3.9) | 12.3 (6.1) | 10.6 (6.5)* | 10.7 (6.8) | 17.6 (10.8) | 10.6 |
| **% Below 150% of the Poverty Line** | | | | | | | |
| Tracts with CAFOs | 26.1 (15.3)* | 16.5 (7.2)* | 31.8 (10.1) | 27.8 (10.9)* | 29.6 (10.0)* | 23.1 (12.0) | 25.8 |
| Tracts without CAFOs | 21.1 (14.5)* | 23.4 (15.3)* | 32.6 (17.4) | 24.1 (15.0)* | 25.3 (15.4)* | 25.1 (16.9) | 25.3 |
| **% Living with a Disability** | | | | | | | |
| Tracts with CAFOs | 12.1 (5.1)* | 12.0 (3.5)* | 19.1 (6.1)* | 17.2 (4.9)* | 17.6 (5.1)* | 15.5 (5.4)* | 15.6 |
| Tracts without CAFOs | 11.0 (5.1)* | 12.7 (5.3)* | 16.6 (6.7)* | 13.4 (6.2)* | 14.7 (6.1)* | 12.0 (6.0)* | 13.4 |

^n=number of CAFOs in the state and total overall count
*p-value <0.05 for Welch Two Sample t-test

Table 3: Sociodemographic Comparison of Census Tracts with and without High Exposure (Top 25th Percentile) to CAFOs, Overall and By State

| | **California (n= 2,095)** | **Iowa (n=12,541)** | **Mississippi (n=1,469)** | **North Carolina (n=2,280)** | **South Carolina (n=997)** | **Texas (n=642)** | **Overall (n=20,024)** |
|---|---|---|---|---|---|---|---|
| | **N (%)** | **N (%)** | **N (%)** | **N (%)** | **N (%)** | **N (%)** | **N (%)** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **Number of High Exposure Census Tracts (Q4)** | 74 (27.6) | 104 (25.3) | 41 (25.6) | 114 (28.6) | 60 (27.1) | 53 (33.5) | 446 |
| **Number of Low Exposure Census Tracts (Q1-3)** | 194 (72.4) | 307 (74.7) | 119 (74.4) | 284 (71.4) | 161 (72.9) | 105 (66.5) | 1,170 |
| **Number of Farms Considered High Exposure** | 7 | 38 | 13 | 5 | 6 | 3 | 14 |
| | **Mean (SD)** | **Mean (SD)** | **Mean (SD)** | **Mean (SD)** | **Mean (SD)** | **Mean (SD)** | **Overall Mean** |
| **% Unemployed** | | | | | | | |
| High Exposure | 7.5 (4.4) | 2.6 (1.7)* | 6.3 (4.5) | 6.3 (4.1) | 7.7 (4.9) | 3.4 (3.1) | 5.6 |
| Low Exposure | 8.6 (8.4) | 3.3 (2.4)* | 6.5 (5.8) | 5.9 (3.9) | 6.5 (5.5) | 4.5 (3.8) | 5.9 |
| **% Minority** | | | | | | | |
| High Exposure | 58.3 (20.2) | 6.9 (5.6) | 32.3 (20.2) | 41.7 (18.6)* | 41.1 (21.6) | 41.6 (22.4) | 37.0 |
| Low Exposure | 53.9 (24.9) | 7.7 (8.6) | 37.8 (23.4) | 34.3 (22.2)* | 37.1 (22.1) | 40.9 (27.1) | 35.3 |
| **% with No High School Diploma** | | | | | | | |
| High Exposure | 27.5 (13.2)* | 7.6 (3.7) | 17.3 (5.3) | 17.9 (7.6)* | 19.2 (6.9)* | 19.4 (10.9) | 18.2 |
| Low Exposure | 19.8 (14.9)* | 7.0 (4.4) | 17.0 (6.7) | 15.3 (6.6)* | 16.1 (6.2)* | 17.7 (9.9) | 15.5 |
| **% Uninsured** | | | | | | | |
| High Exposure | 9.1 (4.8)* | 5.3 (4.2)* | 12.4 (5.3) | 13.8 (5.8)* | 12.6 (4.5)* | 17.5 (8.4) | 11.8 |
| Low Exposure | 6.8 (4.3)* | 4.4 (3.7)* | 12.1 (5.2) | 11.5 (4.9)* | 10.2 (5.4)* | 16.7 (7.8) | 10.3 |
| **% Below 150% of the Poverty Line** | | | | | | | |
| High Exposure | 27.7 (12.1) | 16.7 (5.9) | 32.3 (10.4) | 30.6 (10.7)* | 33.7 (8.9)* | 23.2 (12.2) | 27.4 |
| Low Exposure | 25.5 (16.4) | 16.5 (7.6) | 31.6 (10.1) | 26.6 (10.8)* | 28.1 (10.0)* | 23.1 (12.0) | 25.2 |
| **% Living with a Disability** | | | | | | | |
| High Exposure | 11.8 (4.6) | 11.7 (3.0) | 19.9 (5.4) | 18.3 (5.1)* | 18.2 (4.4) | 13.9 (4.8)* | 15.6 |
| Low Exposure | 12.2 (5.2) | 12.1 (3.6) | 18.8 (6.3) | 16.7 (4.8)* | 17.4 (5.3) | 16.2 (5.6)* | 15.6 |

