Homework 3: 2021 Texas Blackouts

AUTHOR
Zach Loo

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README

README.md

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Description

This folder contains the contents for homework 3. This homework's main goal is to analyze the disproportionate effects of the 2021 severe winter storm in Houston, Texas.

```
.
├── 3_texas_blackouts.Rproj
├── data
│   ├── ACS_2019_5YR_TRACT_48_TEXAS.gdb
│   ├── gis_osm_buildings_a_free_1.gpkg
│   ├── gis_osm_roads_free_1.gpkg
│   └── VNP46A1/
├── README.md
├── texas_power.pdf
└── texas_power.qmd
```

Flowchart

Data

- Night lights: Data used is from February 7th & 16th, 2021, showing the before and after of the February 2021 Texas winter storm. The Visible Infrared Imaging Radiometer Suite (VIIRS) data is from NASA's Level-1 and Atmospheric Archive & Distribution System Distributed Active Archive Center (LAADS DAAC). The .tif files were downloaded and prepared by the instructors. LAADS DAAC Website
- Roads: From Geofabrik downloads site where OpenStreetMap (OSM) data can be extracted. Geofabrik Website
- Buildings: Also from Geofabrik, data contained are houses in the Houston area.
- Socioeconomic: Obtained from the U.S. Census Bureau's American Community Survey for census tracts in 2019. Used for combining census attribute data to OSM geospatial data.

References

- Román, M.O., Wang, Z., Sun, Q., Kalb, V.L., Miller, S.D., Molthan, A., Schultz, L., Bell, J., Stokes, E.C., Pandey, B., et al. (2018). NASA's Black Marble nighttime lights product suite (VNP46). Remote Sensing of Environment, 210, 113-143. https://doi.org/10.1016/j.rse.2018.03.017
- OpenStreetMap Contributors (2025). OpenStreetMap database. Retrieved from https://www.openstreetmap.org. Distributed by Geofabrik GmbH, Karlsruhe, Germany. Available at https://download.geofabrik.de/
- U.S. Census Bureau. (2020). TIGER/Line Shapefiles and American Community Survey 2019 (5-Year Estimates), Texas — Census Tract Level (ACS_2019_5YR_TRACT_48_TEXAS) [Data set]. U.S. Department of Commerce. Available from https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-data.html
- Lee CC, Maron M, Mostafavi A. Community-scale big data reveals disparate impacts of the Texas winter storm of 2021 and its managed power outage. Humanit Soc Sci Commun. 2022;9(1):335. doi:10.1057/s41599-022-01353-8. Epub 2022 Sep 24. PMID: 36187845; PMCID: PMC9510185.

Author

Zach Loo

```r
# Load packages
library(terra)
library(tidyverse)
library(tmap)
library(kableExtra)
library(stars)
library(maptiles)
```

```r
# Load lights data
lights_07_1 <- read_stars(here::here('data', 'VNP46A1', 'VNP46A1.A2021038.h08v05.001.202103906432

lights_07_2 <- read_stars(here::here('data', 'VNP46A1', 'VNP46A1.A2021038.h08v06.001.202103906432

lights_16_1 <- read_stars(here::here('data', 'VNP46A1', 'VNP46A1.A2021047.h08v05.001.202104809110
```

```
lights_16_2 <- read_stars(here::here('data', 'VNP46A1', 'VNP46A1.A2021047.h08v06.001.202104809110
```

