

# Examining the relationship between race and food insecurity in Texas, U.S.

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This paper reports an analysis of food insecurity in Texas, USA, and its relationship with race. The analysis was carried out at the tract level. Data were obtained from the US Census.

*Keywords:* Food Insecurity, Race, spatial analysis

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```
install.packages("textreg")

## The following package(s) will be installed:
## - textreg [0.1.5]
## These packages will be installed into "~/McMaster/Thesis/4GA3-Project-Group-2/renv/library/windows/R
##
## # Installing packages -----
## - Installing textreg ...          OK [linked from cache]
## Successfully installed 1 package in 14 milliseconds.

df_race <- readRDS("df_race.rds")
```

## **Introduction**

Approximately 18 million households experienced food insecurity at some point in 2023, with almost 7 million facing very low food insecurity (USDA, 2025). This makes up 13.5% of the total households in the United States of America, an increase of approximately one million households from 2022. Texas holds the second-highest rate of all states. 16.9% of Texas households face food insecurity in 2023 (USDA, 2025). This means that 16.9% of households went without access to nutritious and safe foods at some time in 2023. Caring about the impact that race has on food insecurity is crucial, as it highlights the systemic inequalities within marginalized communities. To understand this issue and strive for a state with adequate food for all residents, further understanding of the problem is needed.

Additionally, studies have shown that access to food is impacted by race (Beaulac et al., 2009). This paper aims to examine the relationship between race and food insecurity in the state of Texas, U.S., using food stamp usage as a proxy measure for food insecurity. The goal is to understand the relationship between these variables and why this phenomenon may occur. By the end of this paper, a better understanding of the overarching topic of racial disparities in food insecurity, specifically in Texas, will be found.

Three research questions guide the analysis in this paper: (1) How do race and food stamp usage vary across Texas counties?

- (2) Are there any clusters of food insecurity, and do these clusters correlate with racial composition?
- (3) Does racial composition predict food insecurity after accounting for socioeconomic factors and other confounders, and does this relationship vary geographically?

Our report will cover three primary sections:

### *Descriptive Statistics*

The first section of analysis will analyze the basic patterns of race and food stamp usage, calculating descriptive statistics for both variables to address the first research question. The results of this section are summarized in tables of descriptive statistics. Choropleth maps are used to visualize the spatial trends in this data. This section identifies the baseline geographic patterns of food insecurity and racial composition.

### *Spatial Statistics*

Next, to address research question two, food insecurity and racial composition will be tested to identify any clustering or distribution. These are methods of spatial autocorrelation. Food stamp usage hotspots are tested for overlap with clusters of certain racial groups.

### *Inferential Statistics*

The final analysis section uses OLS regression models to control for confounding variables such as income or education. Regression analysis will reveal the extent to which race plays a role in predicting food insecurity, independent of any possible confounders in order to address the third research question. Methods of geographically weighted regression models are used to better understand the role of geography in shaping this relationship.

## **Background**

### *Defining Food Insecurity*

Food insecurity refers to the lack of reliable access to sufficient, nutritious food which encompasses four dimensions: availability, access, stability and utilization (Uppal, 2023). Insecure household may face difficulties in acquiring food, affording nutritious meals or maintain stable access due to infrastructure or economic disruption. According to the USDA, food insecurity can range from limited dietary variety and quality to severe disruptions like insufficient food intake (Coleman-Jensen et al., 2019). Beyond nutritional concerns, it

is closely linked to a higher likelihood of chronic illnesses, mental health issues, frequent hospital visits and even mortality (Uppal, 2023). In 2018, around 11.1% of households in the United States, over 14 million, struggle with food insecurity, including 4.3% that experienced very low food security (Coleman-Jensen et al., 2019). On a global scale, rates of food insecurity have been increasing, driven by factors of inflation, economic uncertainty, and systemic inequalities. While these national statistics are alarming, Texas often exceeds national averages, particularly in marginalized and rural areas. In 2020-2022, 15.5% of households were food insecure, exceeding the national average of 12.8% (USDA ERS, 2023). Therefore, highlighting its urgency as a case study for deeper spatial and racial food access disparities (Dean & Sharkey, 2010; Janda et al., 2022). The complex and multifaceted nature of food insecurity calls for both large-scale policy reforms and locally tailored, community-driven strategies.

### *Structural Causes of Food Insecurity*

Food insecurity is associated with various structural inequalities, including income disparities, access to capital, and systemic barriers rooted in racism. Several studies revealed that food insecurity is the result of compounding factors that disproportionately affect racialized communities in the United States. In a systematic review of studies on food deserts by Beaulac et al. (2009), they concluded that socioeconomic deprivation at the community level intensifies individual-level disparities in the United States. Their review concluded that low-income neighbourhoods that were predominantly African American continuously had fewer supermarkets while experiencing limited geographic access to affordable, healthy food (Beaulac et al., 2009). This structural disadvantage hinders an entire community's access to nutritious foods, especially in areas dominated by convenience stores that typically offer unhealthy and expensive food items.

Similarly, Myers and Painter (2017) examined the relationship between race/ethnicity, nativity and food insecurity. They found that Black and Latino households in the United States suffer more than twice as much from food insecurity in comparison to white households, even when accounting for socioeconomic status (Myers & Painter, 2017). Given that minority neighbourhoods have fewer quality supermarkets regardless of socioeconomic status, the authors suggest this gap stems from spatial inequalities. These spatial inequalities indicate that race, independent of income, shapes access to nutritious food. Nam et al. (2015) confirm these findings in their analysis of racial disparities in food insufficiency. In their study, the authors found that Black, Hispanic, and American Indian families experience food insecurity at a statistically significantly higher rate than White families (Nam et al., 2015). When the authors conducted a breakdown of contributing factors, they discovered that this disparity among the minority groups was tied mainly to lower home ownership rates, access to credit, and insufficient financial assets (Nam et al., 2015). These economic disparities increase susceptibility during times of financial hardship, restricting minority families' ability to protect themselves from food insecurity. Collectively, the research conducted emphasizes that the intersection of race and socioeconomic class creates compounded disadvantages for families of non-White backgrounds. Furthermore, this suggests that food insecurity in the United States, particularly in Texas, is not solely tied to income but several other systemic barriers that are shaped by racial inequality.