*p-value <0.05 for Welch Two Sample t-test

Table 4: Multivariable Logistic Regression Results of High CAFO Exposure vs. Low CAFO Exposure, Overall and By State

| | **California** | **Iowa** | **Mississippi** | **North Carolina** | **South Carolina** | **Texas** | **Overall** |
|---|---|---|---|---|---|---|---|

| Variable | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* |
|---|---|---|---|---|---|---|---|
| % Unemployed | 0.41 (0.38-0.44) | 0.14 (0.12-0.16) | 0.99 (0.92-1.06) | 0.85 (0.80-0.91) | 1.16 (1.08-1.23) | 0.34 (0.31-0.38) | 0.70 (0.67-0.74) |
| % Minority | 0.92 (0.90-0.94) | 1.91 (1.81-2.02) | 0.80 (0.78-0.82) | 1.05 (1.04-1.06) | 0.86 (0.84-0.87) | 0.92 (0.90-0.94) | 0.77 (0.76-0.78) |
| % No High School Diploma | 1.71 (1.64-1.78) | 1.96 (1.76-2.19) | 1.14 (1.07-1.21) | 1.19 (1.14-1.29) | 1.44 (1.36-1.53) | 1.37 (1.28-1.47) | 1.32 (1.28-1.35) |
| % Uninsured | 1.90 (1.76-2.05) | 1.18 (1.08-1.28) | 0.95 (0.87-1.02) | 2.02 (1.92-2.12) | 1.74 (1.64-1.86) | 0.94 (0.89-1.00) | 0.51 (0.50-0.53) |
| % Below 150% of the Poverty Line | 0.85 (0.82-0.88) | 0.91 (0.87-0.96) | 1.35 (1.29-1.41) | 1.11 (1.08-1.14) | 1.73 (1.65-1.80) | 1.13 (1.08-1.18) | 1.54 (1.51-1.58) |
| % Living with a Disability | 0.79 (0.74-0.85) | 0.54 (0.49-0.59) | 0.88 (0.82-0.94) | 1.25 (1.18-1.31) | 0.97 (0.90-1.03) | 0.31 (0.29-0.34) | 0.56 (0.54-0.57) |

*Represents the odds of being in a high exposure census tract for each 10% increase in the variable.

Table 5: Sensitivity Analyses of Percent Minority and Percent No High School Diploma, California and Texas

**California** **Texas**

| Variable | Full Model | % Minority Removed | % No Diploma Removed | Full Model | % Minority Removed | % No Diploma Removed |
|---|---|---|---|---|---|---|
| | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* | OR (95% CI)* |
| % Unemployed | 0.41 (0.38-0.44) | 0.40 (0.37-0.43) | 0.41 (0.38-0.44) | 0.34 (0.31-0.38) | 0.34 (0.30-0.38) | 0.35 (0.31-0.39) |
| % Minority | 0.92 (0.90-0.94) | | 1.10 (1.08-1.12) | 0.92 (0.90-0.94) | | 0.98 (0.96-1.00) |
| % No High School Diploma | 1.71 (1.64-1.78) | 1.55 (1.50-1.60) | | 1.37 (1.28-1.47) | 1.18 (1.12-1.25) | |
| % Uninsured | 1.90 (1.76-2.05) | 1.85 (1.71-1.99) | 2.28 (2.12-2.46) | 0.94 (0.89-1.00) | 0.97 (0.91-1.02) | 1.09 (1.04-1.14) |
| % Below 150% of the Poverty Line | 0.85 (0.82-0.88) | 0.84 (0.81-0.87) | 1.04 (1.01-1.07) | 1.13 (1.08-1.18) | 1.09 (1.05-1.14) | 1.18 (1.13-1.23) |
| % Living with a Disability | 0.79 (0.74-0.85) | 0.86 (0.81-0.91) | 0.79 (0.74-0.85) | 0.31 (0.29-0.34) | 0.34 (0.31-0.36) | 0.32 (0.30-0.35) |