1.1 Night Light Intensity Before & After Storm

```
# Merge Feb 7th rasters
lights_07 <- st_mosaic(lights_07_1, lights_07_2)

# Merge Feb 16th rasters
lights_16 <- st_mosaic(lights_16_1, lights_16_2)
```

```
# Create Houston bounding box
houston_bbox <- st_bbox(c(xmin = -96.5,xmax = -94.5, ymin = 29, ymax = 30.5),
                          crs = "EPSG:4326")

# CRS check before cropping
if (st_crs(houston_bbox) == st_crs(lights_07)){
  print("CRS Match. Ready to crop.")
} else {
  warning("Converting Houston bbox to lights CRS:\n", st_crs(lights_07))

  houston_bbox <- st_transform(houston_bbox, crs = st_crs(lights_07))
}
```

```
[1] "CRS Match. Ready to crop."
```

```
# Crop 07 raster
cropped_07 <- st_crop(lights_07, houston_bbox)
# Crop 16 raster
cropped_16 <- st_crop(lights_16, houston_bbox)
```

```
# Plot before & after maps
map_07 <- tm_shape(cropped_07) +
  tm_raster(col.scale = tm_scale_continuous(values = '-brewer.greys'),
            col.legend = tm_legend(show = FALSE)) +
tm_layout(title = "Houston lights before storm (Feb. 7th)",
          title.position = c(0.03, 1),
          title.color = "white")

map_16 <- tm_shape(cropped_16) +
  tm_raster(col.scale = tm_scale_continuous(values = '-brewer.greys'),
            col.legend = tm_legend(show = FALSE)) +
tm_layout(title = "Houston lights after storm (Feb. 16th)",
          title.position = c(0.03, 1),
          title.color = "white") +
tm_compass(position = c('left', 'bottom'),
           size = 3,
           text.size = 0.9,
           color.dark = 'grey50',
           text.color = 'white') +
tm_scalebar(position = c('left', 'bottom'),
            text.size = 0.8,
            color.dark = 'grey50',
            text.color = 'white')

tmap_arrange(map_07, map_16, nrow = 1)
```

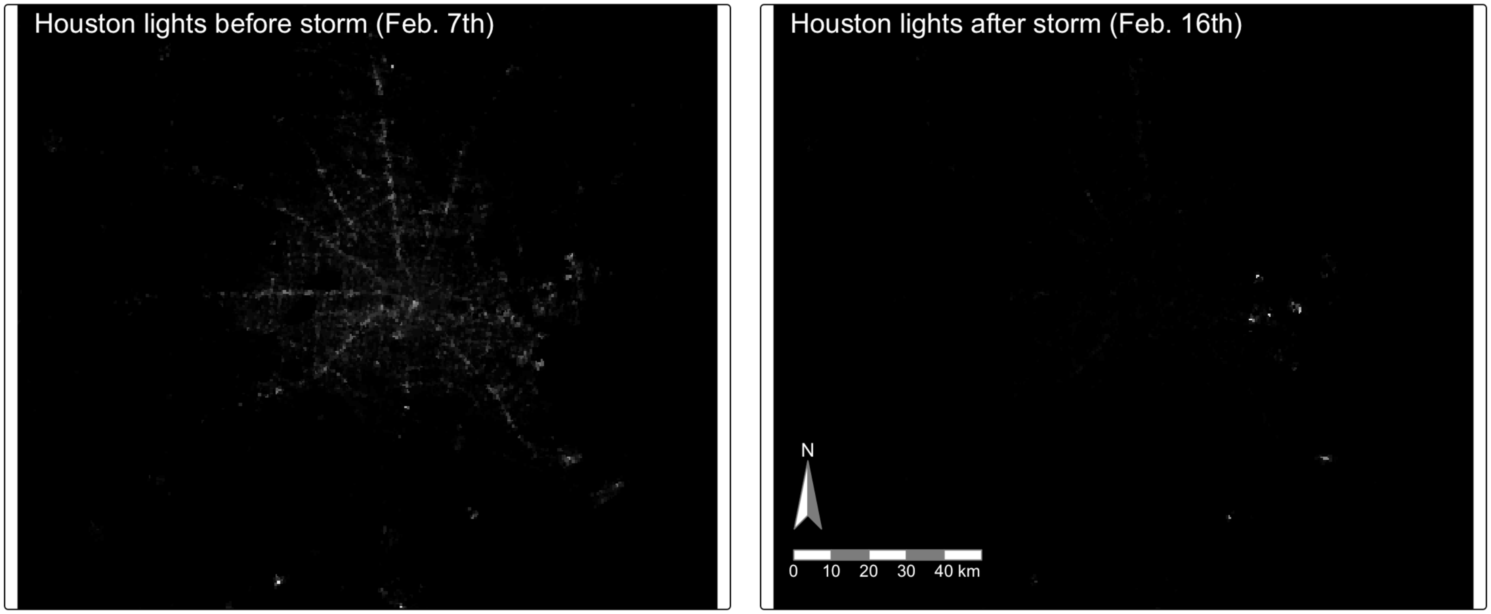

Figure 1: Comparison of Houston Lights Before & After the February 2021 Severe Winter Storm.

