# THE IMPACT OF ENVIRONMENTAL AND SOCIAL CHARACTERISTICS ON SEVERE MATERNAL MORBIDITY: A SPATIOTEMPORAL ANALYSIS IN SOUTH CAROLINA

A Thesis
by
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## Abstract

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Severe Maternal Morbidity (SMM) occurs when a woman nearly dies during pregnancy or delivery. Despite its increasing prevalence, there is little research that evaluates geographic patterns of SMM and the underlying social determinants that influence likelihood. This study aims to examine the spatial clustering of SMM across South Carolina and its associations with place-based social and environmental factors. Hospitalized delivery records from 1999 to 2017 were provided by the South Carolina Department of Health and Environmental Control and identified as SMM based on diagnostic codes. Kulldorff's spatial scan statistic located areas with abnormally high rates of SMM with and without blood transfusions. SMM patients inside and outside risk clusters were compared using Generalized Estimating Equations (GEE) analysis to determine underlying risk factors. Results show that patient (e.g., obesity, minority status) and community-level characteristics (e.g., high temperatures) impact an individual's SMM risk. Most importantly, living in racially segregated low-income communities resulted in the highest potential for SMM risk. As SMM rises in the United

States, it is important that vulnerable populations are accurately targeted. This study spatially identifies SMM patterns and connects individual and area-level variables to likelihood.

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Though the unusual circumstances of this year prevented me from presenting at the Association of American Geographers (AAG) Annual Conference, I would like to recognize the on-campus organizations which planned to provide travel funding. I appreciate the opportunity for support from the Office of Student Research, Graduate School Government Association, and the College of Arts and Sciences. I would also like to recognize the South Carolina Department of Health and Environmental Control, US Census Bureau, Environmental Protection Agency, Health Resources and Service Administration, and US Department of Agriculture's Economic Research Service for providing the data necessary for this project.

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## Foreword

The main body of this thesis is formatted in accordance with the guidelines for manuscript submission to *Hea/th and P/ace*, an interdisciplinary journal dedicated to the study of all aspects of health and health care in which place or location matters.

## Introduction

Severe Maternal Morbidity (SMM) measures the rate of high-risk pregnancies that nearly result in fatality and have lasting influences on the wellbeing of women and newborns. The Centers for Disease Control and Prevention (CDC) classifies adverse pregnancies and deliveries as SMM based on hospital discharge information and codes adapted from the International Classification of Diseases (ICD). ICD diagnosis and procedure codes ICD-9 and ICD-10 are used to identify SMM in the United States (CDC, 2020). In 2012, under the ninth revision of ICD codes, twenty-five indicators were used to label SMM. In October 2015, the United States transitioned to ICD's tenth revision and the CDC re-evaluated SMM to acknowledge only twenty-one indicators. The most common SMM indicator in the United States is blood transfusion, which occurs when there is an unexpectedly high loss of blood during child delivery. Hysterectomy and tracheostomy follow blood transfusion as the most frequent procedures that characterize SMM nationwide (CDC, 2020). The severity of SMM is determined by the presence of multiple indicators. Some patients may have several complications during pregnancy while others may only have one indication of SMM.

SMM impacts populations disproportionately. Existing studies have shown racial minorities (Admon et al., 2018; Aziz et al., 2019; Creanga et al., 2014; Brown et al., 2011; Howell et al., 2016; Metcalfe et al., 2018), residents in rural communities (Lisonkova et al., 2016; Hansen and Moloney, 2019; Laditka et al., 2006), and older women (Booker et al., 2018; Knight et al., 2016; Leonard et al., 2019; Lisonkova et al., 2017a; Oliveira et al., 2014) experience elevated SMM rates. From 1993 to 2014 SMM prevalence increased by nearly 200% nationwide (CDC, 2020). Maternal morbidity and mortality rates in the US surpass those of other developed countries (Creanga et al., 2014; Geller et al., 2018). Rising and disproportionate rates have spurred on maternal health research in the last decade which focuses on social and health determinants of SMM. Despite these efforts, it is not entirely clear why SMM is increasing and unevenly impacting certain populations. Some studies have linked growing rates to an increase in patients with advanced maternal age, obesity, and other comorbidities such as hypertension and diabetes (Grobman et al., 2014). While others have posited that SMM increase is linked to rising rates of cesarean delivery (Guglielminotti et al., 2018a; Leonard et al., 2019; Shamshirsaz and Dildy, 2018).

To our knowledge no published literature spatially analyzes the occurrence of SMM in the US. A geographic approach will develop existing research by evaluating SMM in terms of space and identifying contextual risk factors. The objective of this study is to relate the spatiotemporal patterns of SMM to place-based health determinants in South Carolina. Findings from this study will provide health professionals with information to improve targeted maternal health interventions at the local level.

# THE IMPACT OF ENVIRONMENTAL AND SOCIAL CHARACTERISTICS ON SEVERE MATERNAL MORBIDITY: A SPATIOTEMPORAL ANALYSIS IN SOUTH CAROLINA

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**Keywords:** Maternal Health, Severe Maternal Morbidity, Cluster Analysis, GIS

## Abstract

Severe Maternal Morbidity (SMM) occurs when a woman nearly dies during pregnancy or delivery. Despite its increasing prevalence, there is little research that evaluates geographic patterns of SMM and the underlying social determinants that influence likelihood. This study aims to examine the spatial clustering of SMM across South Carolina and its associations with place-based social and environmental factors. Hospitalized delivery records from 1999 to 2017 were provided by the South Carolina Department of Health and Environmental Control and identified as SMM based on diagnostic codes. Kulldorff's spatial scan statistic located areas with abnormally high rates of SMM with and without blood transfusions. SMM patients inside and outside risk clusters were compared using Generalized Estimating Equations (GEE) analysis to determine underlying risk factors. Results show that patient (e.g., obesity, minority status) and community-level characteristics (e.g., high temperatures) impact an individual's SMM risk. Most importantly, living in racially segregated low-income communities resulted in the highest potential for SMM risk. As SMM rises in the United States, it is important that vulnerable populations are accurately targeted. This study spatially identifies SMM patterns and connects individual and area-level variables to likelihood.

## Introduction

Severe Maternal Morbidity (SMM) rates rose over 200% in the United States from 1993 to 2014, despite increasing healthcare costs and reductions of SMM in other high-income countries (Centers for Disease Control and Prevention, 2020; American Medical Association, 2020; Geller et al., 2018; Lipkind et al., 2019). Maternal morbidity and mortality rates in the US surpass those of other developed countries (Creanga et al., 2014a; Geller et al., 2018). SMM is a composite group of maternal conditions that signifies when a woman nearly dies from pregnancy complications. The Centers for Disease Control and Prevention (CDC) classifies adverse pregnancies and deliveries as SMM based on hospital discharge information and codes adapted from the International Classification of Diseases (ICD). ICD diagnoses and procedure codes ICD-9 and ICD-10 are used to identify SMM in the United States (CDC, 2020). In 2012, under the ninth revision of ICD codes, twenty-five indicators were used to label SMM. In October 2015, the United States transitioned to ICD's tenth revision, and the CDC re-evaluated SMM to acknowledge twenty-one indicators. The most common SMM indicator in the United States is blood transfusion, which occurs when there is an unexpectedly high blood loss during child delivery. Hysterectomy and tracheotomy follow blood transfusion as the most frequent procedures that characterize SMM nationwide (CDC, 2020). The presence of multiple indicators determines the severity of SMM. Some patients may have several complications during pregnancy while others may only have one indication of SMM.

SMM impacts some populations disproportionately. Existing studies have shown racial minorities (Admon et al., 2018; Aziz et al., 2019; Creanga et al., 2014b; Brown et al., 2011; Howell et al., 2016; Metcalfe et al., 2018), residents in rural communities (Lisonkova et al., 2016; Hansen and Moloney, 2019; Laditka et al., 2006), and older women (Booker et al., 2018; Knight et al., 2016; Leonard et al., 2019; Lisonkova et al., 2017a; Oliveira et al., 2014) experience elevated SMM rates. Rising and disproportionate rates in some groups have spurred on maternal health research in the last decade, which focuses on social and health determinants of SMM (Liese et al., 2019; Guglielminotti et al., 2018a). Despite these efforts, it is not entirely clear why SMM is increasing and unevenly impacting certain populations. Some studies have linked growing rates to individual factors like advanced maternal age, obesity, and comorbidities such as hypertension and diabetes (Grobman et al., 2014). While others have concluded that SMM increase is linked to the growing rates of cesarean delivery (Guglielminotti et al., 2018a; Leonard et al., 2019; Shamshirsaz and Dildy, 2018).

To our knowledge, no studies have examined the geographic clustering of SMM risk, nor have they identified underlying risk factors that enhance the clustering of SMM. The objective of this study is to identify spatial and temporal SMM trends and relate these patterns to place-based health and environmental determinants that drive high-risk clustering in South Carolina from 1999 to 2017. Findings from this study will provide health professionals with information to enhance targeted maternal health interventions and improve understanding surrounding underlying contextual factors that influence high rates of SMM in a community.