*Represents the odds of being in a high exposure census tract for each 10% increase in the variable.

Table 6: Multivariable Logistic Regression Results of High CAFO Exposure vs. Low CAFO Exposure Stratified by Poverty Levels, Overall and By State

| | California | Iowa | Mississippi | North Carolina |
|---|---|---|---|---|

| Variable | Low Poverty (n=98)* | High Poverty (n=170)* | Low Poverty (n=247)* | High Poverty (n=163)* | Low Poverty (n=76)* | High Poverty (n=84)* | Low Poverty (n=143)* | High Poverty (n=255)* |
|---|---|---|---|---|---|---|---|---|
| **% Unemployed** | 0.38 (0.34-0.43) | 0.33 (0.31-0.36) | 0.07 (0.06-0.09) | 0.20 (0.16-0.24) | 0.78 (0.70-0.88) | 1.28 (1.15-1.43) | 1.61 (1.40-1.85) | 0.65 (0.60-0.70) |
| **% Minority** | 0.80 (0.77-0.83) | 1.01 (0.98-1.04) | 2.69 (2.43-2.99) | 2.29 (2.11-2.49) | 0.84 (0.82-0.87) | 0.84 (0.82-0.86) | 1.56 (1.51-1.61) | 0.99 (0.97-1.00) |
| **% No High School Diploma** | 3.14 (2.86-3.45) | 1.27 (1.22-1.33) | 4.22 (3.59-4.95) | 0.79 (0.67-0.94) | 0.94 (0.85-1.04) | 1.36 (1.24-1.49) | 1.07 (0.97-1.18) | 1.08 (1.03-1.13) |
| **% Uninsured** | 0.87 (0.72-1.05) | 2.56 (2.33-2.80) | 3.84 (3.25-4.53) | 1.15 (1.02-1.31) | 0.91 (0.81-1.03) | 1.00 (0.90-1.12) | 1.57 (1.43-1.72) | 2.24 (2.11-2.38) |
| **% Living with a Disability** | 0.72 (0.63-0.82) | 0.70 (0.64-0.76) | 0.24 (0.21-0.27) | 1.35 (1.17-1.56) | 0.58 (0.52-0.65) | 1.25 (1.15-1.36) | 0.60 (0.53-0.68) | 1.63 (1.53-1.73) |

| | South Carolina | | Texas | | Overall | |
|---|---|---|---|---|---|---|
| **Variable** | **Low Poverty (n=67)*** | **High Poverty (n=154)*** | **Low Poverty (n=83)*** | **High Poverty (n=75)*** | **Low Poverty (n=678)*** | **High Poverty (n=780)*** |
| **% Unemployed** | 3.79 (3.18-4.52) | 1.08 (1.01-1.16) | 0.45 (0.35-0.57) | 0.50 (0.43-0.58) | 0.35 (0.31-0.39) | 0.87 (0.84-0.91) |
| **% Minority** | 0.89 (0.86-0.93) | 0.91 (0.90-0.93) | 1.20 (1.16-1.25) | 0.78 (0.75-0.80) | 0.58 (0.56-0.59) | 0.87 (0.86-0.88) |
| **% No High School Diploma** | 0.54 (0.45-0.64) | 2.02 (1.89-2.15) | 0.97 (0.85-1.10) | 2.33 (2.12-2.56) | 3.10 (2.92-3.29) | 1.25 (1.22-1.29) |
| **% Uninsured** | 0.76 (0.63-0.90) | 1.93 (1.80-2.07) | 1.38 (1.27-1.50) | 0.68 (0.62-0.74) | 0.20 (0.19-0.21) | 0.96 (0.92-0.99) |
| **% Living with a Disability** | 0.41 (0.34-0.50) | 1.31 (1.22-1.40) | 0.38 (0.34-0.43) | 0.35 (0.31-0.39) | 0.29 (0.27-0.31) | 0.92 (0.89-0.96) |

