

Mapping Power Outages in Houston During the February 2021 Winter Storm

Detecting blackout patterns and socioeconomic disparities using VIIRS night-light data, OpenStreetMap infrastructure, and U.S. Census statistics

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Overview

This repository contains a spatial analysis of the February 2021 Texas winter storm and its impact on electrical power distribution across the Houston metropolitan area. Using satellite imagery, OpenStreetMap infrastructure data, and socioeconomic census data, this project identifies areas that lost power and examines whether outage impacts were disproportionately experienced across income levels.

The project demonstrates skills in raster and vector data processing, spatial joins, and map visualization using R.

Repository Structure

```
EDS223-HW3/ |--- README.md # Project documentation (this file) |--- texas_blackout.qmd # Quarto document containing full analysis  
|--- .gitignore # Prevents data files from being pushed |--- data/ # Contains input datasets (excluded from GitHub) |--- VNP46A1/ #  
VIIRS night light imagery |--- gis_osm_buildings_a_free_1.gpkg |--- gis_osm_roads_free_1.gpkg |---  
ACS_2019_5YR_TRACT_48_TEXAS.gdb |--- outputs/ # Rendered figures and final PDF (if included)
```

Data Access

All datasets used in this analysis are publicly available but are not stored directly in this repository due to size. To reproduce the analysis:

Download all data files from the sources cited below.

Place them inside the data/ folder using the same directory structure shown above.

Run `texas_blackout.qmd` to reproduce the results.

Data Sources and Citations

1. VIIRS Night Lights NASA (2021). Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band Daily Data Product (VNP46A1), Version 1. NASA Level-1 and Atmosphere Archive & Distribution System Distributed Active Archive Center (LAADS DAAC), Goddard Space Flight Center. Tiles used: h08v05 and h08v06, collected on February 7 and February 16, 2021. Retrieved from: <https://ladsweb.modaps.eosdis.nasa.gov>
2. Roads OpenStreetMap contributors (2021). OpenStreetMap Data Extracts — Texas (Road Network). Geofabrik GmbH, Karlsruhe, Germany. <https://download.geofabrik.de/north-america/us/texas.html>
3. Buildings OpenStreetMap contributors (2021). OpenStreetMap Data Extracts — Texas (Building Footprints). Geofabrik GmbH, Karlsruhe, Germany. <https://download.geofabrik.de/north-america/us/texas.html>
4. Socioeconomic Data U.S. Census Bureau (2019). American Community Survey (ACS) 2019 5-Year Estimates: Census Tracts for Texas (State FIPS 48). Retrieved from: <https://www.census.gov/programs-surveys/acs>

Analysis Summary

The analysis proceeds in four key stages:

Blackout Detection:

VIIRS night-light imagery before (Feb 7) and after (Feb 16, 2021) the storm is compared to identify significant reductions in nighttime radiance ($> 200 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$).

Highway Exclusion:

Areas within 200 m of highways are excluded to avoid misclassification from reduced vehicle lighting.

Residential Impact Estimation:

Residential building footprints from OpenStreetMap are intersected with blackout polygons to estimate the number of homes likely impacted.

Socioeconomic Comparison:

Median household income from 2019 ACS census tract data is used to evaluate disparities between tracts that experienced blackouts and those that did not.

Results Overview

Estimated Homes Impacted: `~r format(n_homes_imp, big.mark=",")` homes within Houston metropolitan area

Number of Impacted Census Tracts: `r length(impacted_tract_ids)`

Median Household Income:

Blackout tracts: `$r format(round(income_summary$median[income_summary$blackout == "Blackout"]), big.mark=",")`

Non-blackout tracts: `$r format(round(income_summary$median[income_summary$blackout == "No Blackout"]), big.mark=",")`

The findings suggest that lower-income tracts were disproportionately affected by the 2021 blackout, underscoring the need to consider social vulnerability in energy infrastructure resilience planning.