### *Race, Place, and Access*

Texas food insecurity is deeply shaped by spatial and racial inequalities in food access. In rural Central Texas, residents often face limited access to supermarkets and healthy food outlets, typically traveling long distances for groceries and relying on nearby convenience stores with fewer nutritious options. This geographic isolation, coupled with underdeveloped infrastructure and lack of public transportation, contributes to higher food prices and limited dietary quality compared to urban areas (Dean & Sharkey, n.d.; Dean & Sharkey, 2011). Janda et al. (2022) further support these findings, examining food insecurities across different geographic contexts in Travis County. They found that individuals living in rural zip codes were more than twice as likely to experience food insecurities compared to those in urban areas. This remains significant even after controlling for factors like income, educational level, employment status and access to transportation (Janda et al., 2022). Additionally, Janda's 2020 dissertation research documented rural and peri-urban callers to the 2-1-1 helpline in Central Texas. The finding shows that these areas were significantly more likely to seek help with food assistance. This was true for individuals living in zip codes that lacked supermarkets, emphasizing the role that geographic proximity plays in shaping spatial disparities in food access.

Race and geography shape disparities in food insecurity across Texas. The Supplemental Nutrition Assistance Program (SNAP), formerly known as food stamps, was established to combat food insecurity among low-income populations providing assistance to purchase food. Yet disparities persist even among SNAP-eligible households. Samuel et al. (2023) found that across the United States, SNAP-eligible Black and multiracial households experience higher rates of food insecurities compared to White counterparts. This disparity was especially evident among those who were not enrolled in the program. Among households not participating in SNAP, those that identify entirely Black were 52% more likely to experience food insecurity compared to White households. Similarly, multiracial households faced a 42% higher risk of food insecurity than their White counterparts. Importantly, among households actively participating in SNAP, the racial disparities in food insecurity were no longer observed. This suggests that while food assistance programs can help reduce the effects of structural inequalities, it does not entirely eliminate them (Samuel et al., 2023). In Central Texas, Janda et al. (2022) reported that Hispanic participants had 2.79 times greater odds of being food insecure than participants who were non-Hispanic white. This aligns with the broader finding identifying that race/ethnicity often intersect with income in shaping food insecurity risk (Janda et al., 2022). Janda and others highlight that communities of color are disproportionately affected by systemic barriers such as reduced access to full-service grocery stores and over reliance on small retailers with fewer healthy options (Beaulac et al., 2009; Walker et al., 2010; Janda et al., 2022).

Rural Texans face unique and persistent barriers to food security, often shaped by limited infrastructure, social isolation and inadequate food retail presence. Dean and Sharkey (2011) emphasized that rural areas not only lack supermarkets, but exhibit weaker social networks and less communal support. These factors further undermine resilience against food insecurity. Janda et al. (2022) extends on this understanding by showing that rural residents in Central Texas often live farther from supermarkets, an average of 1.66 miles but closer to convenience stores with an average of 0.67 miles. This proximity gap disproportionately affects low-income and Hispanic households, exacerbating nutritional disparities and increasing vulnerability to food insecurity (Janda et al., 2022).

Moreover, the uneven distribution of food retailers and limited transportation options in rural areas indicate that effective solutions must be customized to local needs and the resident's lived experiences. Janda et al. (2022), emphasize the importance of incorporating factors such as perceived accessibility, community preferences and cultural appropriateness. These factors are often overlooked in conventional approaches to identify food deserts.

### *Policy Landscape and Limitations*

SNAP (formerly known as food stamps) is the largest federal food assistance initiative in the United States. It is designed to alleviate food insecurity by providing financial support for low-income families. While SNAP reduces food insecurity by helping millions of families each year, its effectiveness is still limited by structural and environmental factors. Grummon and Taillie (2018) found that even with SNAP participation, there are still racial disparities in purchasing patterns. Their findings show that Black SNAP participants tended to purchase more processed meats, sweeteners, and low-nutrient foods compared to White participants of the program (Grummon & Taillie, 2018). Notably, these disparities do not appear in non-participating families. This suggests that the SNAP program, although it may aid in access to food, does not enhance diet quality equally among different racial/ethnic groups (Grummon & Taillie, 2018).

Odoms-Young (2018) highlights how these disparities are influenced by structural racism in food systems and public policy. Factors such as housing segregation, financial inequality, and high incarceration rates disproportionately impact communities of colour (Odoms-Young, 2018). These factors create barriers to food assistance and healthy food options. The author also notes that these racial disparities exist even when socioeconomic factors are removed (Odoms-Young, 2018), highlighting once again that race independently impacts access to nutritious foods.

A study of a low-income Latino neighbourhood in Upstate New York by Lopez-Class and Hosler (2010) revealed that most local stores that accepted SNAP still provided limited access to nutritious items and high food prices. For example, only one store in the entire neighbourhood carried high-fiber bread compared to seven in the adjacent non-Latino neighbourhood (Lopez-Class & Hosler, 2010). On top of this, many of the stores were not disability-accessible and public transport to these locations was insufficient (Lopez-Class & Hosler, 2010). Consequently, residents without cars were often forced to rely on smaller retailers with higher

prices and fewer nutritional options, which erodes the intended support of SNAP assistance (Lopez-Class & Hosler, 2010).

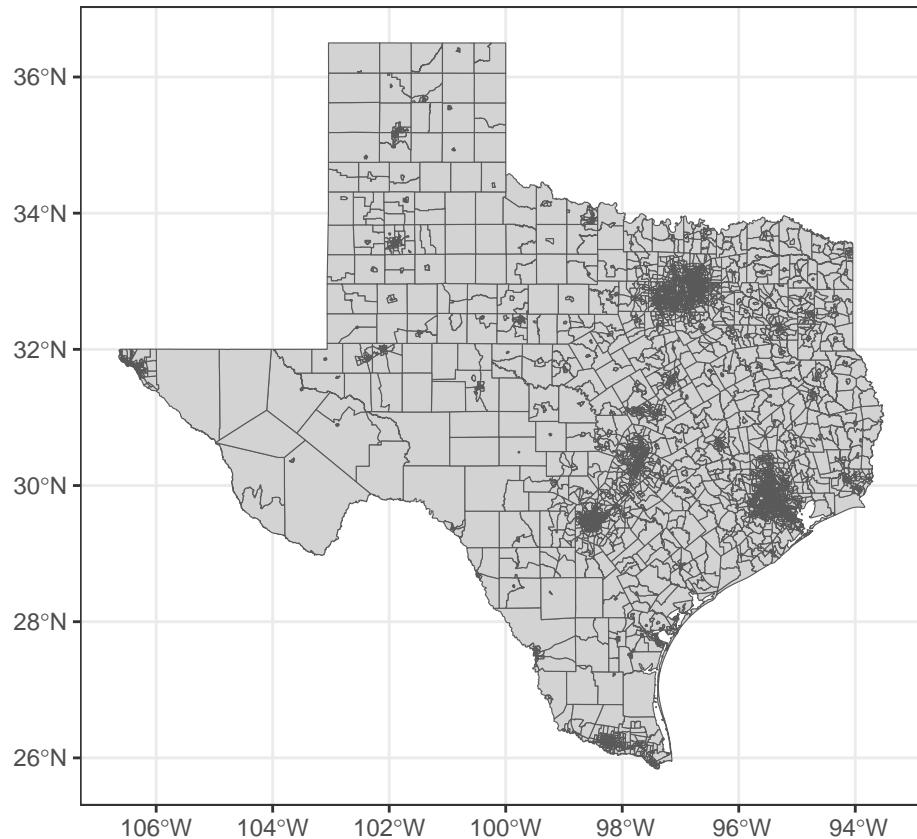
In conclusion, while SNAP has been critical for tackling food insecurity, its current system fails to address the disparities in purchasing patterns of minority groups and the system issues that lead to these racial and geographic disparities. Effective policy reforms are required to consider inequitable food access caused by transportation limitations, and racial and place-based disparities that constrain how SNAP assistance is used.

### *Gaps in the Literature*

Despite substantial research on food insecurity in the United States, particularly in Texas, a significant gap remains. The gaps are seen in studies that integrate both spatial and racial/ethnic dimensions using spatially explicit methods. Most of the existing studies focus on racial disparities (e.g. food insecurity among Black, Latino and immigrant community) or spatial disparities (e.g. rural-urban food deserts) but rarely examine how race, place and poverty interact at a localized scale (Beaulac et al., 2009; Myers & Painter, 2017). Myers and Painter (2017) found persistent food insecurity divide across racial/ethnic and nativity lines, even after controlling for socioeconomic status. On the other hand, spatial studies like Janda et al. (2022) and Lopez-Class & Hosler (2010) underscore geographic barriers like proximity to supermarkets but does not consistently take into account for racialized experiences of those affected. Furthermore, studies examining the impact on SNAP on reducing disparities have primarily used cross-sectional or nationwide datasets. This often fails to capture how SNAP participation intersect with race and geographical context at a local level (Grummon & Taillie, 2018). This leaves an analytically blind spot regarding localized, intersectional factors of food insecurity in Texas. This project hopefully contributed to closing this gap by using inferential and spatial statistical methods to examine how race, income, location and SNAP usage interact, offering a greater understanding of food access inequalities in Texas.