*N=number of exposed census tracts in each category. ORs represent the odds of being in a high exposure census tract for each 10% increase in the variable.
Low poverty: census tracts with % living below 150% of the poverty line that is < state median % (< overall median in overall model)
High poverty: census tracts with % living below 150% of the poverty line that is ≥ state median % (≥ overall median in overall model)

Figure 1: Spearman Rank Correlation Matrices for Covariates, Overall and By State

California Iowa Mississippi North Carolina

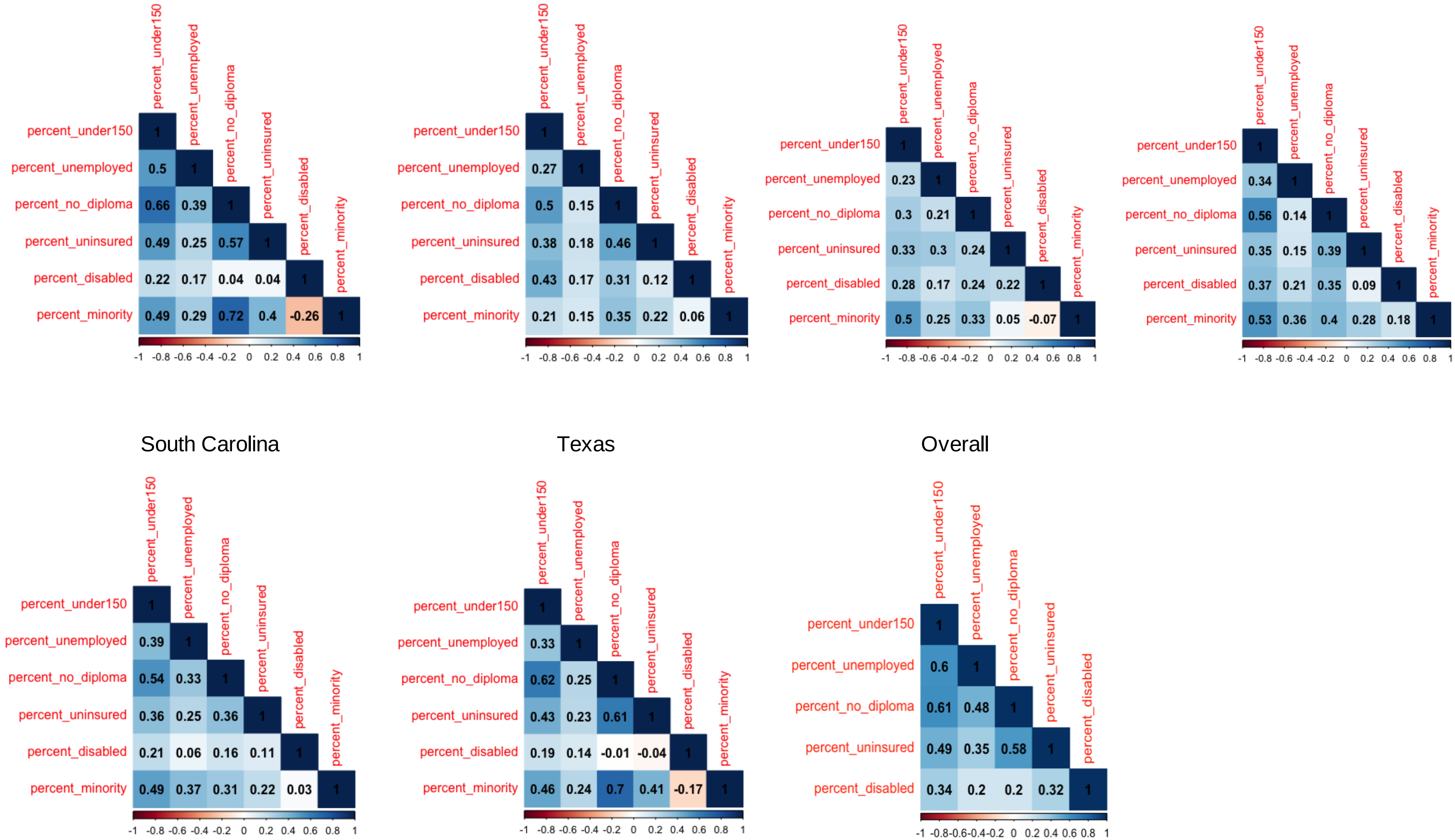



Figure 2: 2020 Census Tract Boundaries and Locations of CAFOs by State as of 2019 (as of 2020 and 2023 for Iowa and California, respectively)