1.2 Create blackout mask

```
# Get raster difference
lights_diff <- cropped_16 - cropped_07
```

```
# Create houston blackout mask
lights_diff[lights_diff > -200] <- NA
```

```
# Vectorize mask
blackout_areas <- lights_diff |>
  st_as_sf() |>
  st_make_valid() |>
  st_transform("EPSG:3083") # Re-project to new crs
```

```r
# Rename first column name
colnames(blackout_areas)[1] <- "light_difference"
```

2. Exclude highways from blackout mask

```r
# Load roads data but only highways
roads <- st_read(here::here('data', 'gis_osm_roads_free_1.gpkg'), query = "SELECT * FROM gis_osm_
  st_transform("EPSG:3083")
```

```r
# Create 200m buffer
roads_buffer <- st_buffer(roads, dist = 200)
```

```r
# Combine road geometries first
roads_buffer_union <- st_union(roads_buffer)

# CRS check before finding difference
if (st_crs(blackout_areas) == st_crs(roads_buffer_union)){
  print("CRS Match. Ready to find difference.")
} else {
  warning("Converting blackout_areas to roads CRS:\n", st_crs(roads_buffer_union))

  blackout_areas <- st_transform(blackout_areas, crs = st_crs(roads_buffer_union))
}
```

```
[1] "CRS Match. Ready to find difference."
```

```r
# Find areas NOT within buffer
blackout_far_areas <- st_difference(blackout_areas, roads_buffer_union)
```

3. Identify homes impacted by blackouts

```
homes <- st_read(
  here::here("data", "gis_osm_buildings_a_free_1.gpkg"),
  query = "
    SELECT * FROM gis_osm_buildings_a_free_1
    WHERE (type IS NULL AND name IS NULL)
       OR type IN ('residential', 'apartments', 'house', 'static_caravan', 'detached')", quiet =
  st_transform("EPSG:3083")
```

```
# CRS check before filtering
if (st_crs(homes) == st_crs(blackout_far_areas)){
  print("CRS Match. Ready to filter.")
} else {
  warning("Converting homes to blackout_far_areas CRS:\n", st_crs(blackout_far_areas))

  homes <- st_transform(homes, crs = st_crs(blackout_far_areas))
}
```

```
[1] "CRS Match. Ready to filter."
```

```
# Find homes in blackout areas
homes_blackout <- homes |>
  st_filter(y = st_union(blackout_far_areas))
```

```
tm_shape(homes_blackout) +
  tm_polygons(col = 'blue') +
  tm_basemap('CartoDB.VoyagerNoLabels') +
  tm_graticules(x = seq(-96.4, -94.8, 0.4), alpha = 0.2) +

tm_add_legend(labels = c("Homes That Lost Power"),
              fill = c('blue'),
              type = 'polygons',
```

```
            position = c('left', 'top')) +


tm_layout(bg.color = 'grey90')
```