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License

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Introduction

In February 2021, a series of severe winter storms caused one of the most extensive power crises in Texas history. Millions of residents across the state lost electricity as infrastructure failed under extreme cold. This analysis focuses on the Houston metropolitan area, examining the spatial extent of power outages and their relationship to community characteristics.

Using satellite-based observations of nighttime lights, we identify areas that experienced a significant reduction in illumination following the storm—interpreted as power outages. We then estimate the number of homes affected and investigate whether these impacts were disproportionately concentrated in communities of differing socioeconomic status. By combining geospatial and demographic data, this analysis provides insight into how climate-related infrastructure failures intersect with social vulnerability, informing future resilience and equity planning.

i. Data Overview

This analysis integrates three complementary datasets:

1. VIIRS Night-Light Data

- *Source:* NASA's Visible Infrared Imaging Radiometer Suite (VNP46A1 Day/Night Band)

- *Use:* Two 500 m-resolution images from February 7 (pre-storm) and February 16, 2021 (post-storm) are compared to detect areas with large declines in radiance ($\geq 200 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$), indicating potential blackouts.

2. OpenStreetMap (OSM) Building and Road Data

- *Source:* Geofabrik OSM extracts
- *Use:* Residential building footprints are used to estimate the number of homes within blackout zones. Motorways are buffered by 200 m and excluded to prevent false detections related to changes in traffic lighting.

3. American Community Survey (ACS) 2019 5-Year Estimates

- *Source:* U.S. Census Bureau
- *Use:* Socioeconomic attributes, including median household income, are joined to census tract geometries to compare income distributions between tracts that experienced blackouts and those that did not.

Together, these datasets enable a spatially explicit assessment of the extent, scale, and social context of the February 2021 Houston blackout—illustrating how Earth observation and demographic data can be combined to evaluate the human dimensions of extreme weather events.

ii. Data Citation

- 1. Night Lights (VIIRS Day/Night Band)** NASA (2021). Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band Daily Data Product (VNP46A1), Version 1. NASA Level-1 and Atmosphere Archive & Distribution System Distributed Active Archive Center (LAADS DAAC), Goddard Space Flight Center, Greenbelt, MD, USA. Tiles used: h08v05 and h08v06 collected on 2021-02-07 and 2021-02-16. Accessed from: <https://ladsweb.modaps.eosdis.nasa.gov>
- 2. Roads (OpenStreetMap / Geofabrik)** OpenStreetMap contributors (2021). OpenStreetMap Data Extracts — Texas (Road Network). Geofabrik GmbH, Karlsruhe, Germany. Retrieved from: <https://download.geofabrik.de/north-america/us/texas.html>
- 3. Buildings (OpenStreetMap / Geofabrik)** OpenStreetMap contributors (2021). OpenStreetMap Data Extracts — Texas (Building Footprints). Geofabrik GmbH, Karlsruhe, Germany. Retrieved from: <https://download.geofabrik.de/north-america/us/texas.html>
- 4. Socioeconomic Data (U.S. Census Bureau)** U.S. Census Bureau (2019). American Community Survey (ACS) 2019 5-Year Estimates: Census Tracts for Texas (State FIPS 48). Data distributed as File Geodatabase (ACS_2019_5YR_TRACT_48.gdb). Retrieved from: <https://www.census.gov/programs-surveys/acs>