### **Study area**

Food insecurity was studied at the tract level in the state of Texas (see Figure 1). There are 6896 tracts in the state, and each of these tracts was used in the analysis. In the U.S., around 11.1% of households experience food insecurity. Texas faces higher rates, with 14% of families identifying as food insecure in 2018 (Coleman-Jensen et al. 2019). The state was selected for this reason, having a higher rate of food insecurity in the country. Many studies conducted in Texas have detailed the relationship between food insecurity and other variables. A study by Beaulac et al. (2009) found that food access in the U.S. is significantly impacted by income and race. This study was conducted to analyze the spatial patterns between these variables and discuss the potential reasons for them.



Data

The data used for the project primarily comes from the U.S. Census Bureau. This data can easily be imported into R using the “tidycensus” package. Additionally, the “tidyverse” package will be used since it contains key libraries such as “ggplot2” which will allow us to plot the census data for each county within Texas, making any spatial patterns easily identifiable. The full list of packages included within the tidyverse is available on their website. The “sf” package for Simple Features will also be imported to make spatial data easier to create and visualize. Likewise, we will use packages such as “gt” and “kableExtra” to create clean looking tables.

Listed below are the U.S. Census Bureau variables used with their respective R codes (that allow us to import the data directly into R through the `tidycensus` package). The data used will be from 2023 which is the most recent year in which the data is available in R.

The food stamp count is crucial to use to identify food security or insecurity in each county, as that is the most relevant quantitative data relating to food security that we could find. By converting food stamp usage to per capita rates (using the population for each county), the similarities and/or differences in food stamp usage (and consequently, food security/insecurity) can be mapped using ggplot2. This can then be compared to racial demographics (mapped by comparing the white, black, Asian, American Indian and to see if there is a potential correlation between race and food insecurity/food stamp usage.

## Methods

### *Methods for Descriptive & Spatial Statistics*

County-level data on food stamp usage and race in Texas were analyzed using the df\_race.rds shapefile. This shapefile included variables such as the percentage of residents receiving food stamps and racial composition. It was imported into R and reprojected using st\_transform() to EPSG:3857 to ensure accurate distance-based and spatial relationship calculations.

To visualize the geographic distribution of food stamp usage, an initial choropleth map was created using ggplot() and geom\_sf(), with the variable food\_stamp\_p representing the percentage of food stamp recipients in each county. The scale\_fill\_viridis\_c() was used to apply a colour gradient that improves interpretability for viewers by emphasizing variation in values. Prior to analysis, counties with missing values were excluded using filter(!is.na(food\_stamp\_p)) to prevent skewed results and ensure clean spatial computations.

To analyze local spatial interactions, a neighbourhood structure was established using Queen contiguity through the poly2nb() function, which identifies counties as neighbours if they share a boundary or a corner point. This structure was then transformed into a spatial weights matrix using nb2listw(), allowing the influence of neighbouring counties to be incorporated into subsequent spatial analyses.

Spatial moving averages (SMAs) were computed using lag.listw() for key variables such as food stamp usage (sma\_food\_stamp\_p) and racial proportions (e.g., sma\_white\_p, sma\_black\_p, sma\_asian\_p, sma\_amERICAN\_inDIAN\_p, sma\_pacific\_islander\_p, sma\_other\_p). SMAs provide a smoothed view of regional patterns by averaging the values of surrounding counties instead of the raw data. This approach emphasizes clusters of consistent low or high values, making the broader spatial trend easy to identify.

A null simulation envelope was generated to assess whether observed spatial patterns were stronger than would be expected under random distribution. It involved randomizing the food stamp usage values using a sample (food\_stamp\_p) and recalculating the SMA of the randomized data. Therefore, it created a baseline scenario representing spatial randomness, allowing for visual and statistical comparison with the actual SMA pattern. The difference between the observed and randomized results offers insight into the presence and strength of spatial autocorrelation within the data.

The local Gi\* statistic (Local G) was computed using localG() from the spdep package to identify areas of statistically significant clustering. This technique evaluates each county's value relative to the average of its neighbouring counties and generates a Z-score. This Z-score determines whether it belongs to a statistically significant high-value cluster (hotspot) or a low-value cluster (coldspot). The analysis was applied to food stamp usage and racial proportion to explore the spatial overlap between race and food insecurity. The resulting Gi\* values were incorporated using mutate() and converted to numeric format using as.numeric() to enable plotting. Since localG() outputs a specialized object class, converting the results to numeric format was required to ensure compatibility with ggplot() for mapping and visualization.

Lastly, maps were generated to visualize the Gi\* Z-scores using ggplot() and scale\_fill\_gradient2(), with a midpoint of zero. Red tones indicated statistically significant hotspots (high-value clusters), blue/green tones indicated coldspots (low-value clusters), and yellow areas represented neutral or non-significant regions. This mapping approach successfully highlighted clusters of food insecurity and racial distribution, offering a spatial perspective for understanding systemic disparities among the counties in Texas.

### *Methods for Regression Analysis*

Regression models were estimated using tract-level data on per-capita food stamp usage, racial composition, and several control variables, including unemployment rate, median household income, and per-capita households with children.

Initial analyses employed methods of Ordinary Least Squares (OLS) regression to examine the relationship between food stamp usage and racial composition, controlling for socioeconomic factors. To resolve the challenge of perfect multicollinearity, the White racial category was omitted as the reference group. Both linear and log-transformed models were tested to explore differences in functional form. However, a Moran's I test using the moran.test() function revealed significant spatial dependence, prompting further investigation.

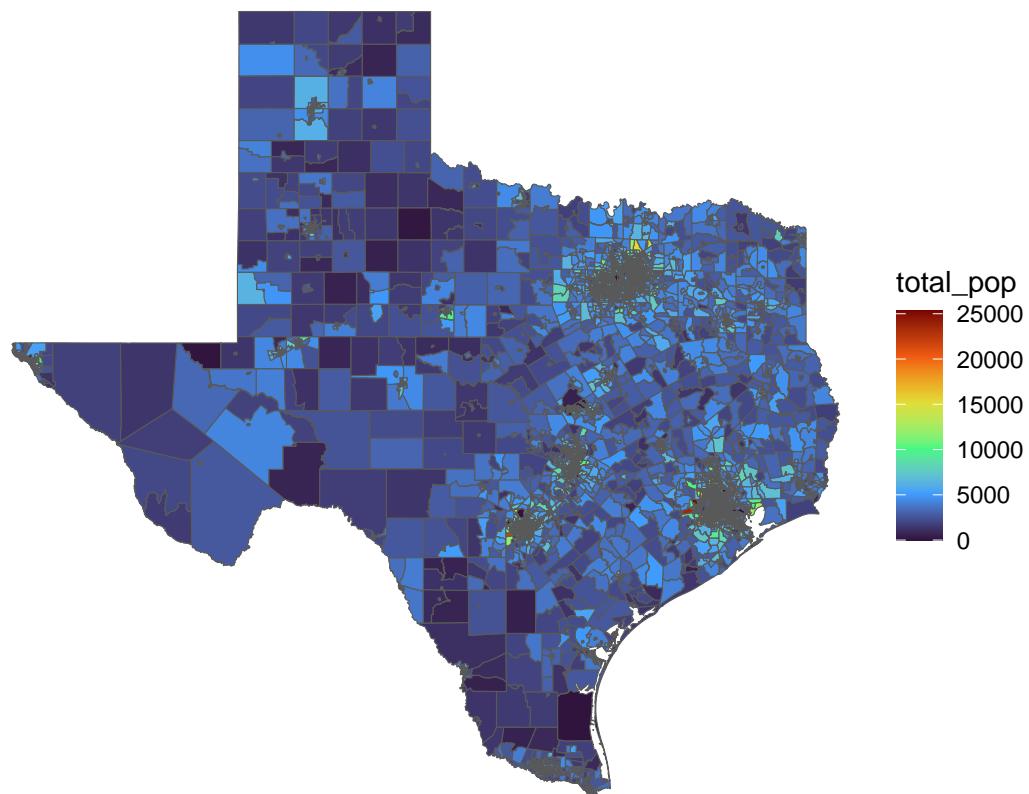
To address spatial autocorrelation in the OLS residuals, a spatial weights matrix was constructed using a k-nearest neighbors approach. Tract centroids were calculated using st\_centroid(), and neighborhoods were

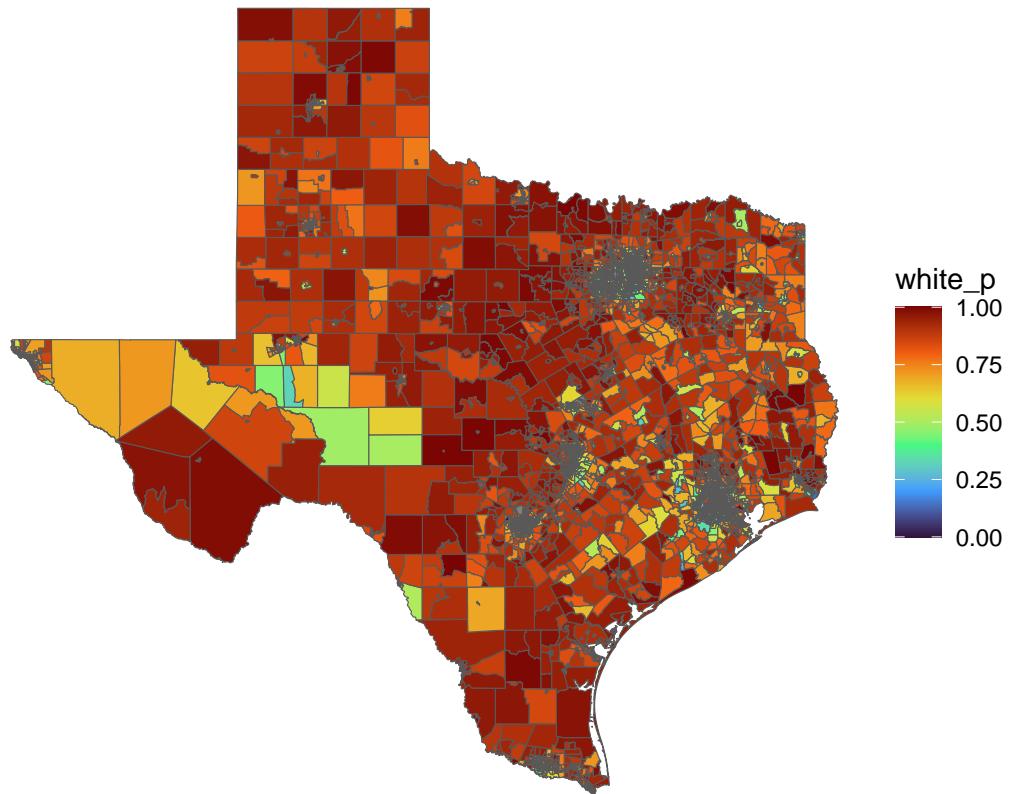
defined with  $k=4$  using `knearneigh()`. The final spatial weights matrix was constructed using `nb2listw()`. A geographically weighted regression (GWR) model with Gaussian weighting was then estimated using `gwr.sel()` and `gwr()` to produce localized estimates. However, residuals from the GWR model remained spatially autocorrelated, as indicated by a Moran's I test.

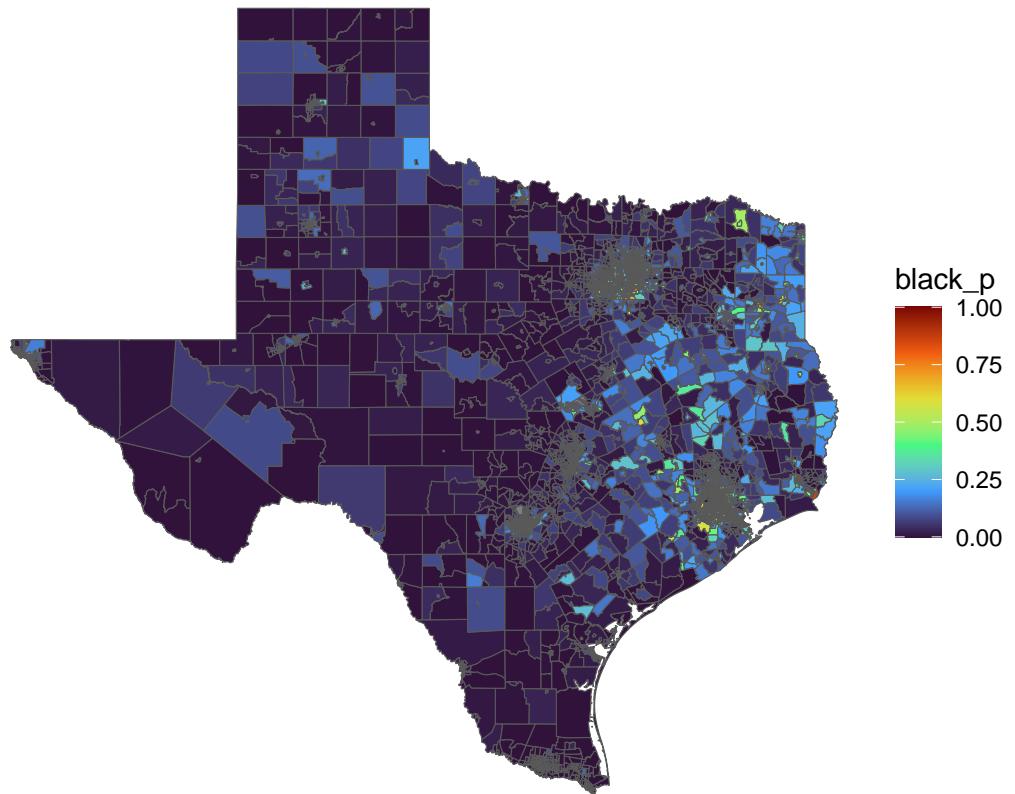
To explicitly account for residual spatial dependence, a Spatial Error Model (SEM) was estimated. This method accounts for spatial autocorrelation by incorporating a function of the spatially dependent residuals within the error term. A Moran's I test confirmed spatial independence of the SEM residuals, indicating the validity of the estimates.

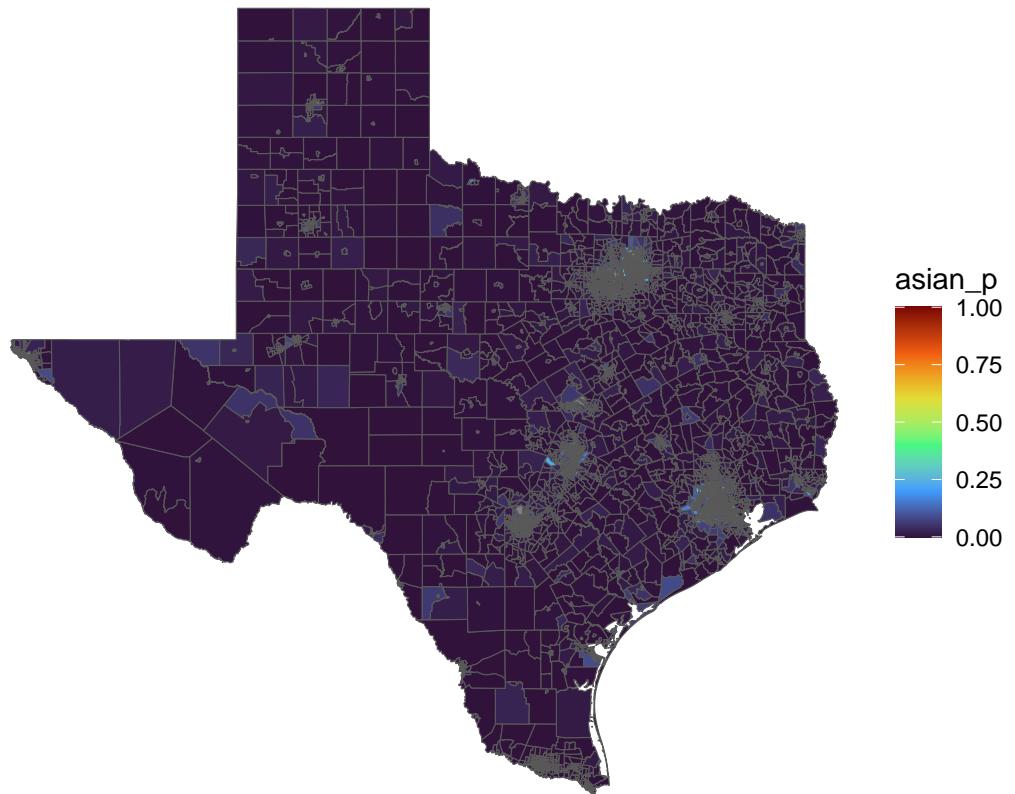
## Analysis

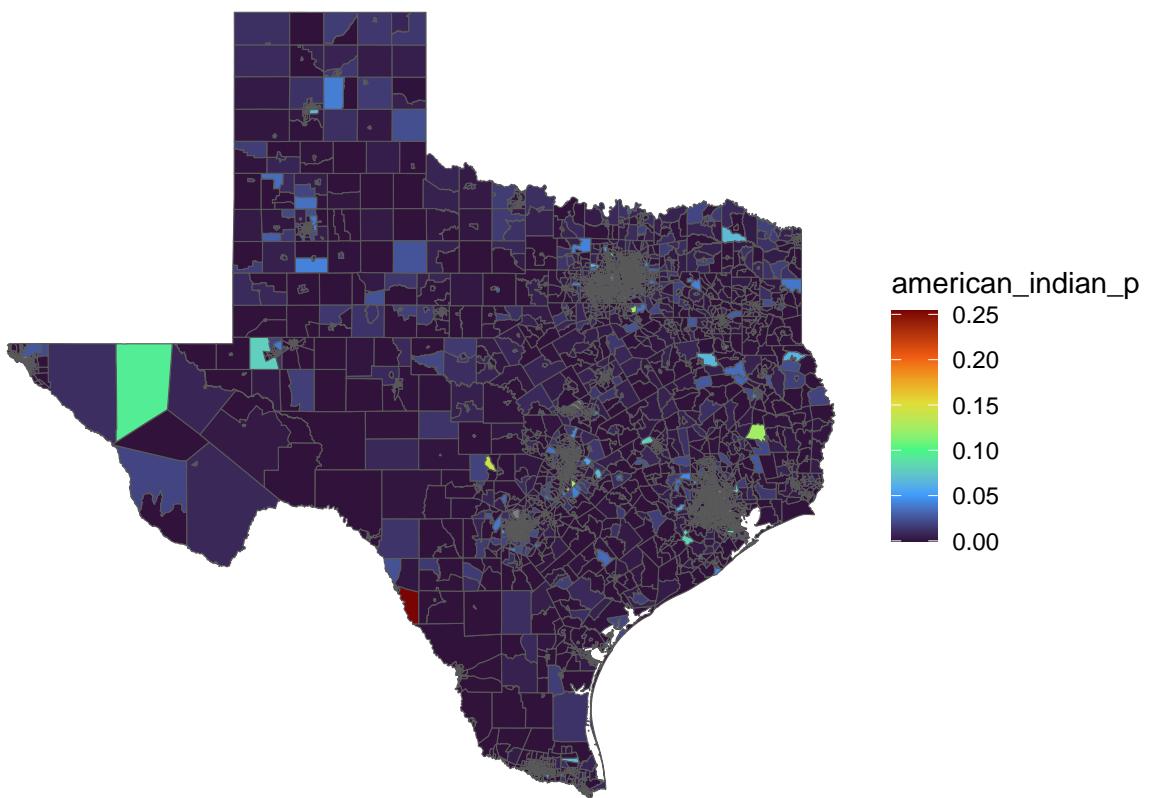
### *Descriptive Statistics*

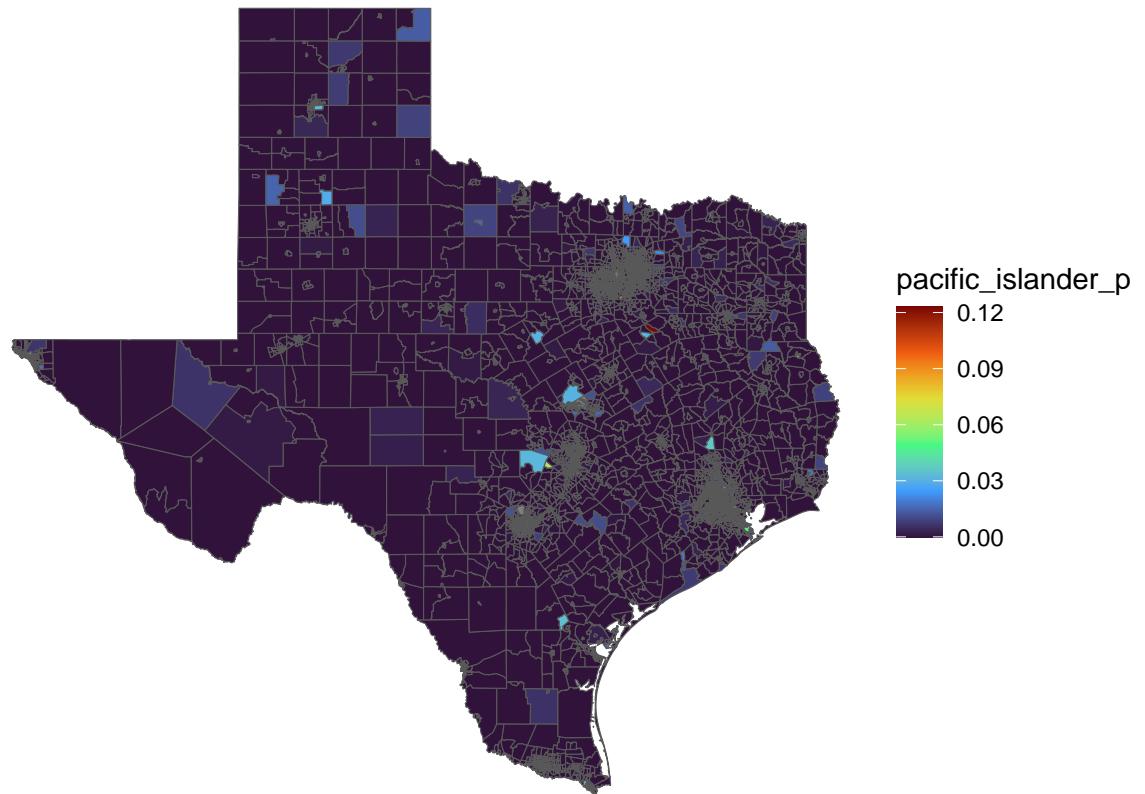


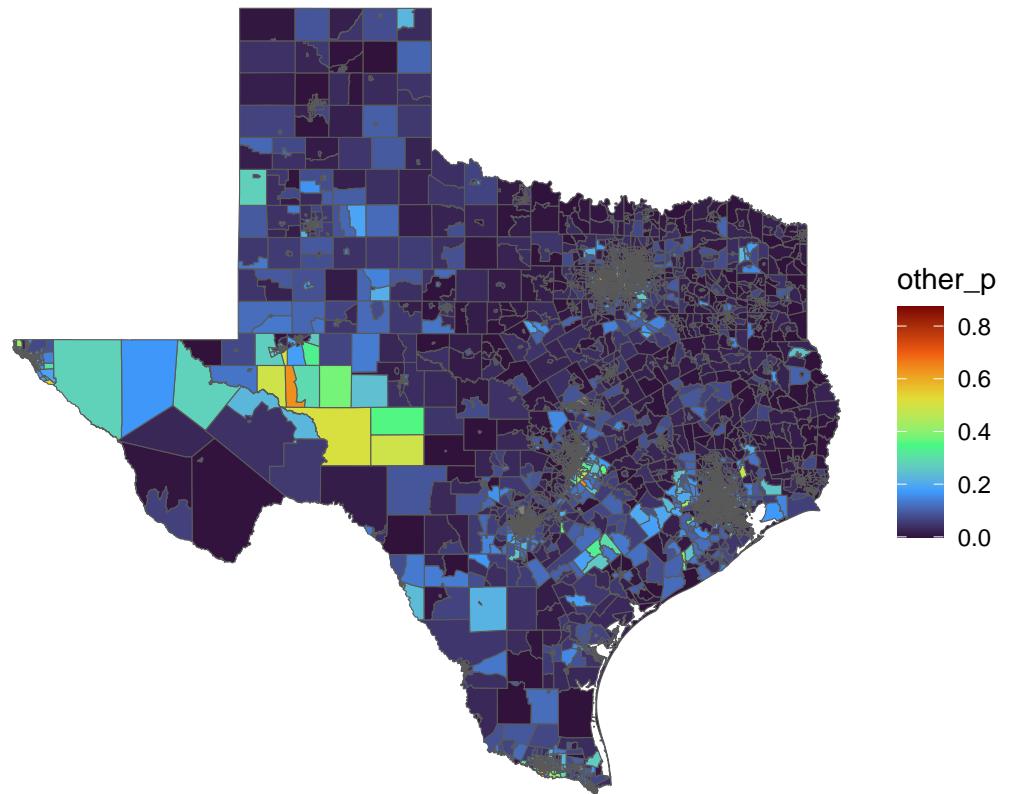


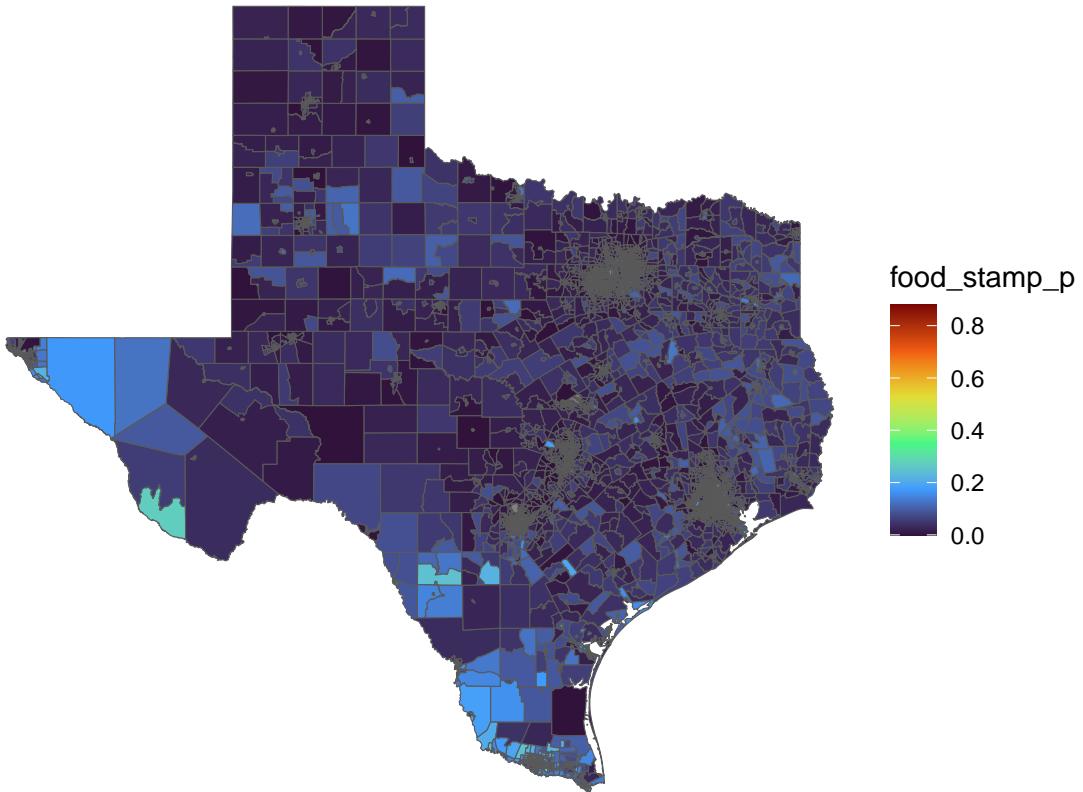












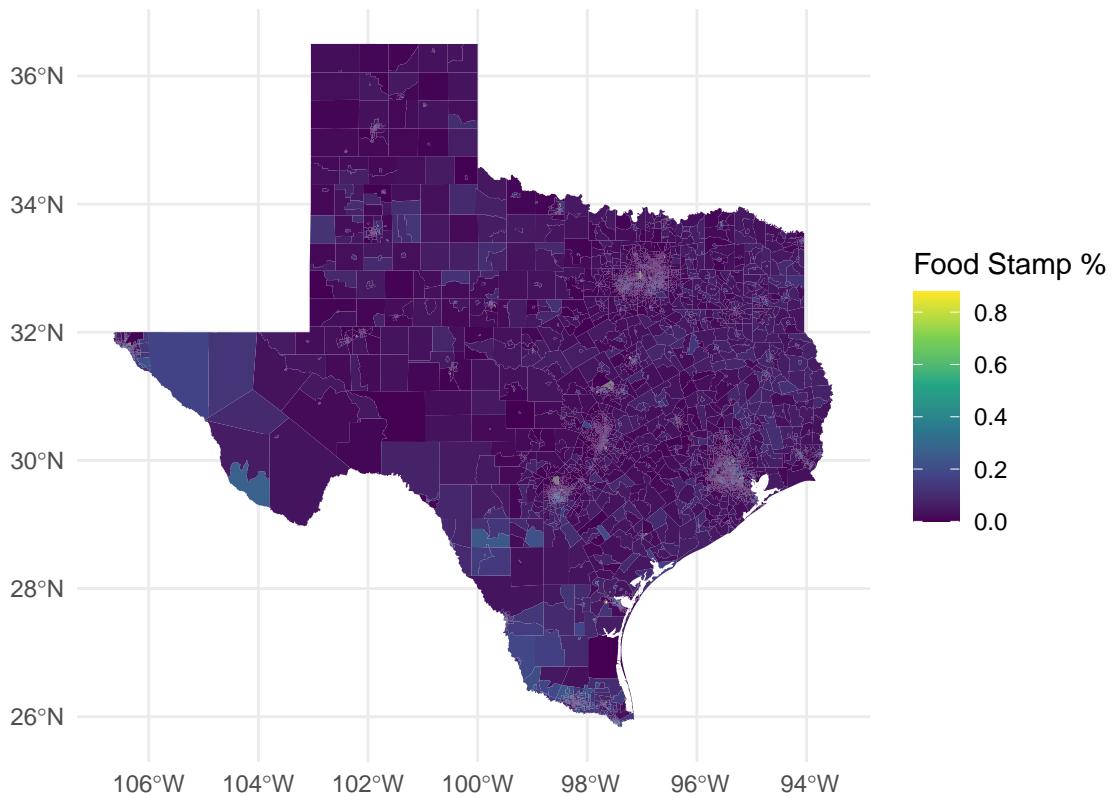
### Spatial Statistics