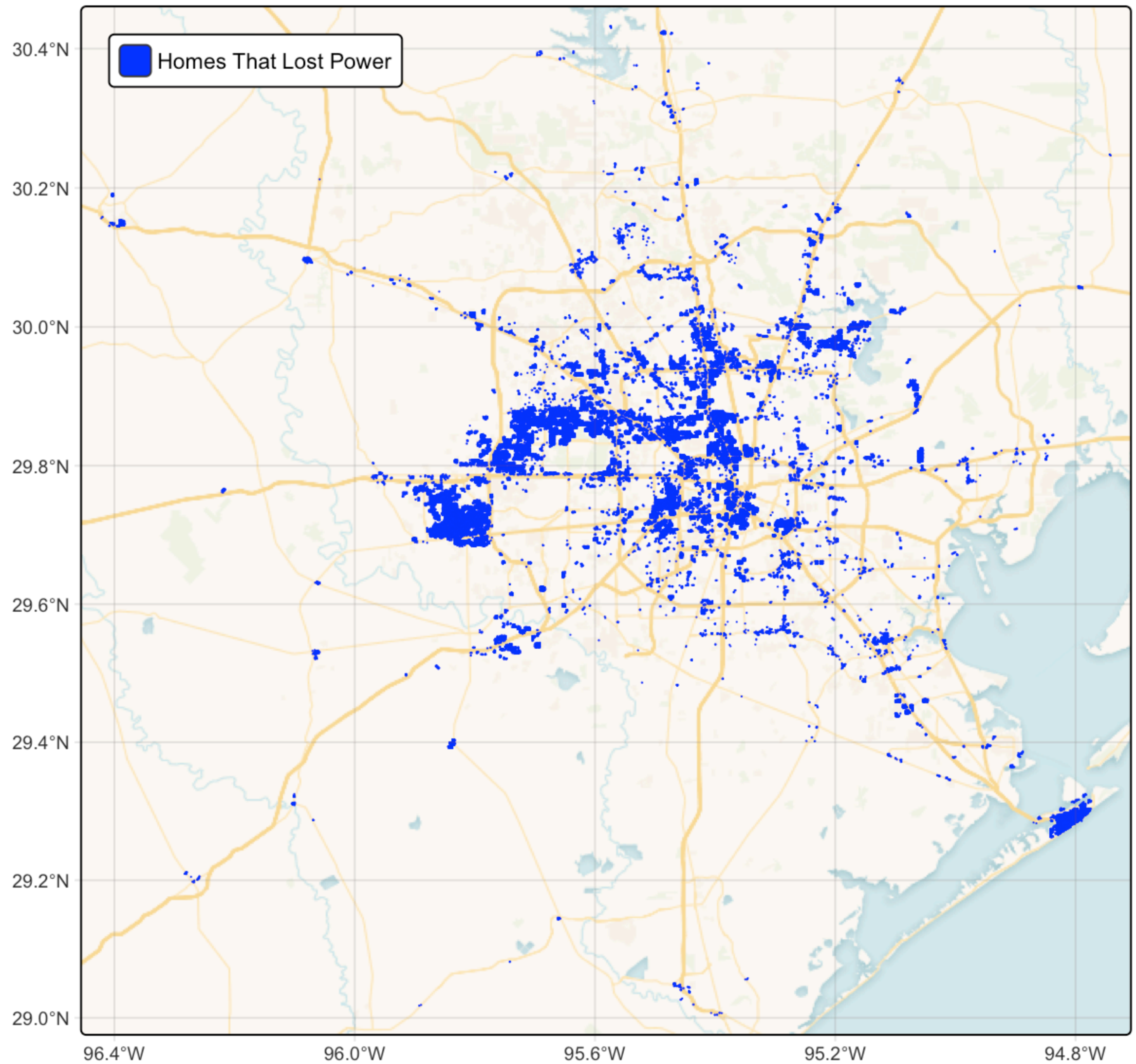

Figure 2: Map of Homes That Lost Power.

```r
# Table of homes that experienced blackouts
homes_df <- homes_blackout |>
  group_by(type) |>
  summarise(count = n(),
            percent = round((n() / nrow(homes_blackout)) * 100, digits = 2)) |>
  st_drop_geometry()

# Add total row
homes_df <- homes_df |>
  add_row(type = 'Total', count = sum(homes_df$count))

# Change type NA to character string
homes_df$type[6] <- "NA"
```

```r
# Display kable table
options(knitr.kable.NA = "")
kable(homes_df,
      col.names = c("Home Type", "Count", "Percentage (%)"), align = 'c')
```

Table 1: Estimate of Homes That Experienced Blackouts by Home Type

Home Type	Count	Percentage (%)
apartments	1136	0.72
detached	353	0.22
house	19760	12.51
residential	1395	0.88
static_caravan	80	0.05
NA	135246	85.61
Total	157970	