Data Preparation

```
# Load required packages
library(terra)
library(sf)
library(stars)
library(tmap)
library(dplyr)
library(ggplot2)
library(here)
library(gridExtra)

# Bring in the data
# Night lights
lights_1a <- rast(here("data", "VNP46A1", "VNP46A1.A2021038.h08v05.001.2021039064328.tif"))
lights_1b <- rast(here("data", "VNP46A1", "VNP46A1.A2021038.h08v06.001.2021039064329.tif"))
lights_2a <- rast(here("data", "VNP46A1", "VNP46A1.A2021047.h08v05.001.2021048091106.tif"))
lights_2b <- rast(here("data", "VNP46A1", "VNP46A1.A2021047.h08v06.001.2021048091105.tif"))

# Give the rasters a name and put them into a list
rasters <- list(lights_1a, lights_1b, lights_2a, lights_2b)
names(rasters) <- c("1a","1b","2a","2b")

# Socioeconomic data from the geodatabase. We know the layer to get the census tracts is in A
texas <- st_read(here("data", "ACS_2019_5YR_TRACT_48_TEXAS.gdb"),
                  layer = "ACS_2019_5YR_TRACT_48_TEXAS",
                  quiet = TRUE)
```

Initial Visualization

To get a sense of the impact of the storm on night lights, we will first create a map showing the intensity of night lights before and after the storm

```
# First create the bounding box -- this will help visualize the change as it will zoom in on us
hou_bbox <- st_polygon(list(rbind(
  c(-96.5, 29.0),
  c(-96.5, 30.5),
  c(-94.5, 30.5),
  c(-94.5, 29.0),
  c(-96.5, 29.0)
))) |> st_sfc(crs = 4326)
```

```

# hint: this will require creating a raster object for each day (2021-02-07 and 2021-02-16)
# Create rasters with the combined tiles of each day
day1 <- mosaic(lights_1a, lights_1b)
day2 <- mosaic(lights_2a, lights_2b)

# Ensure grids align
day2_aligned <- resample(day2, day1, method = "bilinear")

# Convert full rasters to stars for tmap
day1_stars <- st_as_stars(day1)
day2_stars <- st_as_stars(day2_aligned)

# Crop to Houston area
# First transform bbox to match the raster CRS
bbox_raster_crs <- st_transform(hou_bbox, st_crs(day1))

# Crop the rasters to Houston
day1_houston <- st_crop(day1_stars, bbox_raster_crs)
day2_houston <- st_crop(day2_stars, bbox_raster_crs)

```

```

# Make sure we are in plot mode
tmap_mode("plot")

# Build the before map with its legend outside (this will act as the legnd for both maps)
map_before <-
  tm_shape(day1_houston) +
    tm_raster(
      col_alpha = 1,
      palette = "-viridis",
      title = "Night Light Intensity\n(nW cm-2 sr-1)",
      style = "cont",
      legend.reverse = TRUE
    ) +
    tm_layout(
      main.title = "February 7, 2021 (Before Storm)",
      main.title.size = 1.2,
      legend.outside = TRUE,
      legend.outside.position = "left",
      legend.bg.color = "white",
      legend.reverse = TRUE,
      legend.frame = FALSE,
      frame = FALSE
    )

```

```

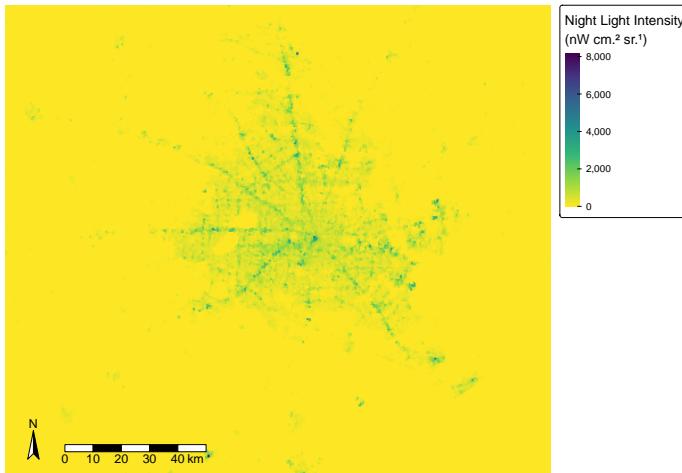
tm_compass(type = "arrow", position = tm_pos_in("left", "bottom"), size = 2) +
tm_scalebar(position = c(0.09, 0.09), text.size = 0.8)

# Create the map after with opposite viridis as well so that the scale bar and north arrow are
map_after <-
  tm_shape(day2_houston) +
  tm_raster(
    col_alpha = 1,
    palette = "-viridis",
    title = "Night Light Intensity\n(nW cm-2 sr-1)",
    style = "cont",
    legend.show = FALSE
  ) +
  tm_layout(
    main.title = "February 16, 2021 (After Storm)",
    main.title.size = 1.2,
    legend.show = FALSE,
    frame = FALSE
  ) +
  tm_compass(type = "arrow", position = tm_pos_in("left", "bottom"), size = 3) +
  tm_scalebar(position = c(0.09, 0.09), text.size = 0.8)

# Convert to grobs and arrange with more space
grid.arrange(
  tmap_grob(map_before),
  tmap_grob(map_after),
  ncol = 2,
  widths = c(1.3, 1) # Give first plot more width for legend
)