```
df_race <- readRDS("df_race.rds")
```

*Chloropleth Visualization of Food Stamp Usage in Texas*

```
ggplot(df_race) +  
  geom_sf(aes(fill = food_stamp_p), color = NA) +  
  scale_fill_viridis_c() +  
  theme_minimal() +  
  labs(title = "Food Stamp Usage per Capita in Texas",  
       fill = "Food Stamp %")
```

## Food Stamp Usage per Capita in Texas



### Spatial Moving Averages

```
df_race_proj <- st_transform(df_race, crs = 3857) # Defining the projection for the df_race dataset

df_race_filter <- df_race_proj %>% # Filtering out any counties that had values of "NA" for food stamp %
  filter(!is.na(food_stamp_p))

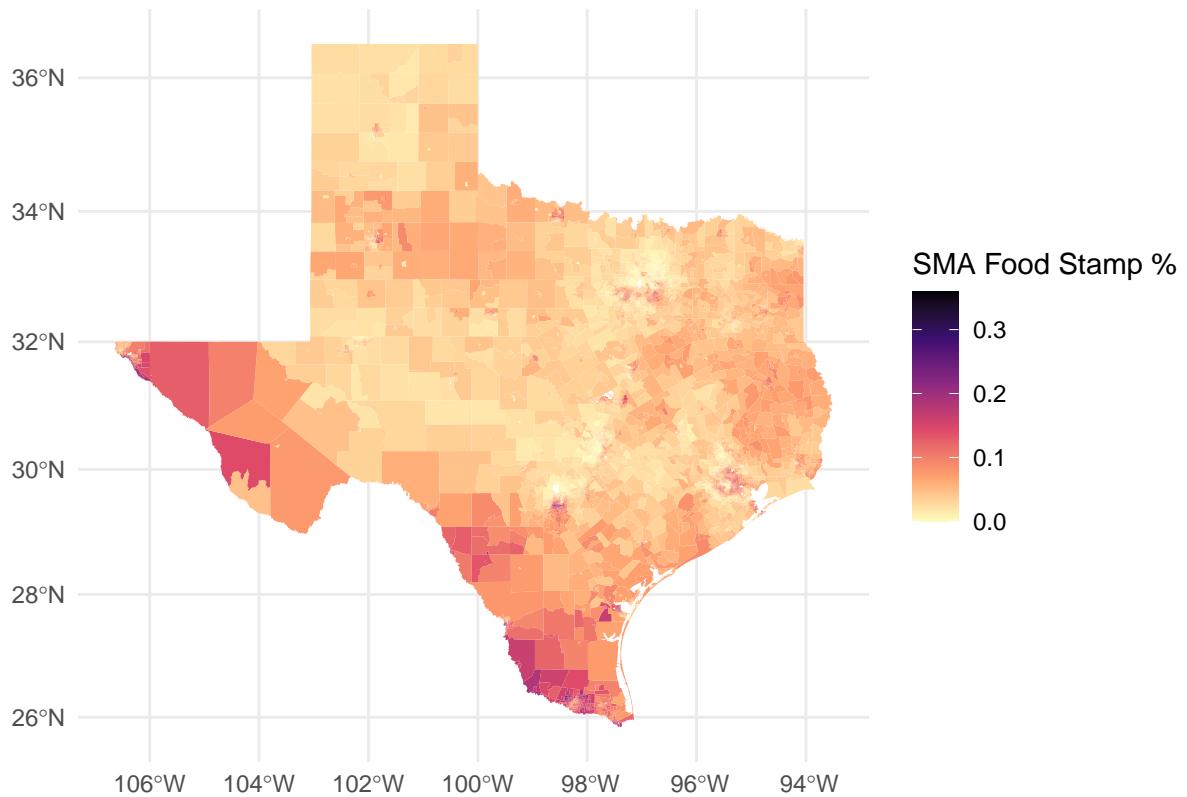
df_race.nb <- poly2nb(df_race_filter) # Setting up the neighbourhood function

df_race.w <- nb2listw(df_race.nb) # Creating the weighted matrix

# Spatial Moving Averages for Food Stamp Usage
df_race_filter <- df_race_filter %>%
  mutate(sma_food_stamp_p = lag.listw(df_race.w, food_stamp_p))

# Plotting SMA for Food Stamps
ggplot(df_race_filter) +
  geom_sf(aes(fill = sma_food_stamp_p), color = NA) +
  scale_fill_viridis_c(option = "magma", direction = -1) +
  theme_minimal() +
  labs(
    title = "Spatial Moving Average of Food Stamp Usage in Texas",
    fill = "SMA Food Stamp %"
  )
```

## Spatial Moving Average of Food Stamp Usage in Texas



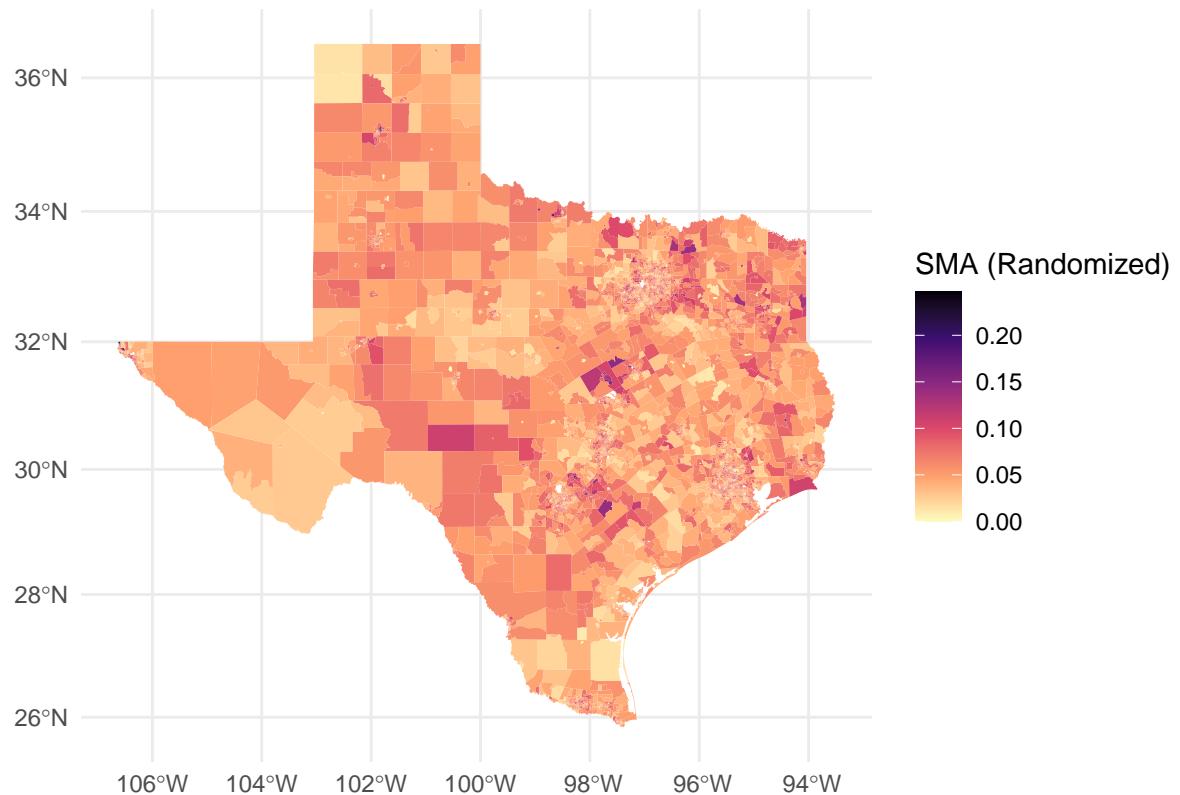
```
# Creating a Null Landscape for the SMA of Food Stamp Usage
set.seed(2025)

df_race_filter <- df_race_filter %>%
  mutate(food_stamp_random = sample(food_stamp_p))

df_race_filter <- df_race_filter %>%
  mutate(sma_food_stamp_random = lag.listw(df_race.w, food_stamp_random))

# Plotting the Null Landscape for the SMA of Food Stamp Usage
ggplot(df_race_filter) +
  geom_sf(aes(fill = sma_food_stamp_random), color = NA) +
  scale_fill_viridis_c(option = "magma", direction = -1) +
  theme_minimal() +
  labs(
    title = "Spatial Moving Average of Food Stamp Usage (Null Landscape)",
    fill = "SMA (Randomized)"
  )
```

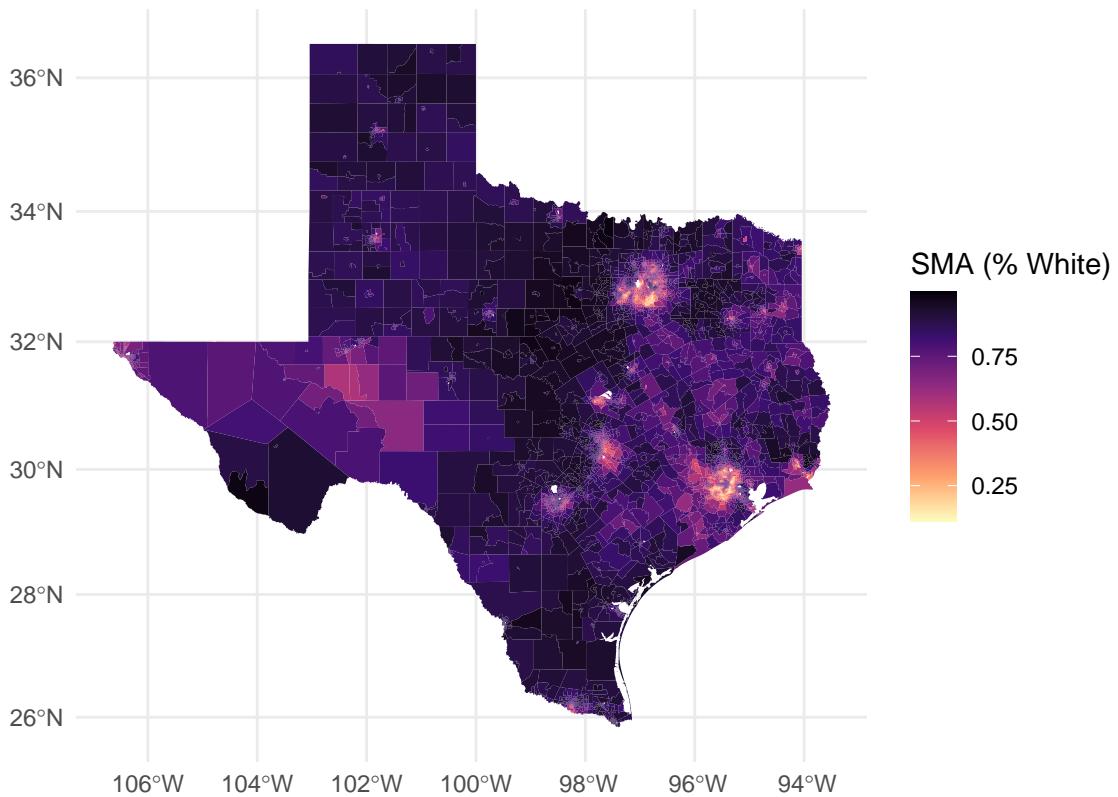
## Spatial Moving Average of Food Stamp Usage (Null Landscape)