## Background

### *Known Risk Factors*

Like most health disparities, SMM likelihood follows patterns of spatially-linked systemic inequality in the US. Geography plays an important role in understanding the racial and ethnic characteristics associated with SMM. The distribution of minority groups and those with lower socioeconomic status is inherently spatial and changes over time (de Souza-Briggs, 2005; Cummins et al., 2007). An array of studies have looked at individual-level factors of race and ethnicity, which may explain discrepancies in access to care. An overwhelming majority of studies concluded that Black women are the most likely racial group to experience conditions related to SMM (Booker et al., 2018; Guglielminotti et al., 2018a; Liese et al., 2019; Grobman et al., 2014; Admon et al., 2018; Aziz et al., 2019; Creanga et al., 2014b; Howell et al., 2016; Brown et al., 2011). Blood transfusions and hysterectomy are more common among minority women, especially Black women. Obstetric hemorrhage, which is preventable in many cases, is closely associated with the need for blood transfusions (Admon et al., 2018). In general, Black women may experience avoidable SMM conditions due to the inaccessibility of quality maternal care. Howell et al., found that hospital quality was closely related to racial and ethnic SMM disparities (2017). In New York City, Hispanic women gave birth in hospitals with higher rates of SMM. The researchers found that 37% of the difference between Hispanic and non-Hispanic white SMM rates was accounted for by delivery location. Identifying low-performance hospitals and improving their capacity for care may alleviate inequalities.

While race is the most widely studied risk factor associated with SMM, researchers have identified a connection between adverse maternal health outcomes and economic status. The association between maternal health and poverty is often measured using health insurance data (Guglielminotti et al., 2018a). The use of public insurance, such as Medicaid or commercial insurance, impacts the prevalence of SMM. In a study of seven US states, around two-thirds of Black, Hispanic, and Native American births were covered by Medicaid compared to the majority of non-Hispanic white women whose deliveries were paid for by commercial insurance (Creanga et al., 2014b). The minority groups covered by Medicaid tended more towards SMM. The relationship between insurance status and SMM is not uniform across study areas. A study in New York State found a lower proportion of Medicaid beneficiaries was associated with increased SMM risk at the hospital-level (Guglielminotti et al., 2018a). Researchers cited the quality of care regardless of insurance status available in New York State as a reason for this. Studies examining racial discrepancies in SMM rates among Medicaid recipients in Durham, North Carolina, and across South Carolina found that white women experienced fewer adverse maternal outcomes than Black women, regardless of insurance status (Brown et al., 2011; Laditka et al., 2006). More access to prenatal care is needed among these populations to decrease avoidable complications among low-income populations.

Spatiotemporal analysis is needed to enhance understanding of the relationship between advanced maternal age and SMM as both have increased over time. Maternal age has been linked to SMM in numerous epidemiological studies (Lisonkova et al., 2017a; Booker et al., 2018; Oliveira et al., 2014; Leonard et al., 2019; Creanga et al., 2014b). Women of advanced age and teenagers experienced comparatively high rates of SMM. Between 1990 and 2013 the percentage of women over forty delivering babies increased from 1.2% to 2.8% (Lisonkova et al., 2017a). Complications in obstetric care are increasing as a greater number of older women in the US become pregnant (Hirshberg and Srinivas, 2017). Maternal age is linked to a higher occurrence of cesarean deliveries, which may partially account for the growth of SMM rates. A cohort study in California estimated that cesarean delivery contributed to 37% of SMM cases between 2007 and 2014 (Leonard et al., 2019). Cesarean sections constituted 32% of US births in 2015, surpassing the World Health Organization guidance of 10-15% (Weimer et al., 2019). The increase of cesareans in 2014 was found to vary across the US, with rates above 30% in the Northeast, California, and Florida which were the highest in the country (Weimer et al., 2019).

Pre-existing health conditions such as hypertension, obesity, and diabetes contribute to SMM. Studies found that hypertension during pregnancy has become increasingly common in the US (Grobman et al., 2014; Hitti et al., 2018; Geller et al., 2018; Guglielminotti et al., 2018b; Hirshberg and Srinivas, 2017). Hypertension during pregnancy significantly increases the odds of maternal morbidity and mortality (Guglielminotti et al., 2018b). Hypertension, which can escalate to preeclampsia and postpartum hemorrhage, was found in over two-thirds of SMM cases across twenty-five US hospitals (Grobman et al., 2014). Diabetes, which is closely related to hypertension, has a salient geographic pattern. A 'diabetes belt' was identified in the southeastern US, which included the majority of South Carolina counties (Barker et al., 2011). Obesity, another related risk factor, was found to increase the number of pregnancy complications in Finland (Pallasmaa et al., 2014). However, another population-based study in California found that obesity was not significantly related to elevated SMM risk (Leonard et al., 2019). The geographic distribution of pre-pregnancy risk factors needs to be compared with SMM to test for a spatial association. Although the literature has identified linkages between individual factors like race and pre-existing medical conditions and SMM, little research to date has examined if these underlying risk factors and SMM cluster spatially. For example, areas with a high prevalence of pre-existing conditions, such as diabetes and obesity, could focus on SMM intervention and study which would spatially identify the relationship between clustering of these comorbidities and adverse maternal health.

A geographic approach identifies the factors that impact maternal health across communities through the identification of high-risk spatial clusters and linking these vulnerable areas to influential neighborhood-level variables. The social variables that contribute to SMM vulnerability are unevenly distributed across the US. SMM deliveries were more likely in the South, including South Carolina, and the Northeast (Fingar et al., 2018). It was found that Black women in the South have the highest proportion of maternal morbidity in the US (Liese et al., 2019). There has been limited research on temporal SMM trends specific to the southeastern US. Across the entire US, SMM has increased unevenly across demographic groups (Creanga et al., 2014a; Guglielminotti et al., 2018b; Leonard et al., 2019; Gibson et al., 2017; Metcalfe et al., 2018). The rate of the twenty-one SMM indicators has also fluctuated disproportionately. Women in US hospitals experiencing SMM more than doubled even though the sample size rose only 20% from 1993 to 2012 (Metcalfe et al., 2018). In New York, secondary pulmonary hypertension during pregnancy rose from 17 to 30 cases per 100,000 deliveries from 2003 to 2014 (Guglielminotti et al., 2018b). Pulmonary hypertension leads to SMM, which also saw an increase during this period (Guglielminotti et al., 2018b). In Wisconsin, blood transfusions during delivery increased by 104% from 2000 to 2014 and excluding blood transfusions, SMM rates rose 15% (Gibson et al., 2017). From 2010 to 2014 overall rates in the study area were stable, but varied by maternal age, race, and public health region (Gibson et al., 2017).

*Geographic Variability of Community Characteristics*

Spatial context is critical in the relationship between environmental exposure factors and individual wellbeing (Dummer, 2008). Toxic release site emissions are one proxy for pollution exposure and may be related to maternal health outcomes. Researchers identified an association between toxic release site proximity and adverse birth outcomes, but have not applied this data to maternal morbidity (Choi et al., 2006; Agarwal et al., 2010). Extreme temperature exposure was found to adversely impact maternal health in one study (Cil and Cameron, 2017). Specifically, heat waves were related to an increase in pregnant hypertension, uterine bleeding, eclampsia, and incompetent cervix. The limited knowledge of this relationship warrants further investigation into the impacts of seasonal temperatures on SMM. Where a person lives greatly impacts their health outcomes since the environment, healthcare access, and disease rates vary within regions (Tunstall et al., 2004). Geography *constitutes* and *contains* the human and physical variables that impact health (Cummins et al., 2007). The identification of geographic SMM clusters through Kulldorff's spatial scan statistic would bridge the gap between knowledge of contributing factors and their physical location. This information would be vital to a maternal health initiative that could identify at-risk groups that would benefit from preventive measures and increased access to appropriate prenatal care. The density of healthcare providers can be used to measure patient access to care, which has been linked to the prevention of negative maternal health outcomes in previous studies (Laditka et al., 2006; Kikuchi et al., 2018). Care access partially explains an urban-rural SMM disparity, where more maternal health risk is found in less populated areas (Laditka et al., 2006; Lisonkova et al., 2016; Hirshberg and Srinivas, 2017; Hansen and Moloney, 2019).

*Research Gaps*

There has been a growing consensus that minority women have a greater risk for SMM (Booker et al., 2018; Guglielminotti et al., 2018a; Liese et al., 2019; Grobman et al., 2014; Admon et al., 2018; Aziz et al., 2019; Creanga et al., 2014b; Howell et al., 2016; Brown et al., 2011). Research has shown that Black women were 115 times more likely than white women to experience SMM in 2015 (Fingar et al., 2018). Studies have found, at varying levels of certainty, that comorbidities and pre-existing health conditions influence SMM likelihood and cite the increase in cesarean deliveries as another possible cause for rising rates (Leonard et al., 2019; Shamshirsaz and Dildy, 2018). Obesity and advanced maternal age are linked to SMM, though the relationship is not apparent across all studies (Leonard et al., 2019; Fingar et al., 2018). Individual SMM indicators have been connected to environmental phenomena such as heat waves and seasonal air pollution, but SMM's environmental impact has not yet been wholly evaluated (Assibey-Mensah et al., 2019; Cil and Cameron, 2017; Oyana et al., 2015). Existing literature lays a foundation but has not analyzed SMM's spatial distribution, which a geographic approach would supplement. In this exploratory study, the distribution of patient, environmental, and community-based factors are measured alongside SMM to fill these research gaps. The clustering of SMM may be explained by the presence of these factors that have not yet been spatially examined.