```

February 7, 2021 (Before Storm)



February 16, 2021 (After Storm)

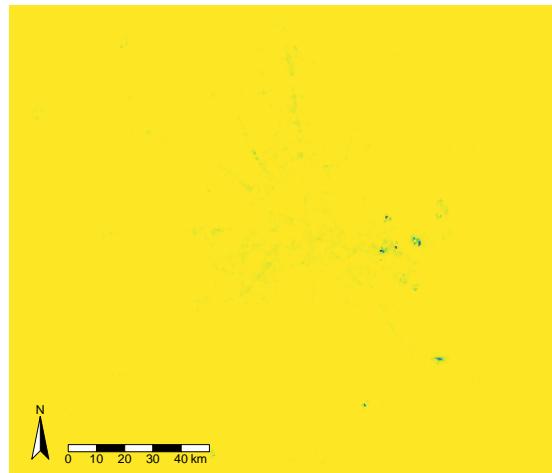


Figure 1: Change in Nighttime Light Intensity in the Houston Metropolitan Area Before and After the February 2021 Winter Storm. VIIRS Day/Night Band imagery showing night-light radiance ($\text{nW cm}^{-2} \text{sr}^{-1}$) on February 7 (Pre-Storm) and February 16 (After Storm). Lighter (yellow) areas in the post-storm image indicate widespread power outages following the February 2021 Texas blackout event.

Impacted Homes

i. Creating the Blackout Mask

In order to identify areas that have experienced a blackout, we need to create a mask that will indicate whether or not each cell has experienced a blackout.

```
# find the change in night lights intensity (presumably) caused by the storm

# Find the difference between the two days
diff <- day1 - day2_aligned

# reclassify the difference raster, assuming that any location that experienced a drop of more
# assign NA to all locations that experienced a drop of less than 200 nW cm-2sr-1 change
mask <- classify(
  diff,
  rcl = matrix(c(-Inf, 200, NA,
                 200, Inf, 1),
               ncol = 3, byrow = TRUE)
)

# Vectorize the blackout mask (1 = blackout, NA = not blackout)
blkout_poly <- as.polygons(mask, values = TRUE, dissolve = TRUE, na.rm = TRUE) |>
  st_as_sf() |>
```

```

st_make_valid()

# Get it into WGS84 in order to crop by lon/lat bounding box
blkout_wgs <- st_transform(blkout_poly, 4326)

# Crop to Houston bounding box

# Then use st_intersection to crop
blk_wgs_crop <- st_intersection(blkout_wgs, hou_bbox) |>
  st_make_valid()

# Finally project to Texas equal-area for buffers / area operations
blkout <- st_transform(blk_wgs_crop, 3083)