```
# Computing SMA for Each Race
df_race_filter <- df_race_filter %>%
  mutate(
    sma_white_p = lag.listw(df_race.w, white_p),
    sma_black_p = lag.listw(df_race.w, black_p),
    sma_asian_p = lag.listw(df_race.w, asian_p),
    sma_american_indian_p = lag.listw(df_race.w, american_indian_p),
    sma_pacific_islander_p = lag.listw(df_race.w, pacific_islander_p),
    sma_other_p = lag.listw(df_race.w, other_p)
  )
```

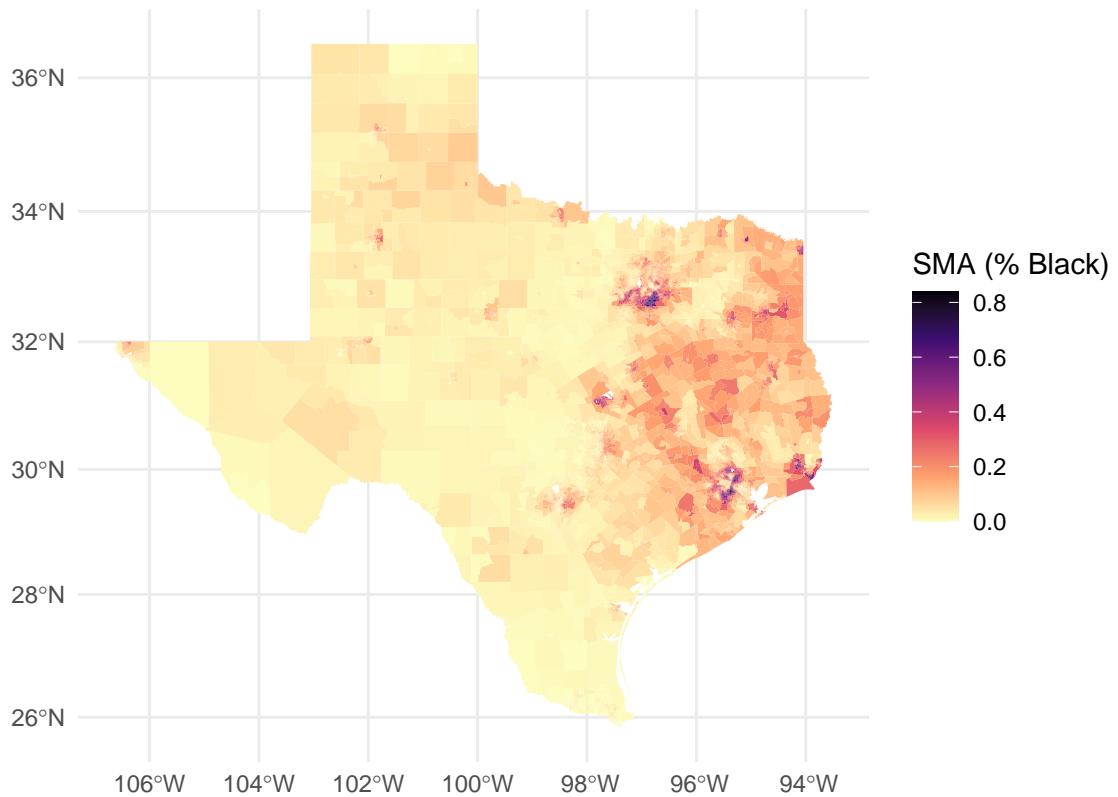
```
# Mapping SMA for the White Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = sma_white_p), color = NA) +
  scale_fill_viridis_c(option = "magma", direction = -1) +
  theme_minimal() +
  labs(
    title = "Spatial Moving Average: % White Population",
    fill = "SMA (% White)"
  )
```

## Spatial Moving Average: % White Population



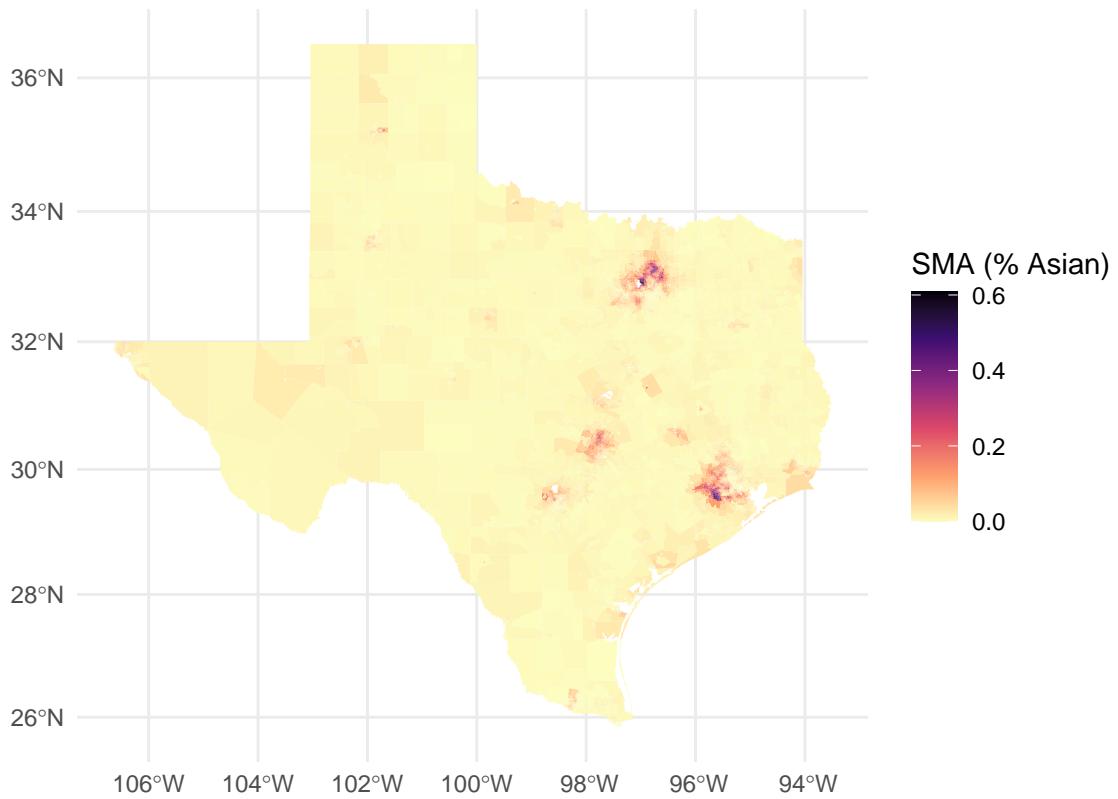
```
# Mapping SMA for the Black Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = sma_black_p), color = NA) +
  scale_fill_viridis_c(option = "magma", direction = -1) +
  theme_minimal() +
  labs(
    title = "Spatial Moving Average: % Black Population",
    fill = "SMA (% Black)"
  )
```

## Spatial Moving Average: % Black Population



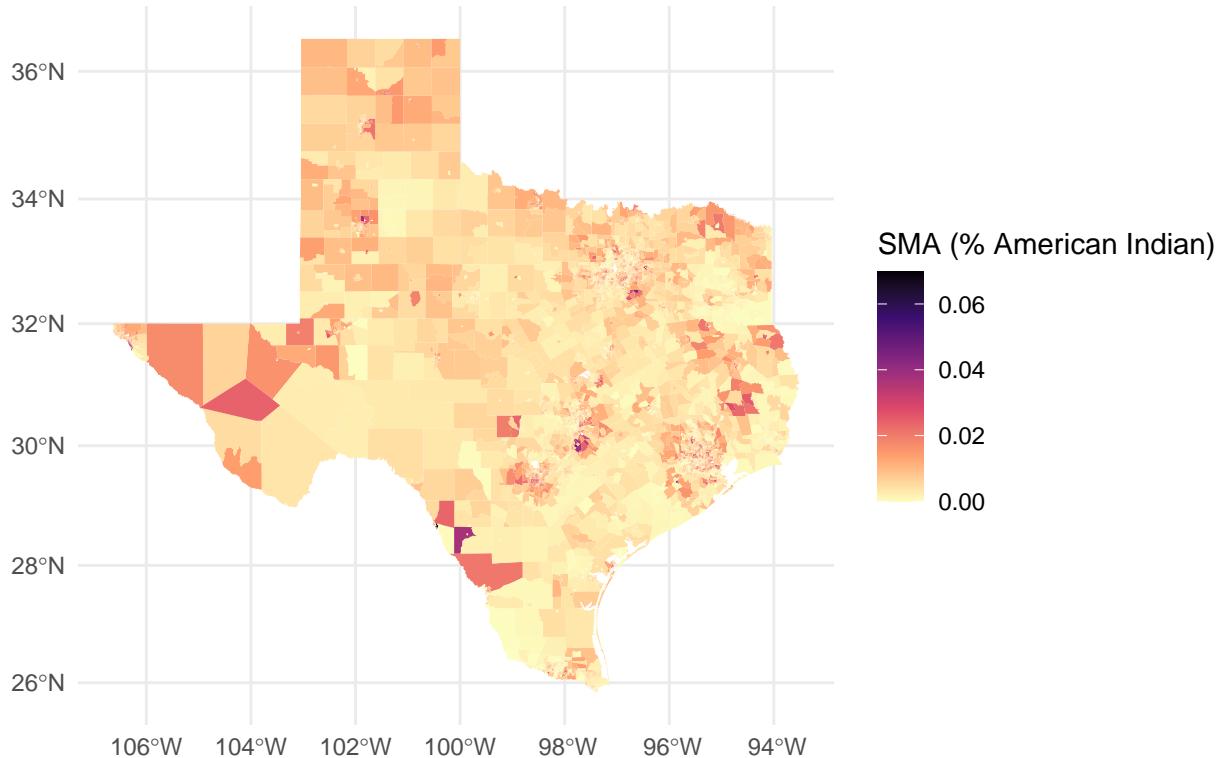
```
# Mapping SMA for the Asian Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = sma_asian_p), color = NA) +
  scale_fill_viridis_c(option = "magma", direction = -1) +
  theme_minimal() +
  labs(
    title = "Spatial Moving Average: % Asian Population",
    fill = "SMA (% Asian)"
  )
```

## Spatial Moving Average: % Asian Population



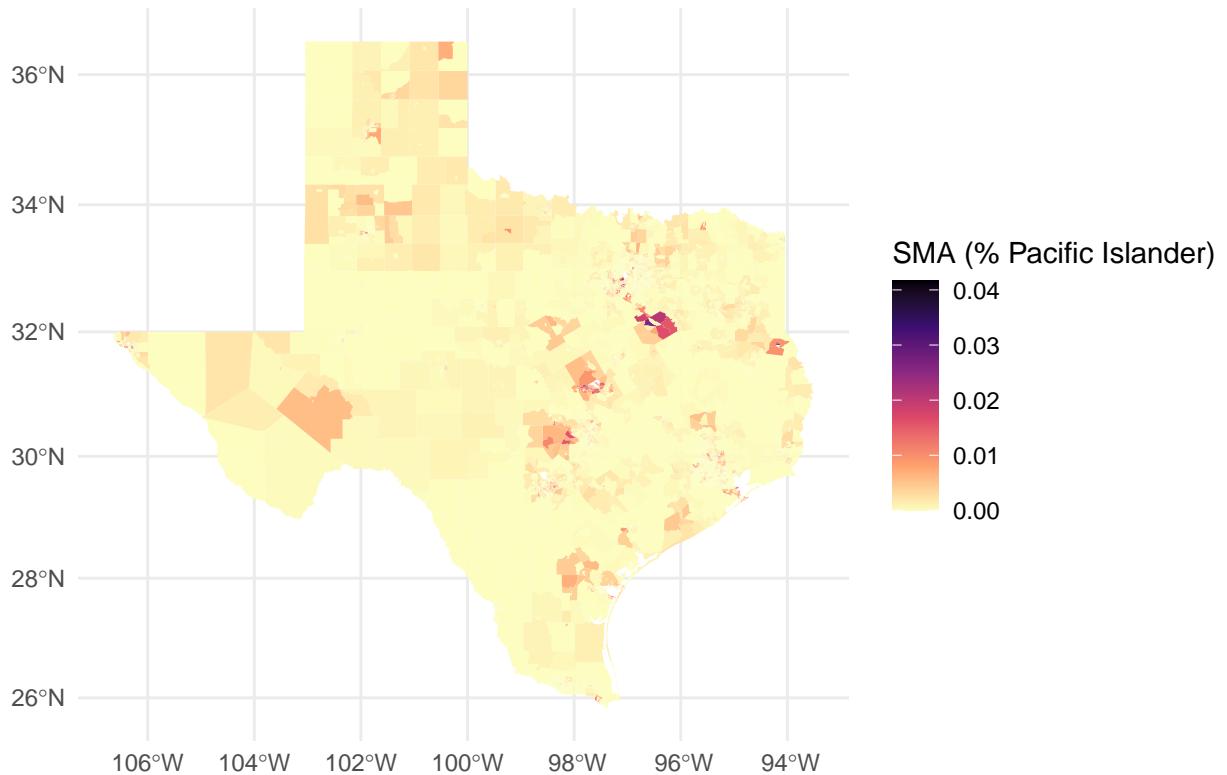
```
# Mapping SMA for the American Indian Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = sma_american_indian_p), color = NA) +
  scale_fill_viridis_c(option = "magma", direction = -1) +
  theme_minimal() +
  labs(
    title = "Spatial Moving Average: % American Indian Population",
    fill = "SMA (% American Indian)"
  )
```

## Spatial Moving Average: % American Indian Population



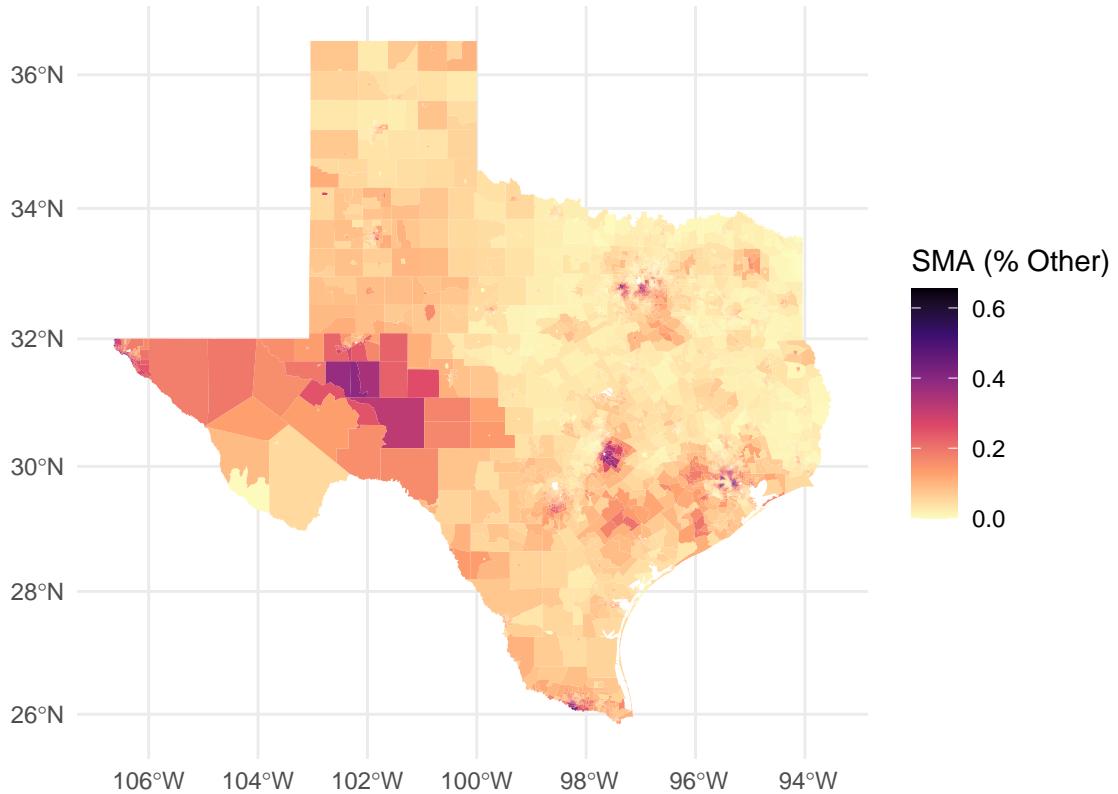
```
# Mapping SMA for the Pacific Islander Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = sma_pacific_islander_p), color = NA) +
  scale_fill_viridis_c(option = "magma", direction = -1) +
  theme_minimal() +
  labs(
    title = "Spatial Moving Average: % Pacific Islander Population",
    fill = "SMA (% Pacific Islander)"
  )
```

## Spatial Moving Average: % Pacific Islander Population