There needs to be a more holistic understanding of what causes SMM as cases continue to rise. The Black-white disparity in SMM highlights social inequality in the US regarding the lack of adequate care among rural and minority women (Howell et al., 2017; Hansen and Moloney, 2019). While maternal health researchers have explored this disparity that exists between groups locally and nationally, a fine-scale spatial study is needed to inform regional healthcare advocates *where* elevated risk areas are located. While limited research has examined geographic disparities in SMM risks, exploration of spatial patterning of SMM risks could identify hotspots of risk and shed insight on the contextual factors driving these clusters. Once vulnerable populations are accurately identified, preventive measures can be put in place to alleviate the factors that influence SMM.

## Methods

### *Data*

We performed a case-only analysis drawing from a retrospective cohort study in South Carolina. De-identified patient information was provided by the South Carolina Department of Health and Environmental Control from 1999 to 2017 (*n*=860,535). SMM was categorized using the CDC definition which includes twenty-one procedures and diagnoses adapted from the ninth revision of the International Classification of Diseases (ICD) codes.

### *SMM Measures*

Previous research has shown that blood transfusion is the most commonly occurring indicator of SMM (Callaghan et al., 2012; Creanga et al., 2014a; Schummers et al., 2018). However, assigned ICD-9-CM procedure codes do not include the number of units of blood transferred and may result in artificially high SMM rates. To address the significant impact of this indicator, the primary study outcomes of interest were: 1) SMM composite measures with blood transfusion (SMM21) and 2) SMM without blood transfusion (SMM20). SMM21 was measured as a composite of twenty-one CDC recognized indicators of SMM. SMM20 included all recognized indicators except for blood transfusions, as it is the leading driver of SMM increase (CDC, 2020).

SMM cases were geocoded to their residential zip code based on hospital administration records. Patients with a SMM diagnosis included in the study were between the ages of 10 and 55 years with a gestation of 20 to 44 weeks. Hospitalized patients were 56.4% white, 32.9% Black, 4.7% Hispanic, 1.1% Asian, 0.3% Native American, and 4.6% another race or ethnicity. 35.9% of hospital expenses were paid with commercial insurance, and 49% were covered using

Medicaid. Patients between 20 and 29 constituted 56.6% of deliveries, followed by women between 30 and 39 (29.5%), 19 and younger (12.1%), and those 40 and older (1.8%).

*Patient-Level Factors*

The following patient-level factors used for statistical analysis were provided directly from hospitalized medical records: year of hospital delivery discharge, age, race and ethnicity, insurance type, and zip code. The following conditions were identified using ICD-9-CM codes: prior cesarean, cesarean diagnosis, cesarean procedure, delivery type, rupture of uterus, preeclampsia, obesity, hypertension, hysterectomy, gestational hypertension, eclampsia, diabetes mellitus, smoking, depression, bipolar disorders, asthma, SMM with and without blood transfusions. Race and ethnicity was categorized into white, Hispanic or Latino, Black, or other with white patients serving as the referent group. Patient age was sorted into four groups: 19 years and younger, 20 to 29 years, 30 to 39 years, and 40 years and older. Insurance type was classified as private, Medicare/Medicaid, self pay, or other with privately insured patients serving as the reference. The ICD-9-CM conditions were represented as binary variables where 1 was indicative of a condition's presence.

*Community-Level Factors*

We defined 'community-level' at the level of the 5-digit zip code geographic area. The following data obtained at the zip code-level was used to represent place-based social and environmental factors that may influence SMM likelihood: toxic release inventory (TRI) site emissions, number of primary care facilities (a proxy for care access), racial residential segregation, income inequality, and racialized economic residential segregation derived from the Index of Concentration at the Extremes (ICE). Temperature maximum and minimum values were collected at the county-level for every year and stratified into quantiles with the lowest group set as the reference. Primary care facility data was provided by the US Health Resources and Services Administration at the zip-code level and separated into three categorical groups: zero facilities, one facility (referent group), two or more facilities. TRI emissions were collected from the Environmental Protection Agency and treated as a continuous variable. Measures used in this study based on the literature can be found in *Table 1*.

Table 1. Factors Associated with Maternal Morbidity from Previous Literature.

| **Variable** | **Measure** | **Relationship** | **Citations** |
|---|---|---|---|
| Race/ Ethnicity | Patient racial characteristics, ICE racialized segregation | Minority women have an increased risk of experiencing SMM. | Booker et al., 2018; Howell et al., 2017; Guglielminotti et al., 2018a; Liese et al., 2019; Grobman et al., 2014; Admon et al., 2018; Hitti et al., 2018; Aziz et al., 2019; Creanga et al., 2014a; Creanga et al., 2014b; Metcalfe et al., 2018; Howell et al., 2016; Haywood et al., 2011 |
| Age | Maternal age at time of delivery | Older women and extremely young women have increased SMM risk. | Lisonkova et al., 2017a; Booker et al., 2018; Oliveira et al., 2014; Leonard et al., 2019; Creanga et al., 2014b |
| Cesarean | Patient diagnoses codes for prior cesarean and cesarean procedure | A growth in cesarean section rates is related to increased risk for blood transfusions and elevated SMM rates. | Leonard et al., 2019; Booker et al., 2018; Howell et al., 2017; Guglielminotti et al., 2018a; Shamshirsaz and Dildy 2018 |
| Comorbidities | Patient diagnoses codes for obesity and hypertension | Pre-existing hypertension, obesity, and diabetes have been linked to increased SMM likelihood. | Leonard et al., 2019; Grobman et al., 2014; Hitti et al., 2018; Geller et al., 2018; Guglielminotti et al., 2018b; Hirshberg & Srinivas 2017; Pallasmaa et al., 2014 |
| Economic Status | ICE economic segregation | Low income and Medicaid status are associated with higher than average SMM rates possibly due to lack of appropriate care access. | Booker et al., 2018; Guglielminotti et al., 2018a; Creanga et al., 2014b; Laditka et al., 2006 |

| | | | |
|---|---|---|---|
| Access, Rurality | HPSA primary care facility numbers, RUCA codes | Less access to prenatal care, which is more common among rural populations, increases SMM risk. | Lisonkova et al., 2016; Hansen and Moloney, 2019; Laditka et al., 2006 |
| Environmental Exposure | TRI site emissions, temperature averages within delivery county | Exposure to heat waves and air pollution have been tied to increased maternal stress and adverse maternal health outcomes. | Assibey-Mensah et al., 2019; Cil and Cameron 2017; Oyana et al., 2015 |

*Deprivation Index*

A spatial framework visualizes the relationship between a health outcome, such as SMM, and measurable determinants. Vulnerable areas can be determined by a deprivation index that measures the impact of human and physical environments across spatial contexts. The Census Bureau's 5-Year American Community Survey (ACS) estimates quantifiable community-level characteristics. Deprivation indices determine the influence of specific areas on health determinants relative to the overall region. There are a variety of indices used to measure vulnerability. The Index of Concentration at the Extremes (ICE) measures racial residential segregation, income inequality, and racialized economic residential segregation (Massey, 1996). The concept of concentrated affluence and poverty that serves as the framework for the ICE measure recognizes the geographic dependence of residential segregation and has been applied mostly to the social sciences, and can help inform underlying health disparities (Massey, 1996; Krieger et al., 2016). The index determines populations that are the most deprived and the most privileged. A value of -1 indicates 100% of the population within a unit is the most deprived while a value of 1 indicates 100% of the population is the most privileged. ICE metrics are generated using three measures of income, race, and a combination of race and income. A recent analysis applied the index to public health monitoring to evaluate county-level residential segregation and breast cancer survival (Krieger et al., 2016). In the study, counties with a concentration of racial and economic privilege had a positive association with higher breast cancer survival.

The relationship between structural racism and birth outcomes was measured using ICE (Chambers et al., 2019). Individuals who experienced preterm birth or infant mortality were more likely to reside in the least privileged zip codes in California. To our knowledge, maternal health has not yet been evaluated using this metric. We hypothesize that trends in SMM will follow patterns of racialized economic segregation in South Carolina since poverty has been linked to decreased maternal care access and comorbidities such as obesity and hypertension (Nagahawatte and Goldenberg, 2008). Detection of at-risk clusters and consideration of environmental and social contexts could identify factors that may threaten the maternal health of minority women.

An index measure adjusting for racial and economic segregation was adapted from the Index of Concentration at the Extremes (ICE) (Massey, 1996). ICE was calculated at the zip code level for the 2017 American Community Survey (ACS) 5-Year Estimates and 2010 Census data. The income formula utilized ACS variable *S1903*, median income in the past 12 months in 2017 inflation-adjusted dollars, and Census variable *P080*, which shows the number of persons in high-income (2' $100,000) and low-income (< $25,000) households. The measure for race used ACS table *B03002*, Hispanic or Latino origin by race, and Census variable *P7*, which showed the total numbers for each racial and ethnic group in each South Carolina zip code. The last formula calculated these income and race/ethnicity variables together. A large proportion of the study population (37.7%) resided in zip codes with an ICE race score greater than 0.5. Due to this uneven distribution, the data was collapsed into tertiles between -1 and 1 instead of quintiles for statistical analysis.