```

ii. Excluding Highways

Highways experience changes in their night light intensities, but these may not be related to the storm. Therefore, we need to exclude any locations within 200 meters of all highways in the Houston area

```

# Re-read only motorways via SQL (faster & cleaner)
highways <- st_read(here("data", "gis_osm_roads_free_1.gpkg"),
                      query = "SELECT * FROM gis_osm_roads_free_1 WHERE fclass='motorway'",
                      quiet = TRUE) |>
  st_make_valid() |>
  st_transform(3083)

# Identify areas within 200m of all highways using st_union and create a buffer and dissolve
highway_buff <- st_union(highways) |>
  st_buffer(200)

# Find areas that experienced blackouts that are further than 200m from a highway
# Take all parts of the blackout polygons that are not within 200m of a highway
blkout_highways <- st_difference(blkout, highway_buff) |>
  st_make_valid()

# Clean up the polygon so that only non empty geometries exist
blk_clean <- blkout_highways[!st_is_empty(blkout_highways), ]

```

iii. Identifying Impacted Homes

Now to visualize where homes were impacted we will need building data from the geopackage. We can intersect this with our blackout dataset to mark impacted homes and quantify them.

```

# Read only residential-ish buildings via SQL
houses_res <- st_read(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 = TRUE) |>
  st_make_valid() |>
  st_transform(3083) # Same CRS as the blackout mask

# Intersect to mark impacted homes
homes_imp <- st_intersection(houses_res, blk_clean)
n_homes_imp <- nrow(homes_imp)

message(sprintf("Estimated homes impacted: %s", format(n_homes_imp, big.mark=",")))

# Reproject data to match basemap (keeps everything aligned)
homes_wgs <- st_transform(homes_imp, 3857) |>
  st_make_valid()

bbox_wgs  <- st_transform(hou_bbox, 3857) |>
  st_make_valid()

# Map all the impacted homes
homes_impacted_map <-
  tm_shape(bbox_wgs) +
    tm_borders(lwd = 0) + # Invisible border to set extent
  tm_shape(homes_wgs) +
    tm_fill(
      fill = "firebrick",      # red dots
      fill_alpha = 0.7,
      size = 0.03,
      col = "firebrick",
      fill.legend = tm_legend_hide()
    ) +
  tm_add_legend(
    type = "fill",
    labels = "Impacted home",
    fill = "firebrick",
    shape = 22,

```

```

size = 0.6,
title = "",
bg.color = "transparent",
frame = FALSE) +
tm_layout(
  legend.position = c("right", "top"),
  legend.outside = FALSE,
) +
tm_compass(type = "arrow", position = tm_pos_in("left", "bottom"), size = 2) +
tm_scalebar(position = c(0.1, 0.1), text.size = 0.5) +
tm_basemap("CartoDB.PositronNoLabels")

homes_impacted_map