4. Census Tract Distribution

```
# View layers in gdb file
#st_layers(here::here('data', 'ACS_2019_5YR_TRACT_48_TEXAS.gdb'))

# Extract income layer
income <- st_read(here::here('data', 'ACS_2019_5YR_TRACT_48_TEXAS.gdb'),
                  layer = 'X19_INCOME', quiet = TRUE) |>
  dplyr::select(c(GEOID, B19013e1, B19013m1))

# Extract census tract layer
census <- st_read(here::here('data', 'ACS_2019_5YR_TRACT_48_TEXAS.gdb'),
                  layer = 'ACS_2019_5YR_TRACT_48_TEXAS', quiet = TRUE) |>
  dplyr::select(-c(GEOID)) |> # Drop GEOID column
  rename(GEOID = GEOID_Data) |>  # Rename GEOID_Data for joining
  st_transform("EPSG:3083")
```

```
# Find how many census tracts in houston bbox
houston_tracts_number <- census |>
  st_crop(st_transform(houston_bbox, crs = "EPSG:3083")) |>
  nrow()

paste0("Number of Houston census tracts: ", houston_tracts_number)
```

```
[1] "Number of Houston census tracts: 1128"
```

```
# Transform Houston bbox before joining
#houston_bbox <- st_transform(houston_bbox, crs = "EPSG:3083")

# CRS check before joining & cropping
if (st_crs(houston_bbox) == st_crs(census)){
  print("CRS Match. Ready to find difference.")
} else {
  warning("Converting houston_bbox CRS to census CRS:\n", st_crs(census))
```

```
  houston_bbox <- st_transform(houston_bbox, crs = st_crs(census))
}

# Join census & income data
census_income <- left_join(x = census, y = income, by = "GEOID") |>
  st_crop(houston_bbox) |>
  filter(ALAND != 0) |>  # Filter out ocean geometries
  dplyr::select(c("GEOID", "B19013e1", "B19013m1")) |>
  rename(median_hh_income_est = B19013e1,
         median_hh_income_moe = B19013m1)
```

```
# Filter to census tracts that lost power
census_blackouts <- census_income |>
  st_filter(y = blackout_far_areas, .predicate = st_intersects) |>
  mutate(blackout = TRUE) # Add blackout column

# Create blackout GEOID for filtering census_income & joining later
blackout_ids <- census_blackouts$GEOID

# Print number of census tracts that experienced blackouts
paste0("Number of Houston census tracts that experienced blackouts: ", nrow(census_blackouts))
```

```
[1] "Number of Houston census tracts that experienced blackouts: 935"
```

```
# Plot blackout areas with census blackouts
tm_shape(census_income) + # Census layer
  tm_polygons() +
tm_shape(census_blackouts) + # Census blackout layer
  tm_polygons(fill = 'orange') +

tm_compass(position = c(0.92, 0.32)) +
tm_scalebar(position = c(0.76, 0.18)) +
tm_add_legend(labels = c("Tracts That Lost Power"),
              fill = c('orange'),
              type = 'polygons',
              position = c('right', 'bottom'))
```