*Cluster Analysis*

SaTScan software is used to spatially and temporally analyze the spread of disease using Kulldorff's spatial scan statistic. It accounts for uneven population distribution and identifies multiple clusters at user-specified window sizes (Sheehan et al., 2004). In spatial science, a cluster refers to a local phenomenon of either abnormally high or low instances of an observed factor. Martin Kulldorff developed the software to locate statistically significant cancer clusters while adjusting for the confounding variables of age, race, parity, and urbanicity (Kulldorff et al., 1997). Clusters are estimated through the option of different probability models. Bernoulli models use case and control files to analyze categorical (0/1) data. Discrete Poisson-based models employ case and population files to examine occurrences in the study region that are approximately Poisson distributed.

The clustering of a birth defect in North Carolina was determined in SaTScan using a discrete Poisson model (Root et al., 2009). This model was used because it can easily adjust for confounding variables and produces more conservative *p*-values than the Bernoulli model. In the study, use of the discrete Poisson model was appropriate due to the high number of covariates and the relatively low occurrence of gastroschisis compared to the total population. Due to the rareness of SMM relative to all deliveries, a discrete Poisson model will be employed in the current study. A study of maternal health in Australia used purely spatial scan statistics in SaTScan to identify populations at risk of smoking during pregnancy (Chong et al., 2013). To determine the impact of covariates on health risk and to differentiate characteristics between cluster and non-cluster deliveries, the researchers used generalized estimating equations (GEE) logistic regression. The models accounted for the association between social and clinical traits of subjects inside and outside of high-risk clusters. The GEE method is best used in longitudinal, nested, or repeated measures study designs (Ballinger, 2004). SaTScan clusters can be further evaluated and explained by these external statistical methods. Though they track different health events, methods from these studies serve as a model for examining SMM.

Spatiotemporal clustering methods have yet to be applied to SMM in the US. SaTScan, a descriptive visualization mapping tool, examined the spatial and temporal clustering of SMM including blood transfusions, SMM21, and SMM without blood transfusions, SMM20. This method accounts for uneven population distribution and uses Kulldorff's statistic to identify geographic hotspots of elevated risk (Sheehan et al., 2004). A discrete Poisson model was used to locate high-risk SMM clusters with (SMM21) and without blood transfusions (SMM20). This model was used as it produces more conservative *p*-values than the alternative Bernoulli model (Root et al., 2009). Clustering analysis was used to detect purely temporal, purely spatial, and space-time clusters using a maximum circular window size set to 20% of the total at-risk population. The maximum size was determined through a sensitivity analysis from 10% to 50%, and based on previous studies (Fang et al., 2006; Chong et al., 2013). A smaller window size scans for localized clusters relative to the default of 50% and is better for informing targeted interventions.

*GEE Models*

We assumed that SMM cases within a community were more likely to be similar compared to SMM cases in other communities due to shared social characteristics and environmental exposure. Generalized estimating equations (GEE) with an exchangeable correlation matrix were used to account for the clustering of SMM cases within zip codes. The previously mentioned individual covariates of race, age, comorbidities, and insurance status were included in the first GEE model. Environmental variables such as TRI emissions, temperature maximums and minimums, ICE measures of racialized and economic segregation, and number of primary care facilities were measured in the second model. The final model incorporated significant factors from both models to determine the most influential characteristics for residing in a high-risk SMM cluster. Odds Ratios (ORs) and their confidence intervals were estimated for individual and community factors. Using stepwise regression, significant covariates for SMM20 and SMM21 were identified at the 95% confidence level.

## Results

*Patient Characteristics*

Between January 1, 1999, and December 31, 2017, there were 8,255 deliveries that resulted in SMM20 and 15,529 characterized by SMM21. These constituted 0.97% and 1.8% of all hospitalized deliveries. The majority of SMM patients were Black despite white patients constituting the population majority (*Table 2*). Black patients accounted for 6,950 (44.8%) of all SMM cases. Blood transfusion, the most frequent indicator, occurred in 56% of SMM deliveries and disproportionately impacted Black and Hispanic patients.

Table 2. Characteristics for Patients with SMM, South Carolina 1999-2017.

| **Characteristic** | **SMM21** (*n*=15529) | **SMM20** (*n*=8251) |
|---|---|---|
| *Race/Ethnicity* | | |
| White | 6690 (43.1) | 3751 (45.5) |
| Black | 6952 (44.8) | 3696 (44.8) |
| Hispanic/Latino | 892 (5.7) | 365 (4.4) |
| Other Race | 995 (6.4) | 439 (5.3) |
| *Age* | | |
| 19 and Younger | 1900 (12.2) | 836 (10.1) |
| 20 - 29 | 7972 (51.3) | 4020 (48.7) |
| 30 - 39 | 5135 (33.1) | 3049 (37.0) |
| 40 and Older | 522 (3.4) | 346 (4.2) |
| *Insurance* | | |
| Medicare/Medicaid | 8659 (55.8) | 4343 (52.6) |
| Private | 5751 (37.0) | 3334 (40.4) |
| Self Pay | 488 (3.1) | 229 (2.8) |
| Other | 631 (4.1) | 345 (4.2) |

*Geographic Clustering of SMM Risk*

Six significant ($p < .01$) high-risk spatial clusters were present throughout the entire study period for SMM21 (*Figure* 1). Two significant ($p < .01$) high-risk spatial clusters were present throughout the entire study period for SMM20. The spatial SMM21 clusters were concentrated in eastern South Carolina. The primary cluster was located in the south along the state's border with Georgia. The two high-risk spatial clusters for SMM20 were located in the north and south-central regions.

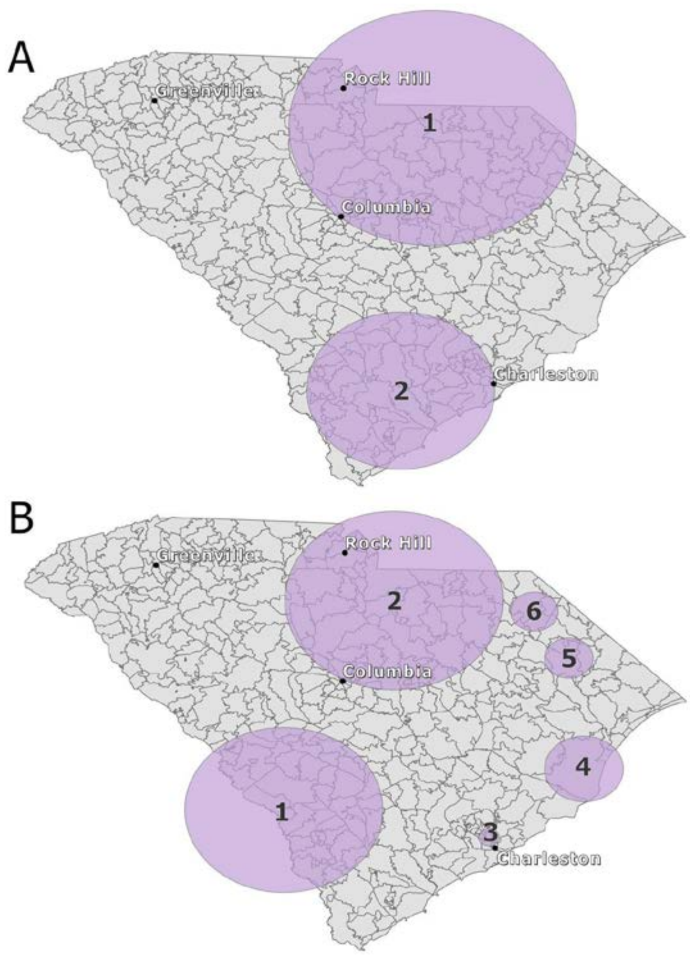


Figure 1. Purely Spatial High-Risk Clusters for 20% of the Population at Risk. (A) SMM20 (B) SMM21

The percent of deliveries marked by SMM has increased steadily over the study period (*Figure 4*). Purely temporal clusters tracked the incidence of SMM from 1999 to 2017 for the entire study area. Using both a four year and two year maximum cluster size, SMM20 clusters occurred during 2016 and 2017 (RR=1.78, $p$<.001). SMM21 clusters with a two-year maximum temporal window were identified during 2016 and 2017 (RR=1.35, $p$<.001), while clusters with a four year maximum window occurred from 2017 to 2017 (RR=1.33, $p$<.001).