```

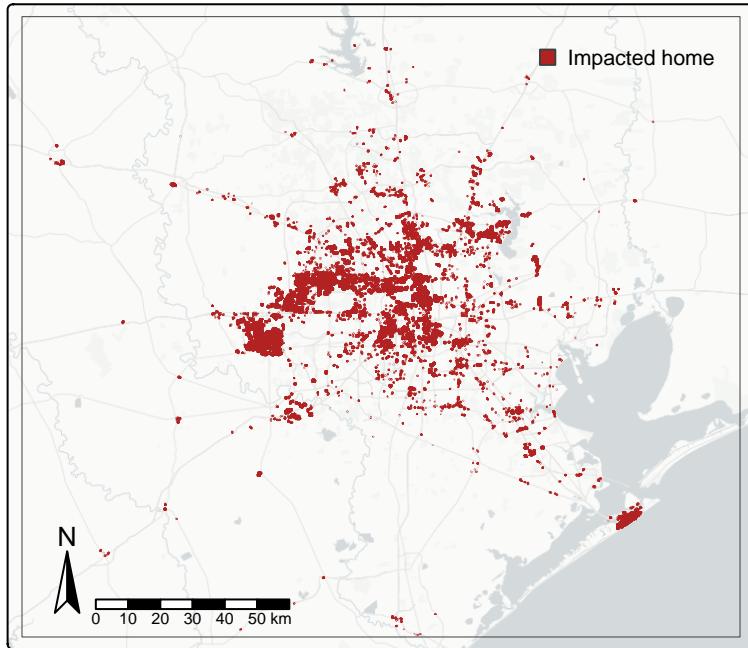


Figure 2: Estimated Locations of Homes Impacted by Power Outages in Houston, February 2021. Residential buildings located within areas of significant night-light reduction ($\geq 200 \text{ nW cm}^{-2} \text{ sr}^{-1}$) and beyond 200 m from major highways are shown in red. These structures represent homes likely affected by power outages during the February 2021 Texas winter storm.

Census Tract Analysis

i. Mapping Census Tracts that Lost Power

To map the census tracts that lost power, we first need to join the texas and blackout data together. We can use an intersection here. After we assign blackout or no blackout to each tract, we can zoom in on Houston and plot a map.

```

# Transform blackout areas and census tracts to same CRS
blk_clean_4269 <- st_transform(blk_clean, st_crs(texas))

# Find which census tracts intersect with blackout areas
tracts_impacted <- st_intersection(texas, blk_clean_4269) |>
  st_make_valid()

# Get unique tract IDs that experienced blackouts
impacted_tract_ids <- unique(tracts_impacted$GEOID)

# Add a column to full texas data indicating blackout status
texas <- texas |>
  mutate(blackout = ifelse(GEOID %in% impacted_tract_ids, "Blackout", "No Blackout"))

# Filter to Houston area for visualization
texas_houston <- st_intersection(texas, st_transform(hou_bbox, st_crs(texas))) |>
  st_make_valid()

# Create map
tmap_mode("plot")

tract_map <-
  tm_shape(texas_houston) +
  tm_fill(
    fill = "blackout",
    fill.scale = tm_scale_categorical(
      values = c("Blackout" = "firebrick", "No Blackout" = "gray85")
    ),
    fill.legend = tm_legend(
      title = "Census Tract Status"
    )
  ) +
  tm_borders(col = "white", lwd = 0.5) +
  tm_layout(
    legend.position = c("right", "bottom"),
    legend.bg.color = "white",
    legend.frame = FALSE,
    legend.outside = TRUE,
    frame = FALSE
  ) +
  tm_compass(type = "arrow", position = tm_pos_in("left", "bottom"), size = 1.5) +
  tm_scalebar(position = c(0.09, 0.09), text.size = 0.5)

```

tract_map

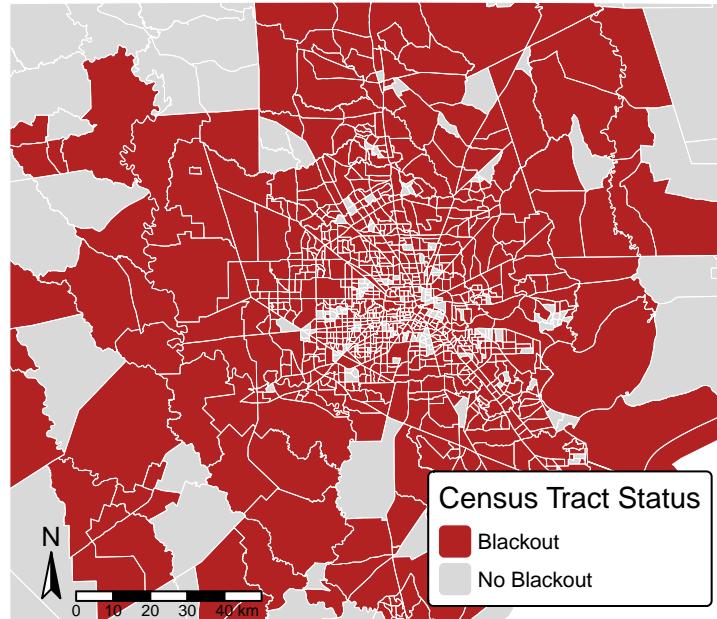


Figure 3: **Census Tracts in Houston Experiencing Power Outages During the February 2021 Winter Storm.** Houston-area census tracts classified by power outage status, based on reductions in night-light intensity between February 7 and 16, 2021. Tracts shown in red experienced significant decreases in radiance ($\geq 200 \text{ nW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}$), indicating likely blackouts, while gray tracts did not. Data: NASA VIIRS (VNP46A1), U.S. Census Bureau (ACS 2019), and OpenStreetMap.