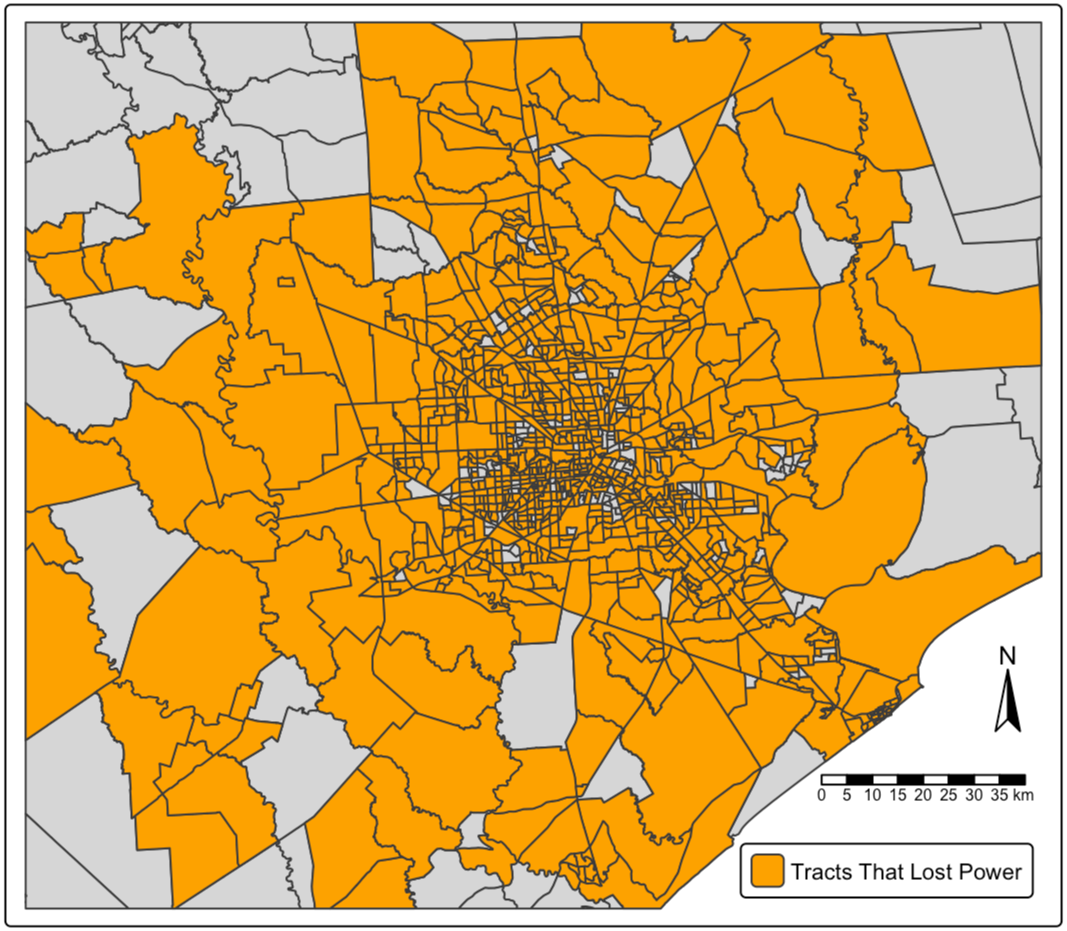

Figure 3: Houston Census Tracts That Lost Power.

```
# Create boolean column whether tract had a blackout or not
census_blackout_tf <- census_income |>
  mutate(blackout = GEOID %in% blackout_ids)

# Get value counts for blackout column
table(census_blackout_tf$blackout)
```

```
FALSE  TRUE
```

```
191    935
```

```
# Median household income plot
ggplot(census_blackout_tf, aes(blackout, median_hh_income_est)) +
  geom_boxplot() +

  scale_x_discrete(labels = c('No Blackout', 'Blackout')) +
  labs(y = "Median Household Income (Estimate) in Census Tract") +

  theme_classic() +
  theme(panel.grid.major.y = element_line(color = 'grey'),
        axis.title.x = element_blank())
```