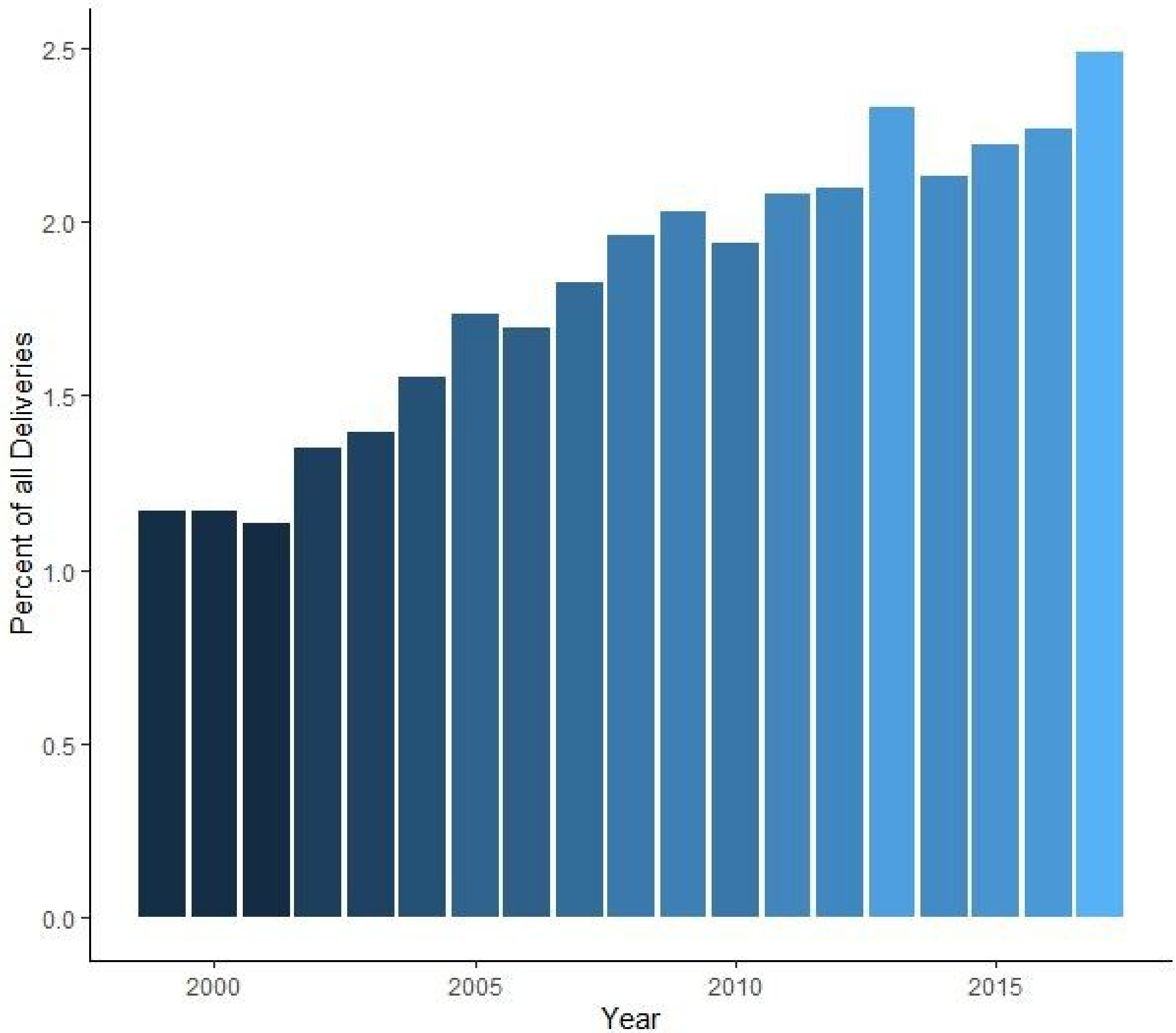


Figure 2. Annual Trends of Hospitalized Deliveries Characterized by SMM (Percentage), South Carolina 1999-2017

A space-time SaTScan analysis using a 20% spatial window scanned for significant clusters ($p<.01$) using 2 year intervals (*Figure 3*). Three space-time clusters for SMM20 were present from 2016 to 2017 in the north and northwest. During the same period, the primary cluster was identified in the southeast (RR=2.19). Three space-time SMM21 clusters were present in different areas of South Carolina than SMM20. The primary SMM21 cluster was found in the south-central region between 2016 and 2017 (RR=1.8). Secondary clusters were identified in the north during 2013 and 2014 and in a localized southeastern area between 2007 and 2008.

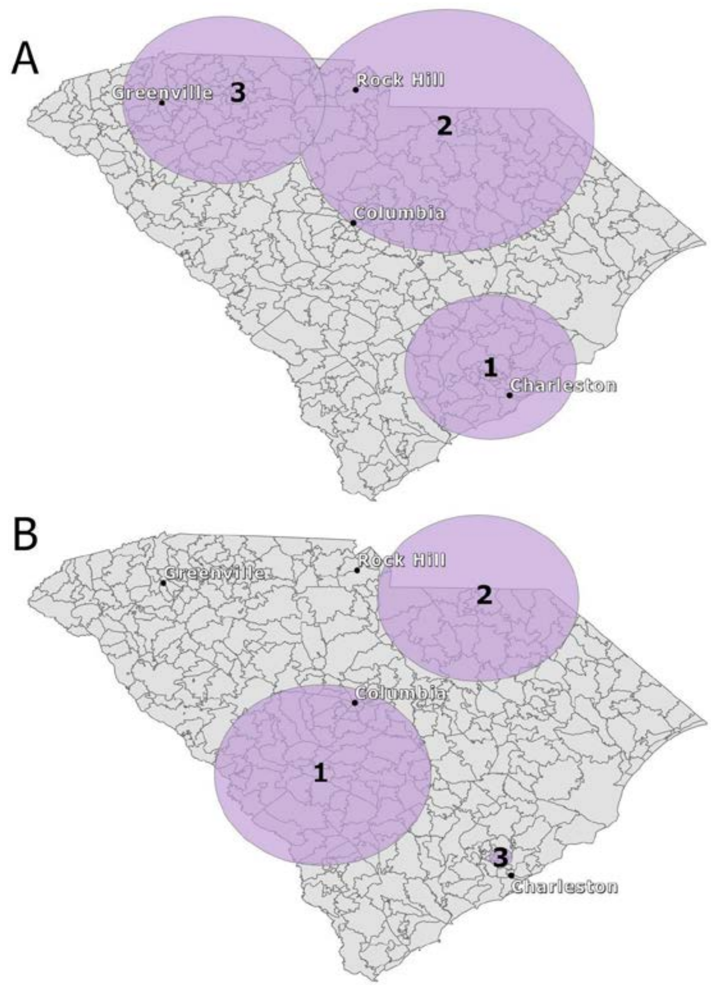


Figure 3. Spacetime High-Risk Clusters for 20% of the Population at Risk. (A) SMM20 (B) SMM21

Patient and place-based risk factors varied for women with SMM who resided inside clusters and outside of clusters. While 37.6% of Black patients characterized cases outside of high-risk SMM21 clusters, 62.5% of clusters were composed of Black patients. These initial findings within the study population support existing literature that race and ethnicity are closely linked to SMM risk (Creanga et al., 2014b; Admon et al., 2018; Aziz et al., 2019; Brown et al., 2011; Howell et al., 2016; Metcalfe et al., 2018). Hispanic and Latino women were only more likely to reside in an SMM20 cluster. This makes sense given the variability in Hispanic SMM rates found in other studies which remain lower than rates for Black women (Aziz et al., 2019; Booker et al., 2018; Creanga et al., 2014b). Racialized economic segregation also influenced likelihood for living in a SMM21 cluster. Outside of a cluster 23.1% of patients lived in a zip code with the most deprivation while it was 60.6% for women inside an SMM21 cluster. In SMM20 clusters 54.9% of women were Black and outside of these clusters 37.2% were Black. Outside of SMM20 clusters 27.7% of deliveries occurred in the most deprived zip codes while inside clusters the percentage was 42.2% of deliveries.

*ICE Metric*

The socioeconomic characteristics that informed the metric varied substantially across South Carolina zip codes. The ICE metric highlighted locations of extreme racial and economic residential segregation in the more privileged western region (positive ICE value) and more deprived southeast (negative ICE value) with the exception of urban centers in the southeast. For the measure of racial residential segregation, 102 zip codes had a value below zero, indicating a higher concentration of Black non-Hispanic persons. The highest score of +1, indicative of an entirely white non-Hispanic population, was present in 10 areas. Values above zero occurred in

320 zip codes, where there was a higher concentration of white persons. *Figure 2* shows the distribution of racial and economic residential segregation across South Carolina. These results highlight a disparity of socioeconomic privilege in South Carolina, which has been associated with poor or reduced access to maternal healthcare (Howell et al., 2017; Liese et al., 2019).