ii. Income Distribution Comparison

First we need to find the correct layer in the geodatabase that holds the income data. Once we have the correct layer, we need to identify which column corresponds to the median household income within that layer. After, we will join the income data to the spatial data (texas), filter to Houston to create an income dataset.

```
# Check the layers to see which has income data
layers <- suppressMessages(suppressWarnings(st_layers(here("data", "ACS_2019_5YR_TRACT_48_TEXAS.gdb"))))

# We see that the income data is in layer X19_INCOME. We will need to load that layer and join
# Load the income layer
income_data <- st_read(here("data", "ACS_2019_5YR_TRACT_48_TEXAS.gdb"),
                        layer = "X19_INCOME")
```

Reading layer `X19_INCOME' from data source

`/Users/jacksoncoldiron/Documents/Bren/Fall 2025/EDS 223/EDS223-HW3/data/ACS_2019_5YR_TRACT_48_TEXAS.gdb' using driver `OpenFileGDB'

```

# Check what income columns are available
income_names <- names(income_data)

# From checking the metadata we can see that median household income column is: B19013e1 - "ME...
income_data_clean <- income_data |>
  mutate(GEOID = sub("14000US", "", GEOID))

# Join income data with spatial data using GEOID
texas_with_income <- texas |>
  left_join(income_data_clean |> st_drop_geometry(), by = "GEOID")

# Filter to Houston and create the income comparison
texas_houston_income <- st_intersection(texas_with_income, st_transform(hou_bbox, st_crs(texas))
  st_make_valid())

# Create the income dataset
texas_income <- texas_houston_income |>
  st_drop_geometry() |>
  filter(!is.na(B19013e1), B19013e1 > 0) |>
  select(GEOID, median_income = B19013e1, blackout)

```

Now with the new income dataset, we can create a comparison plot that investigates the differences in distribution of median household income census tracts that did and did not experience blackouts.

```

# Create comparison plot
ggplot(texas_income, aes(x = blackout, y = median_income, fill = blackout)) +
  geom_boxplot(alpha = 0.7, outlier.alpha = 0.3) +
  scale_fill_manual(
    values = c("Blackout" = "firebrick", "No Blackout" = "gray60"),
    guide = "none"
  ) +
  scale_y_continuous(
    labels = scales::dollar_format(),
    limits = c(0, 200000)
  ) +
  labs(
    x = "",
    y = "Median Household Income"
  ) +
  theme_minimal(base_size = 12) +
  theme(
    plot.title = element_text(face = "bold", size = 14),

```

```

    panel.grid.major.x = element_blank()
)