```
# Mapping SMA for the Other Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = sma_other_p), color = NA) +
  scale_fill_viridis_c(option = "magma", direction = -1) +
  theme_minimal() +
  labs(
    title = "Spatial Moving Average: % Other Population",
    fill = "SMA (% Other)"
  )
```

## Spatial Moving Average: % Other Population



The Spatial Moving Average (SMA) map for food stamp usage reveals a clear spatial clustering pattern, particularly concentrated in the southern and southwestern regions of Texas. These clusters are characterized by darker shading, indicating that high food stamp usage is not randomly distributed but spatially grouped. This visual pattern is further supported when compared to the randomized null SMA map, which lacks any coherent structure or concentration, reinforcing the idea that the observed clustering is meaningful rather than due to chance. When the food stamp map is visually compared to the SMA maps for racial demographics, some alignment emerges, but the degree of overlap varies across groups. For example, the Black population displays strong clustering in the eastern part of the state, where there is also notable food stamp usage, suggesting a potential spatial relationship. The white population is more heavily clustered in central and northwestern Texas, with only partial overlap in the southwest, where some food stamp clustering also appears. Other racial groups, including Asian, American Indian, Pacific Islander, and those categorized as “Other” show more dispersed or minimal clustering, making spatial comparisons less conclusive. Overall, while visual analysis of the SMA maps highlights several potential co-located clusters, especially for the Black population, these observations remain exploratory. The spatial clustering suggests areas of concentrated socio-economic vulnerability, but the strength of the relationship between race and food stamp usage would require more rigorous statistical testing to confirm.

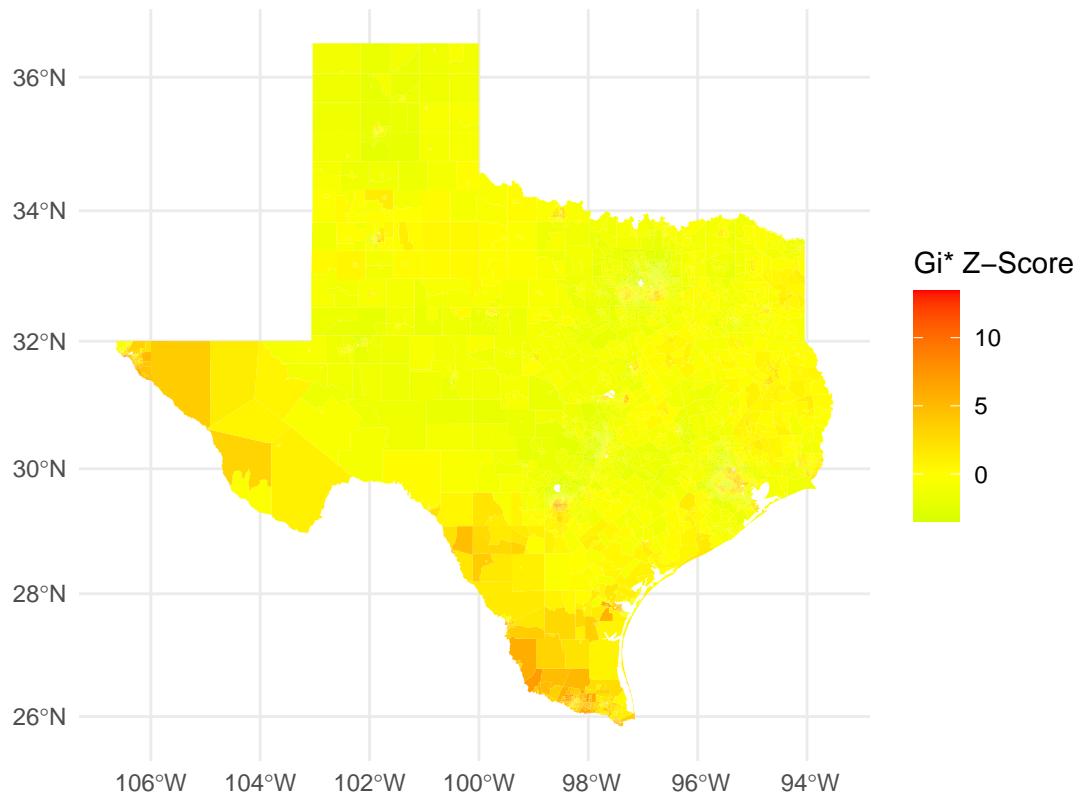
*Local G*

```
# Local G for Foodstamp Usage
foodstamps_g <- localG(df_race_filter$food_stamp_p, df_race.w)

df_race_filter$foodstamps_g <- as.numeric(foodstamps_g)
```

```
# Plotting Local G for Food Stamp Usage
ggplot(df_race_filter) +
  geom_sf(aes(fill = foodstamps_g), color = "NA") +
  scale_fill_gradient2(
    low = "green", mid = "yellow", high = "red", midpoint = 0,
    name = "Gi* Z-Score"
  ) +
  theme_minimal() +
  labs(title = "Gi* Hotspot Analysis of Food Stamp Usage")
```

Gi\* Hotspot Analysis of Food Stamp Usage

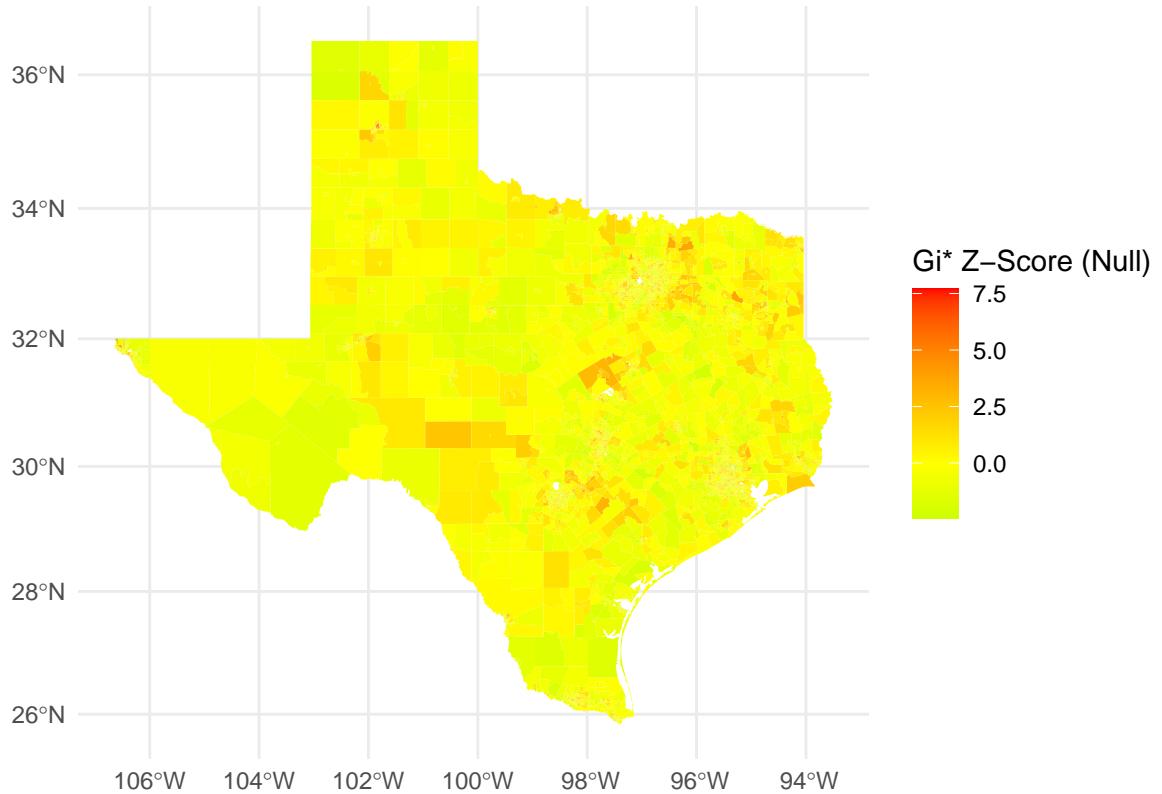


```
# Local G on Null Landscape
foodstamps_g_null <- localG(df_race_filter$food_stamp_random, df_race.w)

df_race_filter$foodstamps_g_null <- as.numeric(foodstamps_g_null)
```

```
# Plotting Local G on Null Landscape
ggplot(df_race_filter) +
  geom_sf(aes(fill = foodstamps_g_null), color = NA) +
  scale_fill_gradient2(
    low = "green", mid = "yellow", high = "red", midpoint = 0,
    name = "Gi* Z-Score (Null)"
  ) +
  theme_minimal() +
  labs(title = "Gi* Hotspot Analysis of Food Stamp Usage (Null Landscape)")
```

## Gi\* Hotspot Analysis of Food Stamp Usage (Null Landscape)

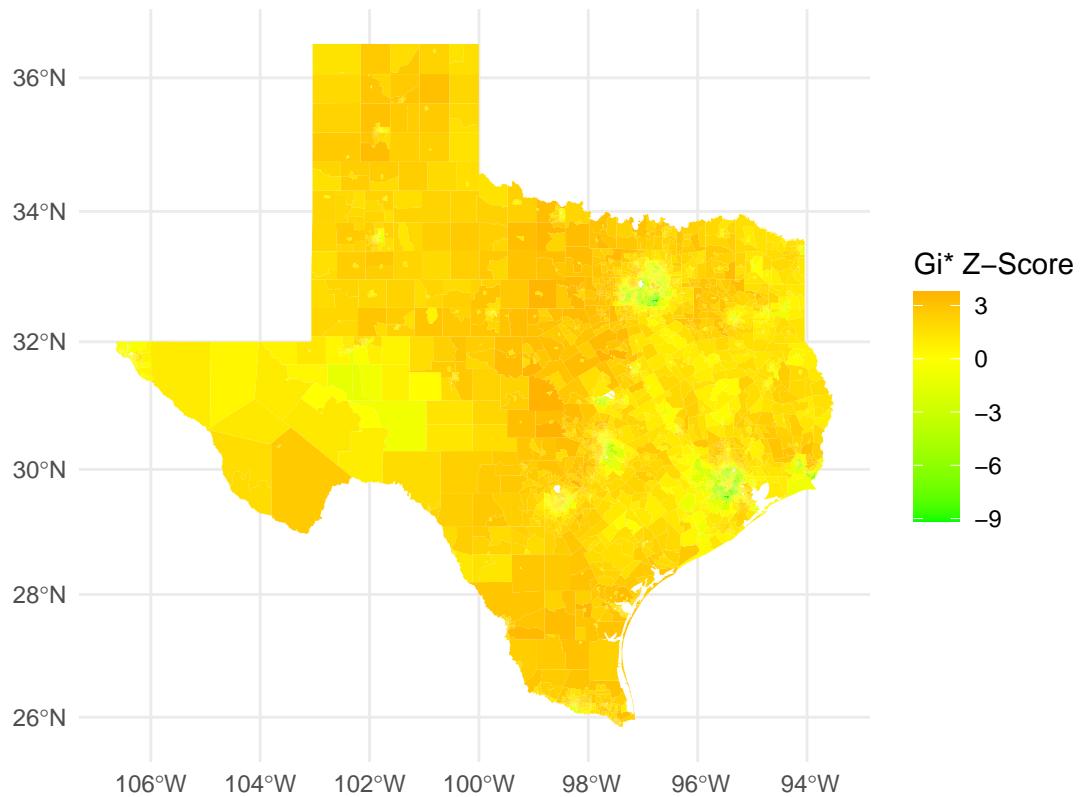


### *Gi\** for Each Race