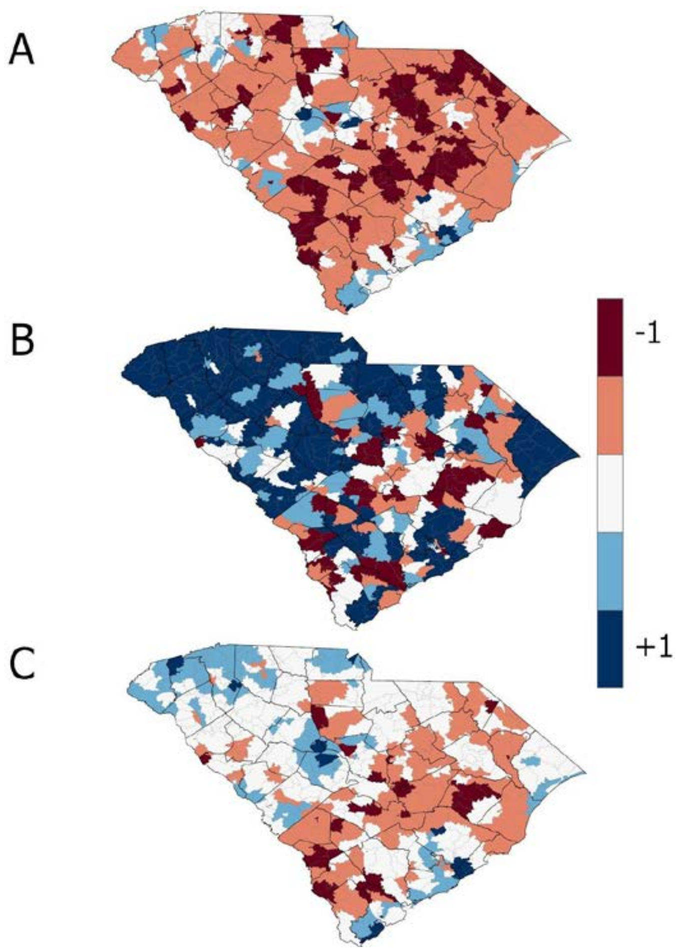


Figure 4. ICE Metrics for 2017. -1 represents everyone in the most deprived group and +1 represents everyone in the most privileged group. (A) Income (B) Race (C) Income and Race

*SMM20 Contextual Risk Factors*

GEE models determined significant covariates for SMM20 cluster risk (*Table 3*). The odds of living in a high-risk SMM cluster was significantly higher for Black women (OR=2.3, *p*<.001), Hispanic or Latina women (OR=1.43, *p*<.01), and those presented with obesity (OR=1.28, *p*<.001). Upon relating community-level factors to SMM clustering, we observed that the odds of living in a high-risk cluster were 45% higher for women who gave birth during temperature minimums of at least 19.27°C/66.7°F (OR=1.45, *p*<.01) and 7.85 times higher for those living in the most racially segregated zip codes (OR=7.85, *p*<.001). Final models combining patient and community factors revealed that the odds of living in a high-risk cluster was 84% higher among Black patients (OR=1.84, *p*<.001), 30% higher among Hispanic and Latina patients (OR=1.3, *p*<.05), and 1.51 times more likely among women living in highly segregated and poorer minority communities (OR=1.51 *p*<.001) compared to those in low-risk clusters. Odds for residing in a high-risk cluster were 31% higher for women with a pre-existing diagnosis of obesity (OR=1.31, *p*<.001) and 23% higher for those who gave birth during a period with temperature maximums above 30.65°C/87.3°F (OR=1.23, *p*<.001) compared to women in low-risk clusters. Forest plots visualizing the contribution of each risk factor can be found in the *Appendix.*

Table 3. SMM20 GEE Models, * *p*-value <.05 ** p-value <.01 *** p-value <.001

| **Model 1:** | | | **Model 2:** | | | **Model 3:** | | |
|---|---|---|---|---|---|---|---|---|
| **Predictors** | **OR** | **CI** | **Predictors** | **OR** | **CI** | **Predictors** | **OR** | **CI** |
| Obesity*** | 1.28 | 1.11, 1.47 | Temperature Minimum Group 2* | 1.19 | 1.00, 1.41 | Obesity*** | 1.31 | 1.13, 1.52 |
| *Race/Ethnicity* | | | Temperature Minimum Group 3 | 1.11 | 0.90, 1.38 | Black*** | 1.84 | 1.65, 2.05 |
| Black*** | 2.3 | 2.0, 2.54 | Temperature Minimum Group 4** | 1.45 | 1.14, 1.84 | Hispanic/Latino* | 1.3 | 1.03, 1.64 |
| Hispanic/Latino** | 1.43 | 1.14, 1.79 | Temperature Maximum Group 2 | 1.07 | 0.91, 1.27 | Medicare/Medicaid* | 0.89 | 0.81, 0.99 |
| White | 1.0 (ref) | | Temperature Maximum Group 3 | 1 | 0.81, 1.23 | Self Pay* | 0.76 | 0.58, 0.98 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *Insurance* | | | Temperature Maximum Group 4 | 0.89 | 0.70, 1.14 | Temperature Maximum Group 2* | 1.14 | 1.01, 1.29 |
| Medicaid/Medicare | 0.96 | 0.87, 1.05 | No Primary Care Facilities*** | 0.03 | 0.02, 0.07 | Temperature Maximum Group 3* | 1.14 | 1.01, 1.28 |
| Self Pay* | 0.76 | 0.59, 0.98 | One Primary Care Facility*** | 0.07 | 0.03, 0.15 | Temperature Maximum Group 4*** | 1.23 | 1.09, 1.39 |
| Private | 1.0 (ref) | | Race ICE Group 1*** | 7.85 | 6.78, 9.09 | No Primary Care Facilities*** | 0.04 | 0.02, 0.08 |
| | | | Race ICE Group 2*** | 4.25 | 3.74, 4.82 | One Primary Care Facility*** | 0.08 | 0.04, 0.18 |
| | | | Income ICE Group 1*** | 0.28 | 0.24, 0.32 | Race and Income ICE (Most Deprived)*** | 1.51 | 1.33, 1.71 |
| | | | Income ICE Group 2*** | 0.46 | 0.40, 0.52 | Race and Income ICE (Middle Group)* | 0.86 | 0.76, 0.98 |

*SMM21 Contextual Risk Factors*

The odds of living in a high-risk SMM cluster was significantly higher for Black women (OR=2.6, $p$<.001) and those enrolled in Medicaid or Medicare (OR=1.13, $p$<.01) compared to those outside of clusters (*Table 4*). Upon relating community-level factors to SMM clustering, we found that the odds of living in a high-risk cluster were 8.6 times higher for women in the most racial segregated zip codes (OR=8.56, $p$<.001) and 20% higher for those living in more extreme poverty areas (OR=1.2, $p$<.01) compared to those outside high-risk SMM clusters. The final model combining patient and community factors revealed that the odds of residence in a high-risk cluster was 6.7 times higher for women living in highly segregated, poor areas (OR=6.69, $p$<.001) and 43% higher among Black patients (OR=1.43 $p$<.001).

Table 4. SMM21 GEE models, * *p*-value <.05 ** p-value <.01 *** p-value <.001

| **Model 1:** | | | **Model 2:** | | | **Model 3:** | | |
|---|---|---|---|---|---|---|---|---|
| **Predictors** | **OR** | **CI** | **Predictors** | **OR** | **CI** | **Predictors** | **OR** | **CI** |
| Black*** | 2.6 | 2.40, 2.83 | No Primary Care Facilities*** | 0.08 | 0.06, 0.12 | Black*** | 1.43 | 1.30, 1.57 |
| Hispanic or Latino | 0.92 | 0.77, 1.11 | One Primary Care Facility*** | 0.26 | 0.18, 0.38 | Hispanic or Latino*** | 0.66 | 0.54, 0.81 |
| Medicaid/Medicare** | 1.13 | 1.04, 1.23 | ICE Race Group 1*** | 8.56 | 7.47, 9.81 | Medicaid/Medicare | 0.96 | 0.88, 1.05 |
| Self Pay*** | 0.69 | 0.55, 0.87 | ICE Race Group 2*** | 2.65 | 2.34, 3.01 | Self Pay*** | 0.6 | 0.46, 0.77 |
| Smoking* | 0.82 | 0.68, 0.99 | ICE Income Group 1** | 1.2 | 1.06, 1.37 | No Primary Care Facilities*** | 0.07 | 0.05, 0.11 |
| Hysterectomy* | 0.82 | 0.69, 0.96 | ICE Income Group 2*** | 1.68 | 1.49, 1.89 | One Primary Care Facility*** | 0.29 | 0.20, 0.41 |
| Under 19 years | 1.07 | 0.96, 1.19 | | | | Race and Income ICE (Most Deprived)*** | 6.69 | 5.88, 7.61 |
| Between 30 and 39 years* | 0.9 | 0.83, 0.98 | | | | Race and Income ICE (Middle Group)*** | 2.33 | 2.05, 2.64 |
| Over 40 years | 1.09 | 0.89, 1.32 | | | | | | |

## Discussion

This study is the first to characterize the geographic clustering of SMM risk in South Carolina and identified the influence that individual, social, and environmental phenomena had on the likelihood of living in a high-risk cluster. Our geospatial approach contributes a novel understanding to factors which influence SMM beyond patient-level characteristics and identifies the impact of systemic racism on maternal morbidity. The findings begin to address the gap in maternal morbidity literature surrounding place-based risk factors by explaining the contextual social and built environment variables that vary greatly across the state. The risk of SMM in South Carolina was found to be spatially clustered in geographic regions, providing valuable information about the geographical disparity of maternal morbidity. Six spatial clusters for SMM21 and two spatial clusters for SMM20 were identified from 1999 to 2017. With the exception of a localized cluster in the southeast in 2008, significant space-time and purely temporal clusters occurred in the final two or four years of the study period. These findings support a growing body of evidence that SMM risk is steadily increasing in the US (Leonard et al., 2019; Fingar et al., 2018; Creanga et al., 2014a), and our findings suggest that SMM risks are place-specific.