```

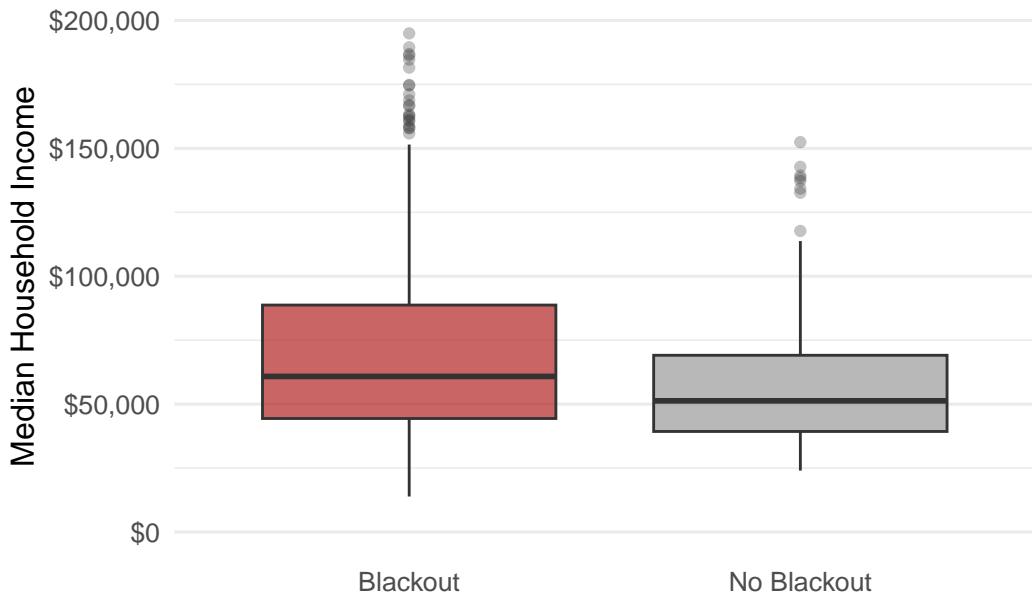


Figure 4: Median Household Income in Houston Census Tracts With and Without Power Outages. Boxplots comparing 2019 ACS median household income for Houston census tracts that experienced blackouts (red) and those that did not (gray). Tracts with blackouts generally show lower median incomes, suggesting socioeconomic disparities in the spatial distribution of outage impacts.

To get a better sense of the numbers behind the distributions. Let's show a table of summary statistics.

```

library(knitr)
library(kableExtra)

# Calculate summary statistics
income_summary <- texas_income |>
  group_by(blackout) |>
  summarise(
    n_tracts = n(),
    median = median(median_income),
    mean = mean(median_income),
    sd = sd(median_income)
  )

# Format numbers with commas and two decimals
income_summary_fmt <- income_summary |>
  mutate(
    median = scales::dollar(median),

```

```

    mean = scales::dollar(mean),
    sd = scales::dollar(sd)
  )

# Create clean, professional table
income_summary_fmt |>
  kable(
    caption = "Summary Statistics of Median Household Income by Blackout Status (Houston Census Tracts, 2019 ACS)",
    col.names = c("Blackout Status", "Number of Tracts", "Median Income", "Mean Income", "SD of Income"),
    align = c("l", "c", "c", "c", "c"),
    booktabs = TRUE
  ) |>
  kable_styling(
    full_width = FALSE,
    position = "center",
    bootstrap_options = c("striped", "hover", "condensed"),
    font_size = 11
  )

```

Table 1: Summary Statistics of Median Household Income by Blackout Status (Houston Census Tracts, 2019 ACS)

Blackout Status	Number of Tracts	Median Income	Mean Income	SD of Income
Blackout	927	\$61,188	\$72,095.42	\$39,605.27
No Blackout	175	\$51,583	\$59,042.76	\$29,889.70

Discussion

i. Results

This analysis estimated that approximately **157,411** homes in Houston lost power during the February 2021 winter storm. The blackout affected 935 census tracts in the Houston area. The income distribution analysis reveals that census tracts experiencing blackouts had a median household income of \$61,188 compared to \$51,583 for unaffected tracts.

ii. Limitations

This study has several constraints. First, the $200 \text{ nW cm}^{-2} \text{ sr}^{-1}$ threshold for identifying blackouts is arbitrary and may miss areas with partial power loss or misclassify areas with other causes of light reduction. Second, excluding areas within 200m of highways may inadvertently remove legitimate residential blackouts near major roads. Third, the building dataset may not accurately represent all residential structures, potentially underestimating impacts. Finally, cloud cover in satellite imagery could obscure true light conditions,

and the temporal resolution (9 days between observations) may miss shorter-duration outages or recovery dynamics.