```
# Computing Local G for Each Race
df_race_filter <- df_race_filter %>%
  mutate(
    g_white = as.numeric(localG:white_p, df_race.w)),
    g_black = as.numeric(localG:black_p, df_race.w)),
    g_asian = as.numeric(localG:asian_p, df_race.w)),
    g_american_indian = as.numeric(localG:american_indian_p, df_race.w)),
    g_pacific_islander = as.numeric(localG:pacific_islander_p, df_race.w)),
    g_other = as.numeric(localG:other_p, df_race.w))
  )
```

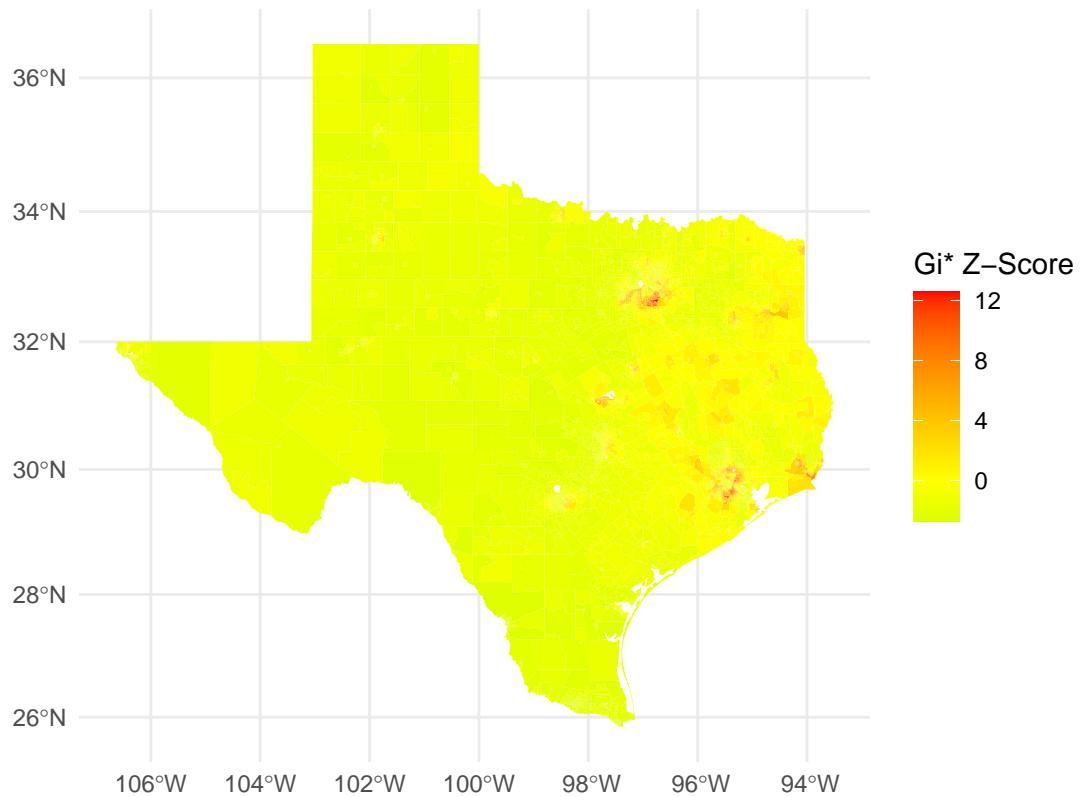
```
#Gi* Plots for the White Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = g_white), color = NA) +
  scale_fill_gradient2(
    low = "green", mid = "yellow", high = "red", midpoint = 0,
    name = "Gi* Z-Score"
  ) +
  theme_minimal() +
  labs(title = "Gi* Hotspot Analysis: % White Population")
```

## Gi\* Hotspot Analysis: % White Population



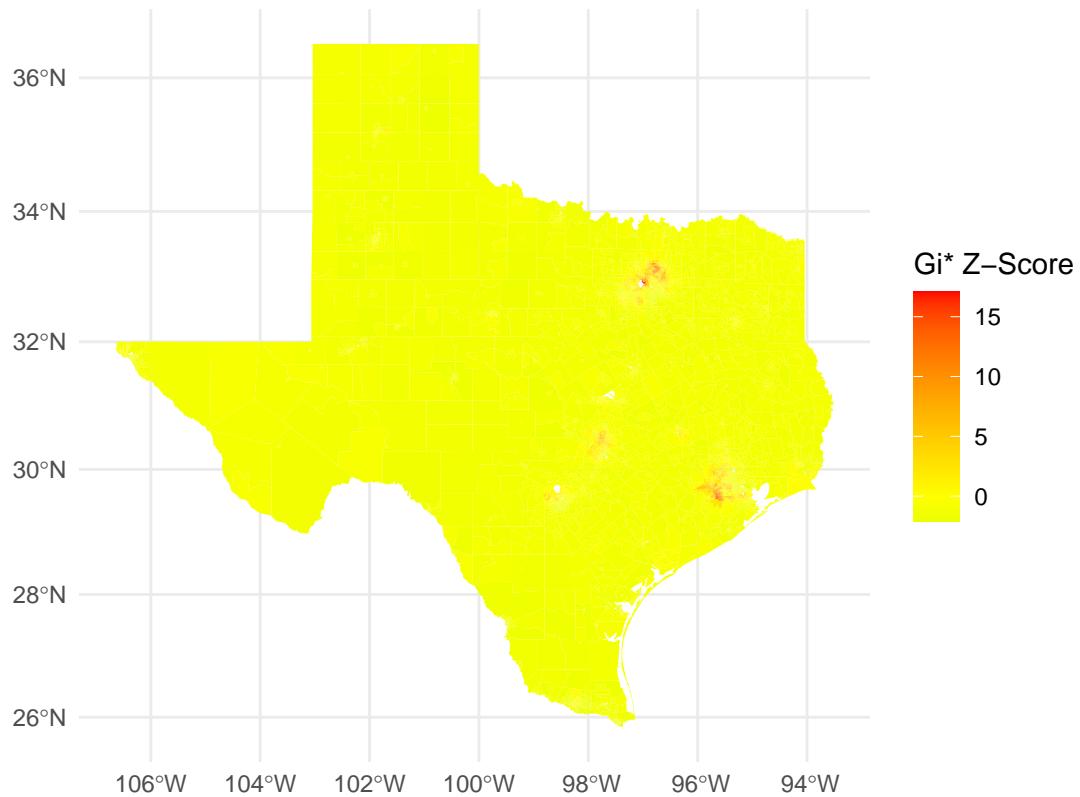
```
#Gi* Plots for the Black Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = g_black), color = NA) +
  scale_fill_gradient2(
    low = "green", mid = "yellow", high = "red", midpoint = 0,
    name = "Gi* Z-Score"
  ) +
  theme_minimal() +
  labs(title = "Gi* Hotspot Analysis: % Black Population")
```

## Gi\* Hotspot Analysis: % Black Population



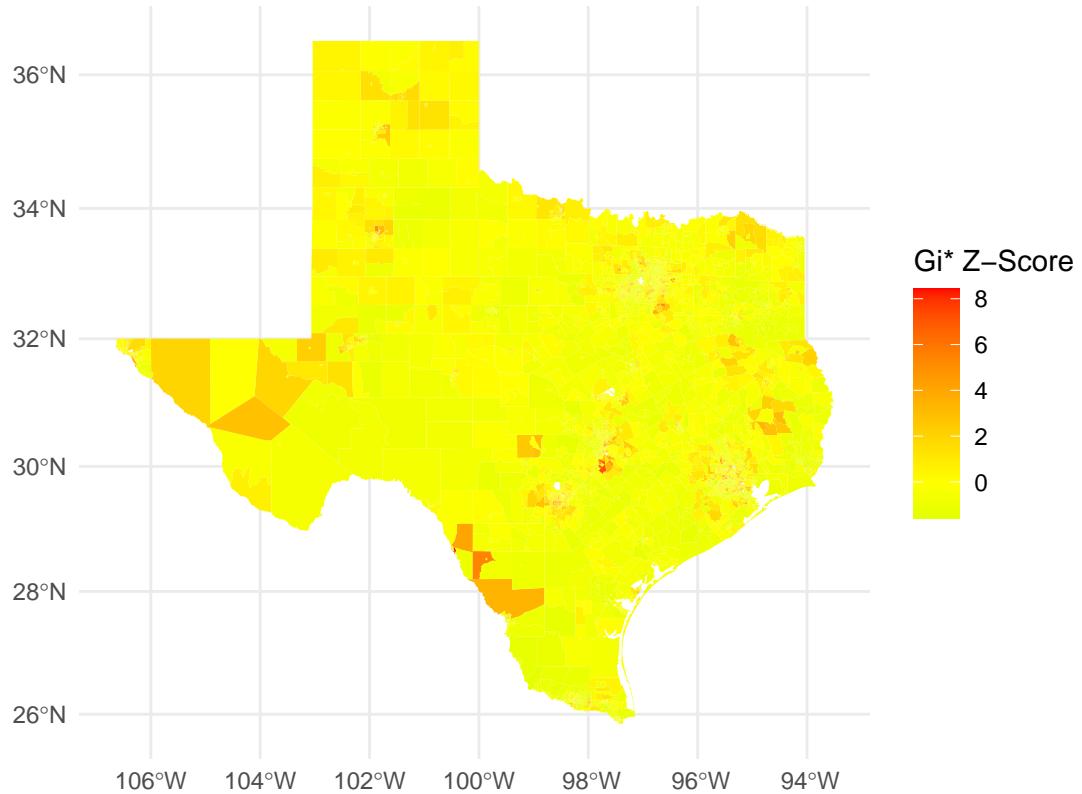
```
#Gi* Plots for the Asian Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = g_asian), color = NA) +
  scale_fill_gradient2(
    low = "green", mid = "yellow", high = "red", midpoint = 0,
    name = "Gi* Z-Score"
  ) +
  theme_minimal() +
  labs(title = "Gi* Hotspot Analysis: % Asian Population")
```

## Gi\* Hotspot Analysis: % Asian Population



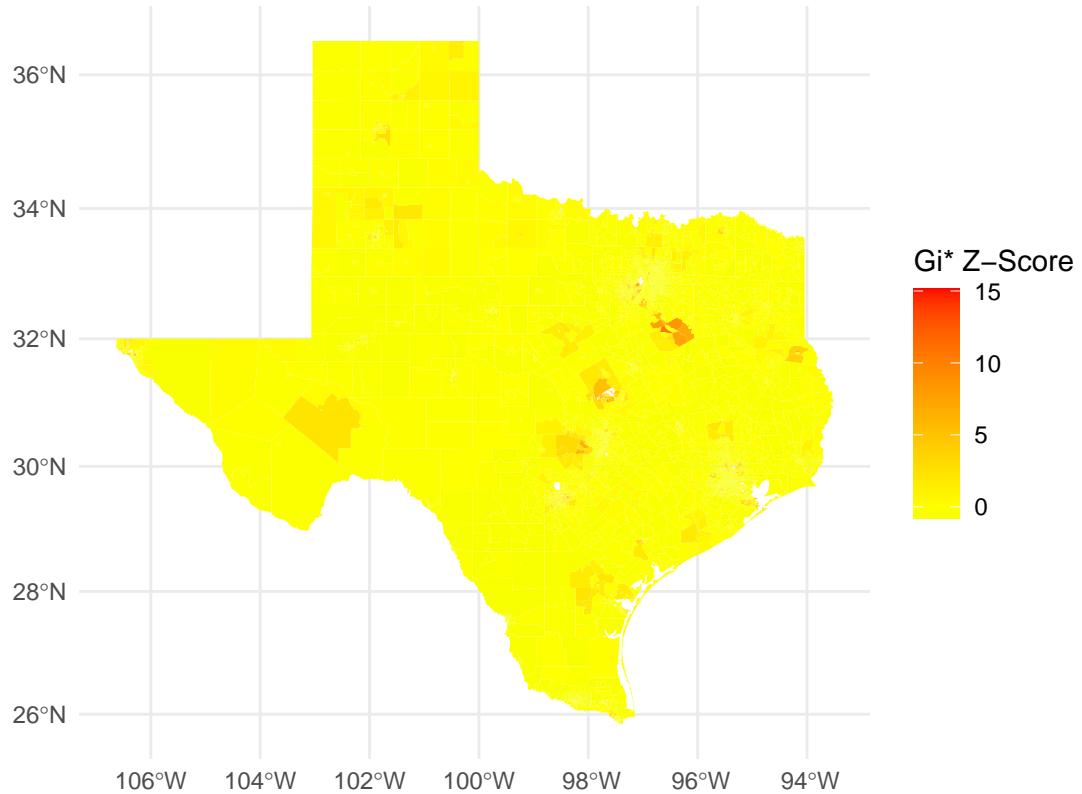
```
#Gi* Plots for the American Indian Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = g_american_indian), color = NA) +
  scale_fill_gradient2(
    low = "green", mid = "yellow", high = "red", midpoint = 0,
    name = "Gi* Z-Score"
  ) +
  theme_minimal() +
  labs(title = "Gi* Hotspot Analysis: % American Indian Population")
```

## Gi\* Hotspot Analysis: % American Indian Population



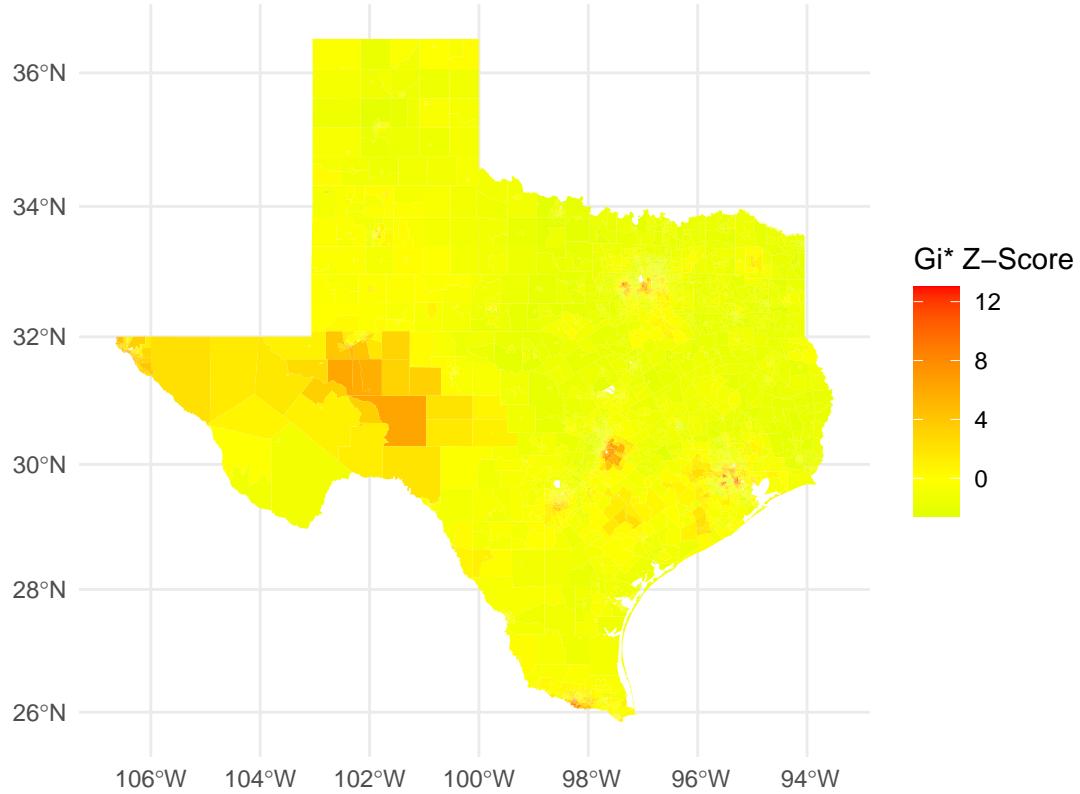
```
#Gi* Plots for the Pacific Islander Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = g_pacific_islander), color = NA) +
  scale_fill_gradient2(
    low = "green", mid = "yellow", high = "red", midpoint = 0,
    name = "Gi* Z-Score"
  ) +
  theme_minimal() +
  labs(title = "Gi* Hotspot Analysis: % Pacific Islander Population")
```

## Gi\* Hotspot Analysis: % Pacific Islander Population