High-risk SMM clusters were composed of a greater proportion of racial minorities and those in segregated low-income areas than regions outside of clusters. This evidence suggests that racialized economic segregation strongly influences SMM risk within poorer minority communities. Numerous studies have linked this systemic discrimination to adverse maternal health and childbirth outcomes (Chambers et al., 2019; Bower et al., 2020; Owens and Fett, 2019). The salient differences between populations inside and outside high-risk clusters were further revealed by GEE analysis. Those residing in high-risk spatial SMM clusters were significantly more likely to live in disadvantaged racialized economic areas. We found similar associations with race and poverty in a previous study (Guglielminotti et al., 2018a). Maps of ICE values show the variability of privilege that exists in South Carolina. Areas with the lowest ICE values tended toward the eastern and southern parts of the state. The primary cluster for SMM21 overlaps with more racialized economically disadvantaged areas in the southeast. The northeast and northwest, areas with relatively high or average ICE values for race and income, did not have any SMM high-risk clusters present. It is important to note that six of the zip codes with the highest racial income ICE values bordered one another in Charleston, an area with concentrated racial and economic disparity (Patton, 2017). This area is contained in a SMM20 high-risk cluster, and SMM rates here may be attributed to the extreme contrasts between the wealthy and the underprivileged in and around Charleston.

To contextualize the patterning of SMM, individual variables associated with lower socioeconomic status measured in previous literature were accounted for in the GEE models. Obesity, a known contributor to adverse maternal health outcomes, was found to only influence SMM excluding blood transfusions in this population. This partially explains the increased likelihood for low income women to have SMM as an overwhelming amount of literature has tied low socioeconomic status with higher rates of obesity (Drewnowski and Specter, 2004; Langenberg et al., 2003). Both high and low body mass index (BMI) slightly increased SMM in a study of Washington state but obesity was not associated with increased risk in a California study (Lisonkova et al., 2017b; Leonard et al., 2019). The strength of the relationship between obesity and SMM therefore remains unclear; however, our findings suggest it influences SMM20 likelihood. We found a spatial connection between risk for residing in an SMM cluster and limited food access based on data provided by the Food Research Atlas (Economic Research Service US Department of Agriculture, 2017). Areas surrounding Rock Hill and Columbia, which were within high-risk SMM20 and SMM21 clusters, contained census tracts with extremely low food access at one mile for urban areas and ten miles for rural areas. The secondary cluster for SMM20 encompassed southeastern South Carolina which had low food access (*Figure 5*).

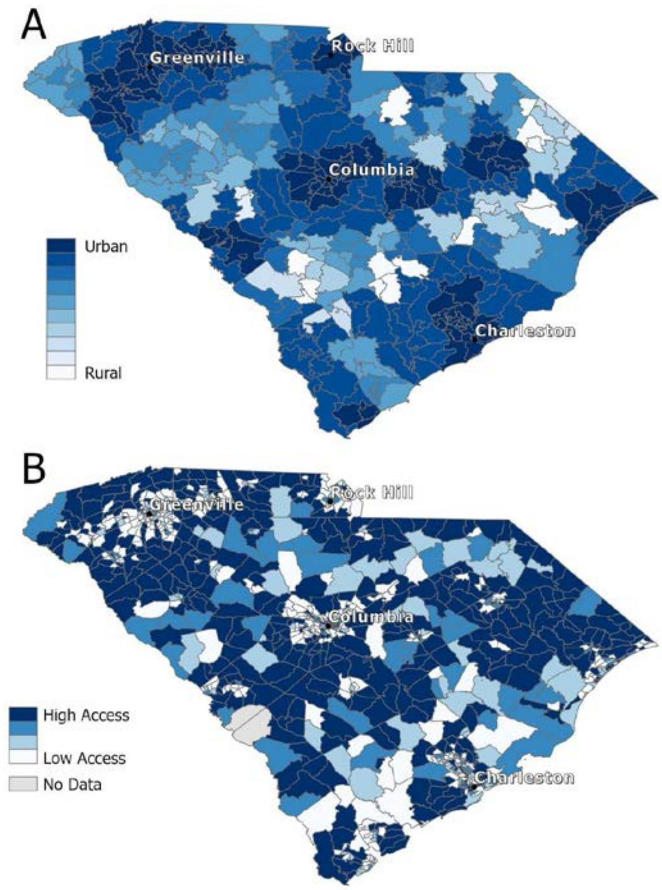


Figure 5. (A) 2017 RUCA Codes for Zip Codes (B) 2017 Food Access for Census Tracts, South Carolina

Medicaid did not increase likelihood for residing in a high-risk cluster. This trend may have occurred because the sample of SMM patients already had a high proportion of Medicaid beneficiaries compared to the overall hospitalized delivery population. A lack of primary care facilities was not found to increase cluster risk either. This might be explained by the relatively small spatial scale presented by zip codes and ability for pregnant women to find prenatal care in a bordering zip code. Future investigation is needed to determine the association between SMM and proximity to appropriate medical facilities.

Despite having areas with higher income inequality and lower food access, it is possible that no spatial SMM clusters were identified in Greenville due to the success of the Centering Pregnancy program which originated in the area. In addition to providing support and pregnancy education, the program has reduced preterm birth by 47% and encouraged public health agencies to invest in greater preventive measures affordable to all patients (Prisma Health, n.d.). The lack of spatial SMM clustering in this region suggests that community-based localized programs are effective in reducing the risk for adverse maternal health outcomes. A greater number of initiatives such as the CenteringPregnancy program could lessen the disparity between low income and minority populations.

Similar programs should be considered in less populated areas as literature has identified a maternal health disparity between urban and rural areas (Laditka et al., 2006; Lisonkova et al., 2016; Hirshberg and Srinivas, 2017; Hansen and Moloney, 2019). A study in Appalachia found that women in rural areas have multiple risk factors that contribute to higher instances of SMM (Hansen and Moloney, 2019). In South Carolina, researchers found that maternal health risks were higher for rural women using Medicaid compared to urban Medicaid beneficiaries. This was attributed to less prenatal care access of reasonable quality (Laditka et al., 2006). These studies indicate that rurality matters in the assessment of maternal health and further research is needed. Using Rural-Urban Commuting Area (RUCA) zip code data, our study found both urban and rural areas inside SMM risk clusters (*Figure 5*). Given that rural areas are generally more vulnerable to SMM and prenatal care shortages, focus should be placed on these areas to lessen the inequality experienced by women in less populated areas.

Though a relationship was not found between TRI emissions and SMM cluster risk in the statistical analysis, it is known that underprivileged populations tend to reside in more hazardous environmental areas compared to more affluent populations (Mohai et al., 2009; Mohai and Saha, 2007; Morello-Frosch et al., 2011). Considering this elevated risk, a focus on areas with more racialized economic segregation may identify and minimize these place-specific toxic environmental hazards.

The final GEE model found that high temperatures were associated with SMM excluding blood transfusions. Our conclusions align with those from Cil and Cameron that heatwaves negatively impact maternal health (2017). It is likely that a strong correlation exists between SMM and climate extremes as literature has identified a relationship between seasonal temperature and adverse birth outcomes (Strand et al., 2011; Basu et al., 2010; Deschenes et al., 2009). An association is likely present between SMM and ambient air pollution linked to seasonality. Previous research indicated that maternal exposure to wood smoke increases hypertensive pregnancies (Assibey-Mensah et al., 2019). Though these results contribute to the limited understanding surrounding maternal health and temperature in the US more research is needed to understand the impacts of climate on SMM.

*Strengths and Limitations*

This study examined a large dataset of maternal characteristics for an entire state from 1999 to 2017. The benefit of this large amount of information is the ability to analyze an array of patient characteristics and potential SMM risk factors. We were able to link multiple births to a single mother, which made for a more accurate longitudinal investigation. The inclusion of geographical analysis at a relatively fine scale provides important information to assist public health and policy makers in the prevention and intervention programs and changes to health-care delivery with focused community interventions (Huang et al., 2009). A further strength of our geographical analysis was the inclusion of time by examining space-time scan statistics, which showed spatial clusters occurring in the most recent study years.

There were several limitations in this study. While a useful visualization tool, SaTScan cannot explain the reason for risk variation in clusters. The use of a circular scan window identifies populations that are in circularly shaped areas, however this is not necessarily the pattern that SMM likelihood follows and use of an elliptical window would provide slightly increased capability for scanning along some geographic features (Chong et al., 2013). The 20% spatial window utilized for the GEE models presented risk clusters at a relatively localized scale compared to the 50% default which is more beneficial for intervention in homogenous communities rather than regional initiatives. Smaller spatial windows can be used to identify subclusters (Fang et al., 2006). The chosen restrictions on Kulldorff's spatial scan statistics may affect the validity of the results, specifically the small spatial bounds we imposed during cluster detection, but the general overlap between 15% and 20% spatial clusters suggest robustness in high-risk SMM clusters.

## Conclusion

The space-time SMM clusters including blood transfusions emerged during the final four years of study period, and 2017 saw the highest rate of SMM deliveries. Black and Hispanic women experienced higher SMM rates, particularly related to blood transfusions, and Black women were more likely to reside in high-risk clusters. These initial findings highlight the need for informed research and intervention at local scales for these populations. Existing literature supports this study's findings that SMM increases over time and that impacts minorities disproportionately. However, our results show that these SMM disparities are also clustered geographically. Economic and racial residential segregation is a form of structural racism that may create this disparity in South Carolina. High temperatures also increased SMM prevalence which warrants a study on seasonality and maternal health outcomes.