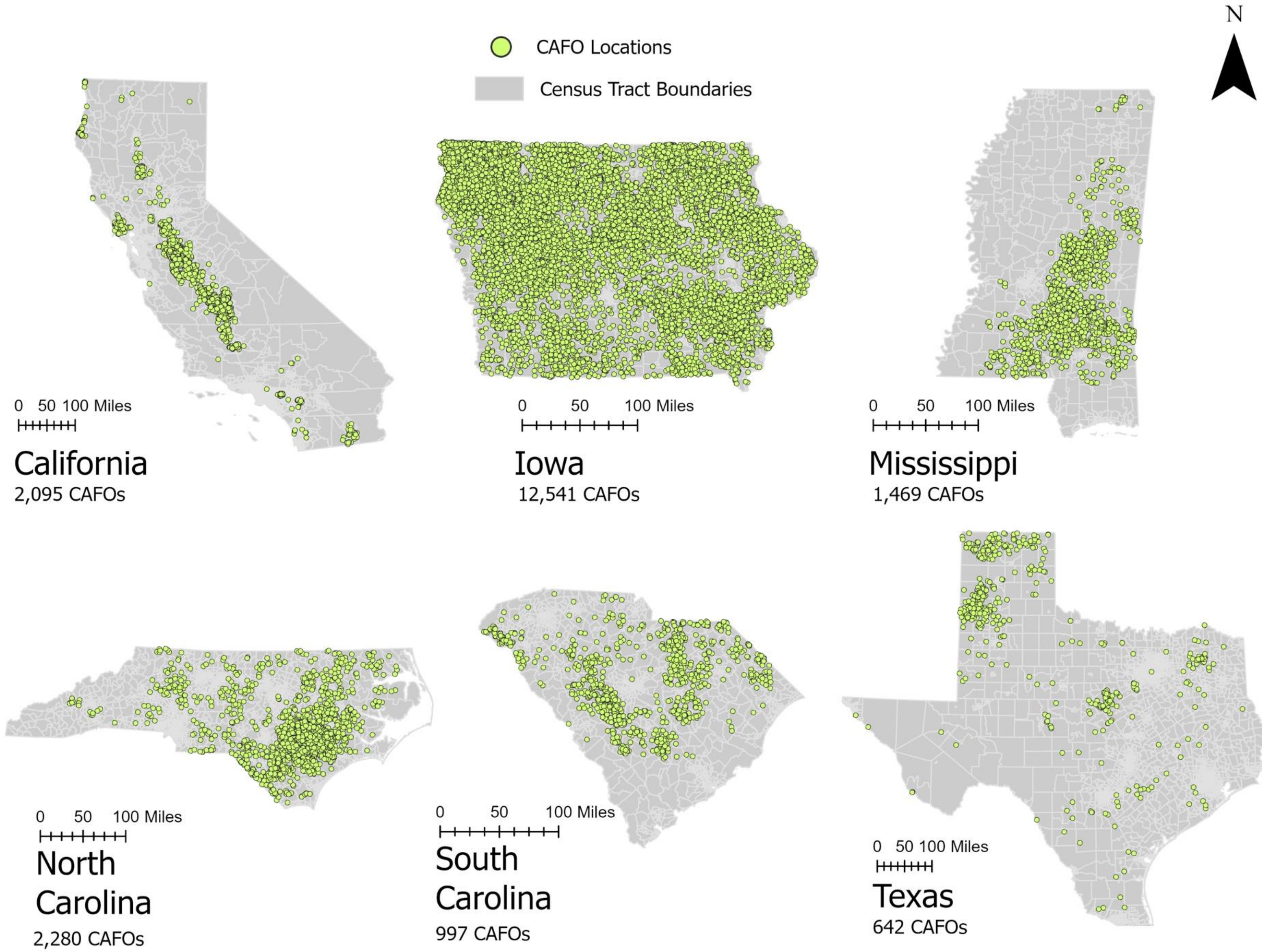



Figure 3: Odds Ratios for Percent with No High School Diploma, By State

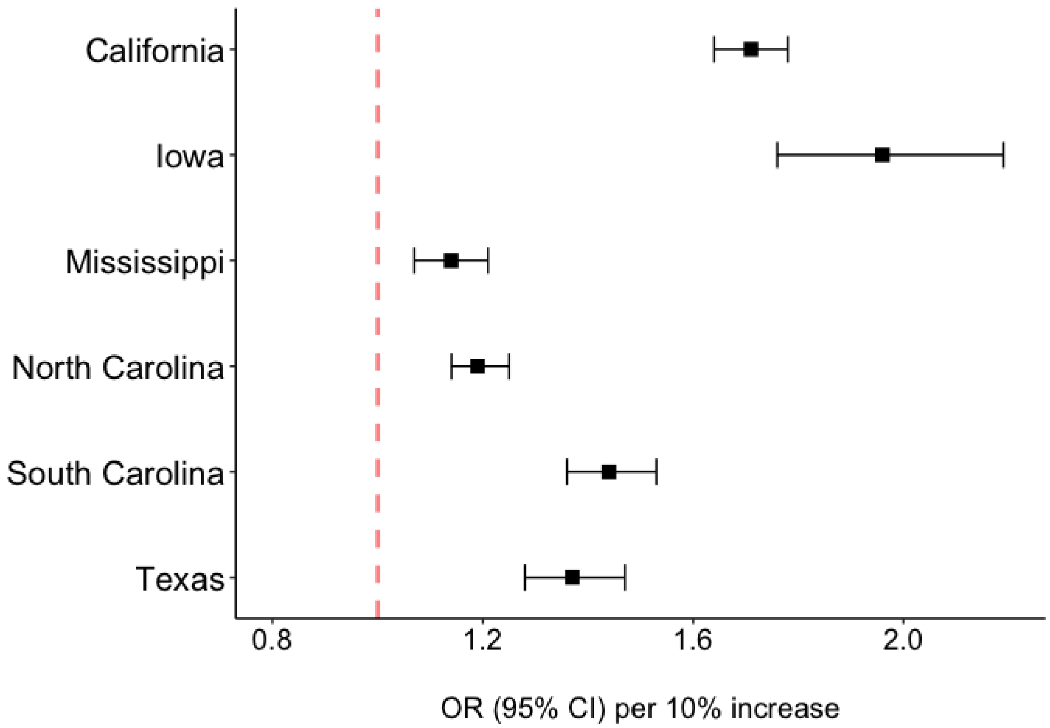