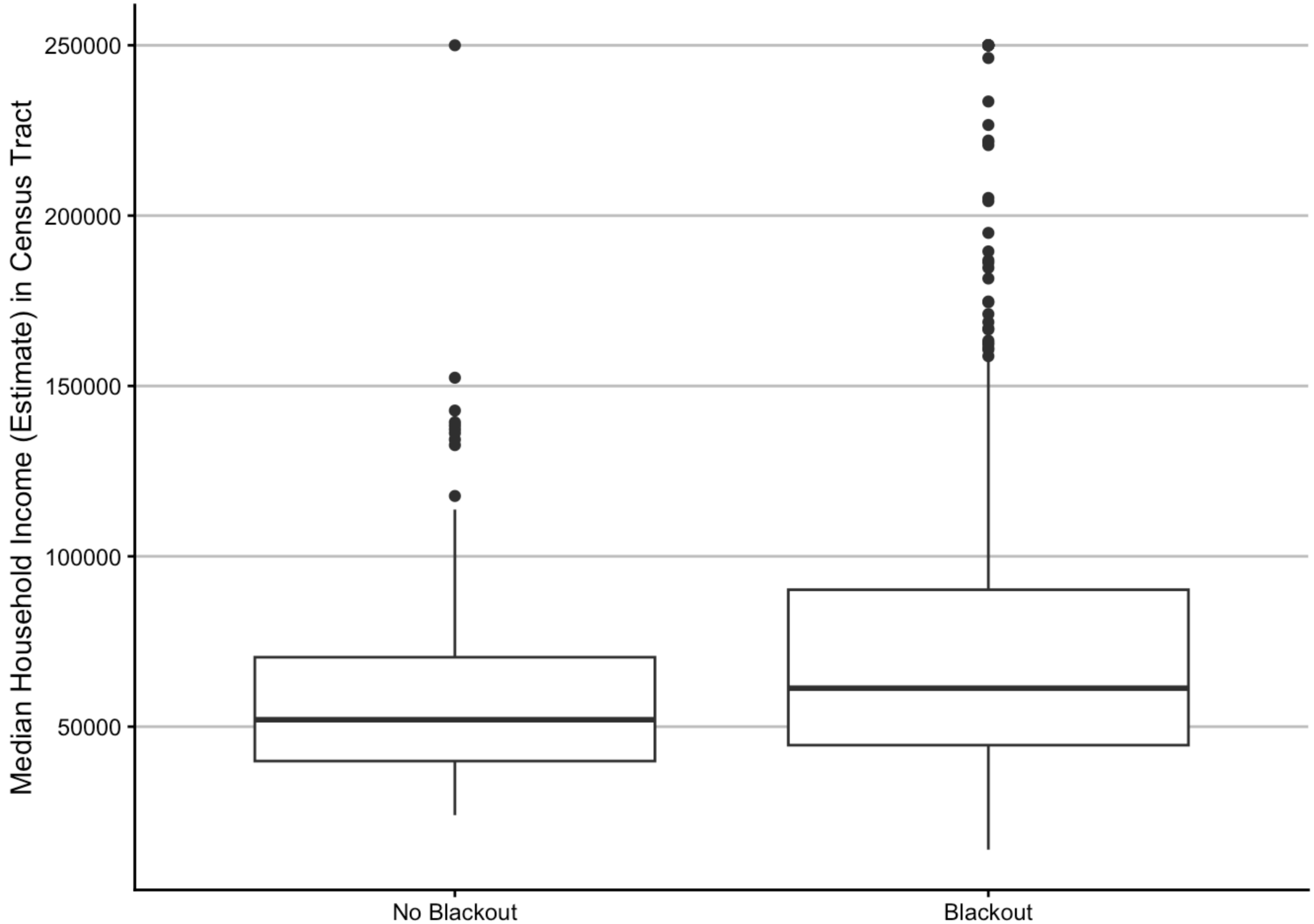

Figure 4: Distribution of Median Household Income for Census Tracts per Blackout Group.

5. Summary

Winter storm Uri hit Texas in February 2021 and impacted over 100,000 homes within about 900 census tracts. It is documented that impacted census tracts did in fact have lower median household incomes on average, indicating that low-income communities in Texas were disproportionately affected by the storm (Lee et al. 2022). However, the boxplots in Figure 4 don't show the expected results. One possible cause for this was the limited amount of data of only 2 days that was used in creating the blackout mask. Perhaps if we had more night light data spanning a range of dates, we could have a more accurate picture of what areas experienced blackouts, thus leading to a more historically accurate conclusion. Additionally, Lee et al. 2022 also faced data limitations as detailed power outage data was not available. Instead, the authors used data from Mapbox Population Activity, the 311 Houston Service Helpline, and SafeGraph POI Visit Data, along with the ACS census tract data to assess community impacts. While night light data provides a broad view of power outages across large areas, the alternative datsets in Lee et al. 2022 proved more effective in revealing the fine details and impacts of the storm.

References

- Román, M.O., Wang, Z., Sun, Q., Kalb, V.L., Miller, S.D., Molthan, A., Schultz, L., Bell, J., Stokes, E.C., Pandey, B., et al. (2018). NASA's Black Marble nighttime lights product suite (VNP46). Remote Sensing of Environment, 210, 113-143. https://doi.org/10.1016/j.rse.2018.03.017
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- U.S. Census Bureau. (2020). TIGER/Line Shapefiles and American Community Survey 2019 (5-Year Estimates), Texas — Census Tract Level (ACS_2019_5YR_TRACT_48_TEXAS) [Data set]. U.S. Department of Commerce. Available from https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-data.html
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