This work applies geographic knowledge to the SMM field and discovers sources of risk disparity in South Carolina. The methodology is applicable to other US regions and provides a means to identify spatial clusters of SMM and risk factors to investigate the associated socio-demographic characteristics of clusters. Findings ultimately inform maternal health advocates and policymakers and can assist in resource allocation or additional preventative care. As SMM rises in the US it is important that vulnerable populations are accurately targeted. This study spatially identifies SMM patterns and connects individual and area-level variables to likelihood.

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**Appendix:**

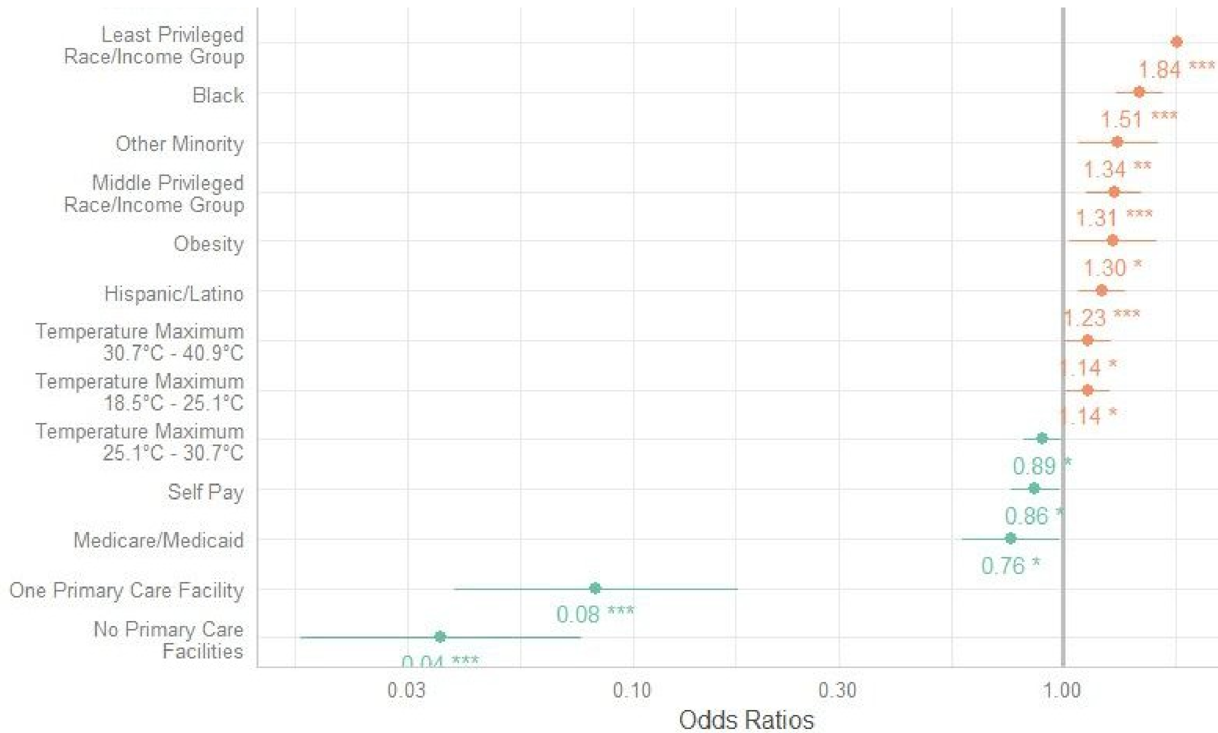


Figure. GEE Forest Plots for High-Risk SMM Clusters Excluding Blood Transfusions.

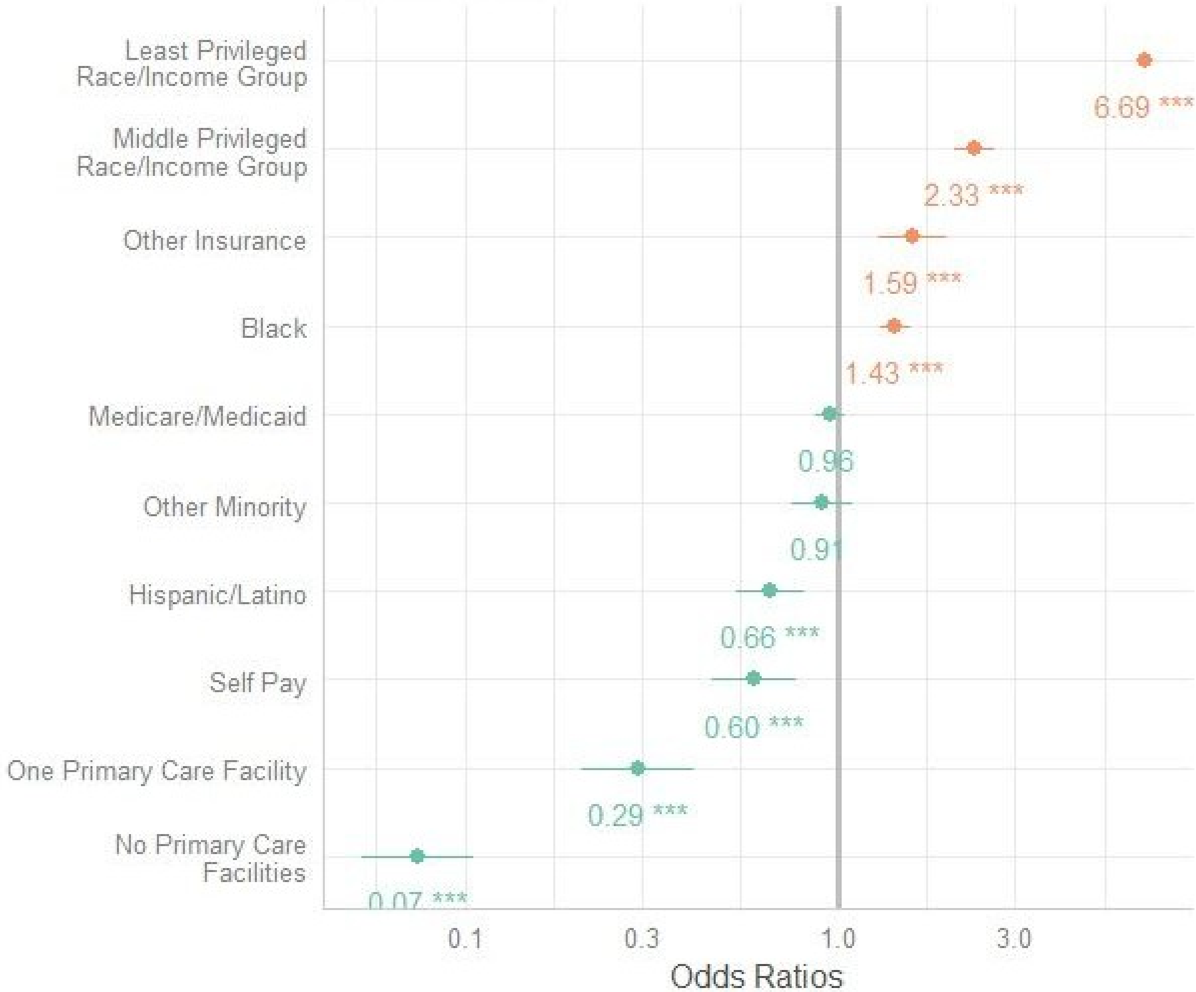


Figure. GEE Forest Plots for High-Risk Spatial SMM Clusters Including Blood Transfusions

Table. Index of Concentration at the Extremes Formulas by Krieger et al., 2016

| | |
|---|---|
| Income | (number of persons in high-income households) - (number of persons in low-income households) / total population with household income data |
| Race | number of white non-Hispanic persons) - (number of Black non-Hispanic persons) / number of persons with race/ethnicity data |
| Income and Race | (number of white non-Hispanic high-income persons) - (number of Black alone low-income persons) / number of persons with race/ethnicity and household income data |

## Vita

Stella Rae Harden was born and raised in a small town outside of Richmond, Virginia. Her parents, Rich and Missy Harden, instilled an appreciation for travel and the outdoors in her from a young age. After graduating from Hanover High School in Hanover, Virginia, in May 2016, Stella decided to move to Boone, North Carolina, to attend Appalachian State University.

As an undergraduate, Stella studied geography and minored in political science. As a junior, Stella participated in a research project with Dr. Maggie Sugg, Dr. Elizabeth Shay, and Lauren Andersen. This opportunity inspired Stella to pursue a master's degree in Geography at Appalachian State University. Stella graduated Summa Cum Laude with a Bachelor of Science in Geography in December 2019. Stella began her full-time graduate education at Appalachian in January 2020. As a graduate student, Stella became involved in mental health and maternal health research with Dr. Maggie Sugg. Upon graduating with a Master of Arts in Geography in December 2020, Stella plans to pursue a career with the consideration of pursuing a Ph.D. in Geography or Migration Studies in the future.