```
#Gi* Plots for the Other Population
ggplot(df_race_filter) +
  geom_sf(aes(fill = g_other), color = NA) +
  scale_fill_gradient2(
    low = "green", mid = "yellow", high = "red", midpoint = 0,
    name = "Gi* Z-Score"
  ) +
  theme_minimal() +
  labs(title = "Gi* Hotspot Analysis: % Other Population")
```

## Gi\* Hotspot Analysis: % Other Population



The Gi\* analysis reveals statistically significant spatial clustering in food stamp usage and racial group distributions across Texas. For food stamp usage, there are strong hotspots (red) in the southwestern and southern parts of the state, indicating counties where food stamp reliance is significantly higher than expected. This hotspot regions are especially seen in the southern border like Rio Grande Valley, reflecting socio-economic challenges faced in that region. A null landscape of food stamps usage was created and confirmed with mapping that these clustered are statistically significant and not random. It highlighted how poverty is geographically concentrated in historically marginalized areas. When examining the racial distribution, distinct spatial patterns were seen. Areas with lower White population densities (coldspos) largely overlap with food stamp usage hotspots. It suggest that food insecurity is more prevalent in counties of Texas with higher proportion of non-White residents. Meanwhile, Asian population hotspots are tightly clustered around urban areas like Houston or Dallas. There is some overlap in these areas with high food stamp usage. It suggest that the Asian community have a better socioeconomic condition in comparison to the others. The American Indian population shows a moderate and localized clustering of Indigenous population. The clusters are seen as rural west and central Texas. Some American Indian hotspots coincide with regions of higher food insecurity, suggesting that rural Indigenous communities face more greater challenges. As they are more isolated geographically and have limited economic opportunities in comparison to the others. However, the clustering is less intense and continuous in compared to the other racial groups. These results reflect a more smaller and more disperse population of American Indian across the region of Texas. The Black population, the hotspots are concentrated east of Texas and major urban centers and shows a great amount of overlap with food stamp usage. This spatial pattern reveals the enduring impact of historical racial segregation and economic marginalization. On the other hand, Pacific Island population hotspots are more isolated and scattered. This is may be likely due to relatively small population numbers. Lastly the other racial category, likely capture multiracial and diverse ethnic groups. This "Other" racial category forms strong hotspots in west Texas and aligns with food stamp hotspots. It suggest that those that are racially diverse population may experience heightened economic vulnerability. Overall these results show that food insecurity in Texas is not evenly distributed and is tied to racial and geographic factors. Minority and marginalized racial groups are likely to be concentrated in regions with persistent poverty.

While certain urban population experience stability. The geographic overlap between racial demographics and food insecurity highlights deeper systemic inequalities, emphasizing the importance of implementing social and economic policies that account for both racial and regional differences.

«««< HEAD ## Regression Analyses

### *Spatial Error Model*

A Spatial Error Model was employed to account for residual spatial dependence. The results for this specification are outlined in the table below:

The Spatial Error Model (SEM) reveals statistically significant relationships between food stamp usage and racial composition across Texas census tracts. Because the per capita proportions for all race groups must sum to 1.00, the White race category was excluded from the regression to avoid multicollinearity. Therefore, “White” serves as the reference group.

Holding all other variables constant, a one percent increase in the share of Black residents corresponds to a 0.057% rise in per capita food stamp usage ( $p < 0.0001$ ), while a one percent increase in the “other” category yields a 0.037% increase ( $p < 0.0001$ ). In contrast, a one percent uptick in the Asian share leads to a 0.018% decrease in food stamp usage ( $p \approx 0.007$ ). The American Indian and Pacific Islander coefficients are not statistically significant at the 10% level ( $p = 0.603$  and  $p = 0.198$ , respectively).

Among the control variables, every additional \$10,000 in median household income predicts about a 0.006% decrease in per capita food stamp usage ( $p < 0.0001$ ). On the other hand, higher values in per-capita households with children and unemployment rate increase reliance on food stamps by 0.197% and 0.133% respectively (both  $p < 0.0001$ ).

The SEM’s spatial error coefficient is  $\lambda = 0.53$  ( $p < 0.001$ ), indicating substantial spatial clustering in the regression errors. This high lambda value justifies our use of the SEM specification. Indeed, the SEM outperforms OLS with a much lower AIC (-26,092 vs. -24,818).

### *Tests for Spatial Independence*

To confirm that we’ve successfully removed residual spatial autocorrelation in the SEM specification, a Moran’s I test on the residuals was employed. The result of Moran’s  $I = -0.0396$  ( $p < 0.0001$ ) reveals a slight negative autocorrelation that is highly significant. This demonstrates that the SEM specification has successfully absorbed spatial dependence in the residuals, thus validating the reliability of our regression coefficients. These results are illustrated below, with the Morans I test and a map of the spatially independent residuals.

#### Moran I test under randomisation

```
data: model.sem1$residuals  
weights: df_race_c.w  
Moran I statistic standard deviate = -4.947, p-value = 3.769e-07 alternative hypothesis: less sample  
estimates: Moran I statistic Expectation Variance -3.960006e-02 -1.471670e-04 6.360299e-05
```

Together, these results reveal a strong relationship between race and food stamp usage across Texas census tracts. Relative to the White population (which serves as the reference group), areas with a higher proportion of Black residents show the largest increase in food stamp usage. Therefore, communities with a high percentage of Black residents experience a disproportionately larger reliance on SNAP compared to any other race group. Similarly, tracts with a greater share of residents classified in the “other” racial category also show higher food stamp usage than White census tracts, though this relationship is slightly weaker than it is for Black communities. In contrast, tracts with a greater proportion of Asian residents actually show lower food stamp usage compared to White tracts. The coefficients for American Indian and Pacific Islander groups are not statistically significant, and so these coefficients are not directly interpretable. Additionally, the control variables follow expected patterns. A higher median household income is associated with lower food stamp use, while greater unemployment and a greater share of households with children correspond with increased food stamp usage.

===== »»> 05fda0a68424cbb9fabac92177bb9c9ea1739791

### Spatial Error Model Results

<i>Dependent variable:</i>	
Food Stamp Usage (% Tract Population)	
Intercept	0.037 *** (0.005)
Other Race (%)	0.057 *** (0.004)
Black (%)	-0.018 *** (0.007)
Asian (%)	-0.014 (0.028)
American Indian (%)	-0.090 (0.070)
Pacific Islander (%)	-0.00000 *** (0.00000)
Median Household Income	0.197 *** (0.008)
Households with Children (%)	0.133 *** (0.011)
Unemployment Rate (%)	0.027 *** (0.003)
Observations	6,796
Log Likelihood	13,057.200
$\sigma^2$	0.001
Akaike Inf. Crit.	-26,092.390
Wald Test	1,797.762 *** (df = 1)
LR Test	1,276.342 *** (df = 1)
<i>Note:</i>	
<sup>*</sup> p<0.1; ** p<0.05; ***p<0.01	
Significance levels: *p < 0.1; **p < 0.05; ***p < 0.01	

Figure 1: regression

## SEM Residuals

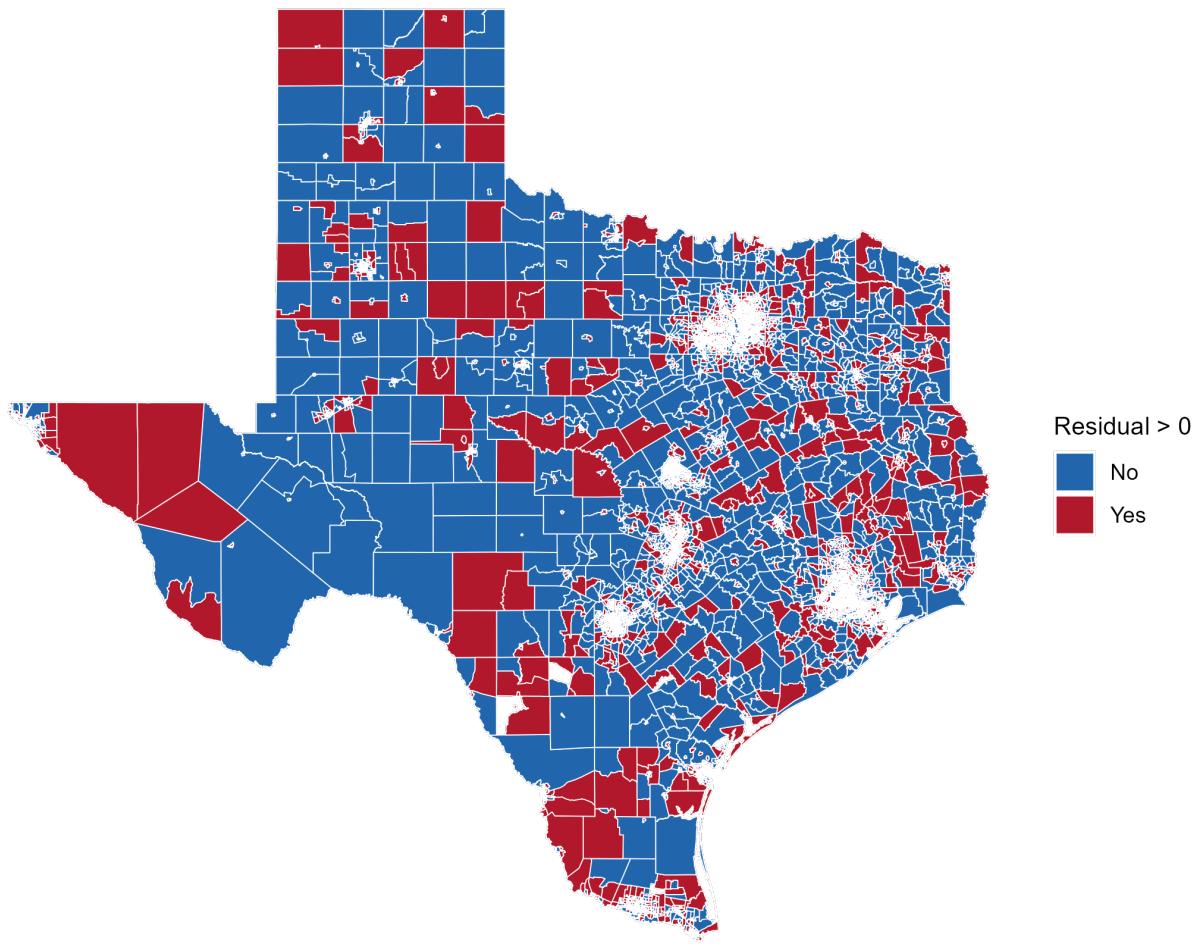


Figure 2: Sem Map Res

## **Conclusions and Recommendations**

Throughout the use of different inferential and spatial statistical methods, patterns of food access inequalities within counties of Texas were revealed which brings a closer look to the relationships between race, income, location, and SNAP usage. It is evident that there are clear patterns of spatial autocorrelation which suggest that high food stamp usage is prevalent in the southern areas of Texas. This is shown by the strong clustering pattern portrayed in the map for spatial moving average, thus, supporting the conclusion that the use of food stamps in counties of Texas are not by random. Moreover, various racial groups such as the Black population portray a strong pattern of clustering while others seem to be more dispersed with minimal clusters shown just like the White population. The clustering patterns may suggest that regions with high food stamp usages also have high concentrations of specific racial groups which can lead to structural and system inequalities within the community. It is recommended that additional research is completed to verify the trends and patterns of this study with higher accuracy and precision. Further exploring the relationship between racial groups, SNAP usage, income, and location will help better understand the importance of each variable. Moreover, implementing stronger statistical and analytical methods that are rigorous in value can further support the concluding results.

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