Figure 4: Odds Ratios for Percent Uninsured, By State

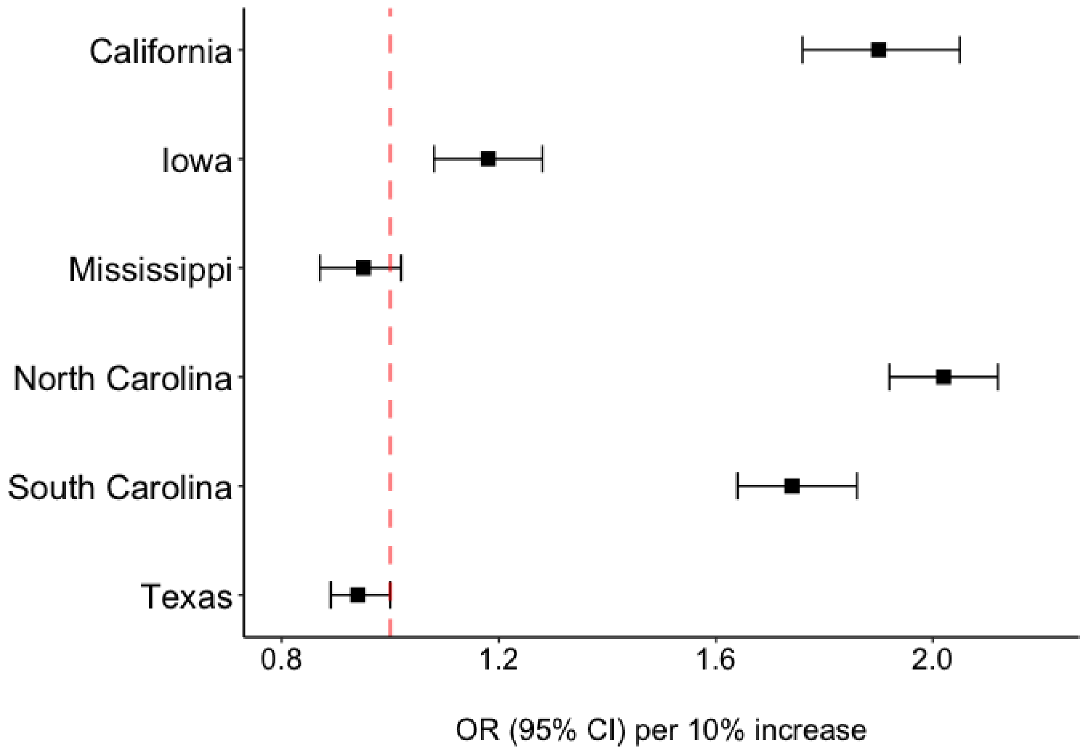
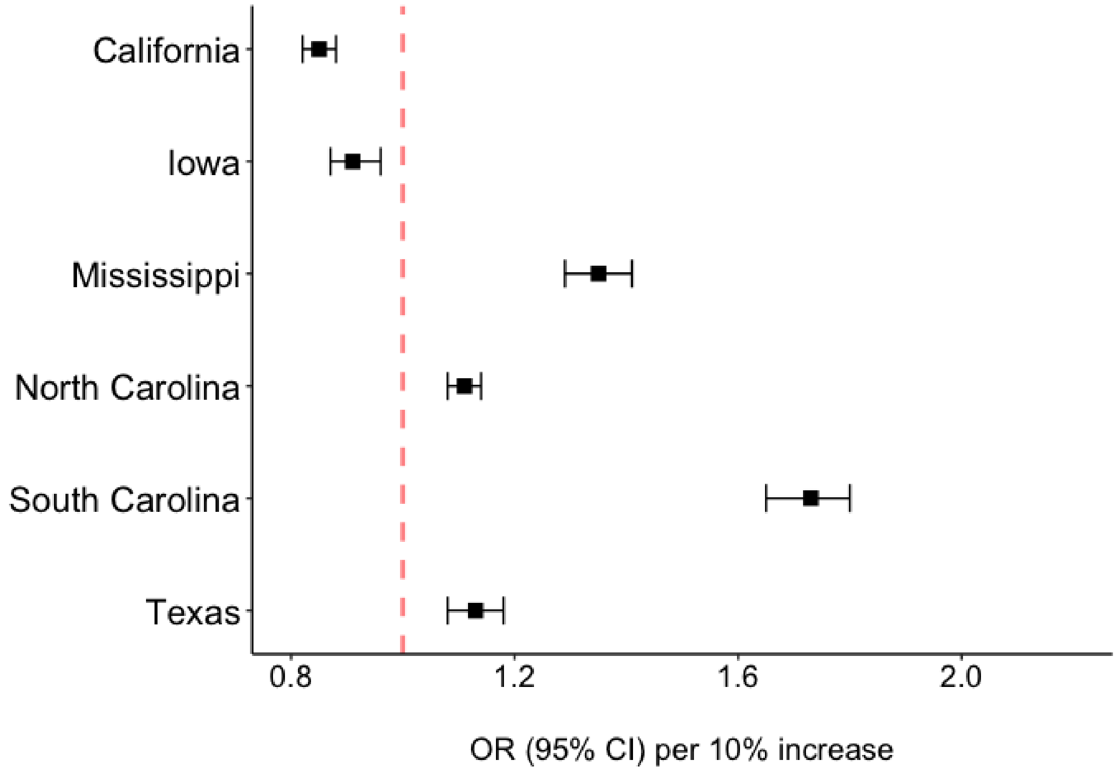



Figure 5: Odds Ratios for Percent Living Under 150% of the Poverty Line, By State


California
Iowa
Mississippi
North Carolina
South Carolina
Texas
0.8
1.2
1.6
2.0
OR (95% CI) per 10% increase