Excess mortality in Puerto Rico after Hurricane María.

2024-12-16

1 Abstract (150-200 words)

This project quantifies excess mortality in Puerto Rico after Hurricane María by leveraging historical mortality data and applying a robust statistical framework. Using data from 1990–2016, expected weekly mortality rates were calculated by age group and sex, accounting for demographic variability, secular trends, and seasonal effects. Weeks with anomalous spikes were excluded to ensure statistical reliability. Post-hurricane mortality data from 2017–2018 were compared against these baselines to estimate excess deaths across demographic groups. One of the weeks was aligned to the landfall of Hurricane María to provide a precise temporal reference for the analysis.

Key findings revealed a significant rise in mortality immediately after the hurricane, with the older population (85+) particularly affected. While females showed higher mortality in older groups, males exhibited larger increases across most age groups. Younger populations were relatively resilient, showing little or no excess mortality. A comparative analysis performed by extracting data from the New York Times report, showed general agreement with our findings but with some discrepancy for November 2017; this is probably because of delayed death registrations. This study illustrates the utility of the excessmort package for detecting and quantifying mortality trends after natural disasters. This clearly indicates that targeted public health interventions are required, addressing the needs of vulnerable groups and enhancing disaster response systems.

2 Introduction (500-600 words)

Estimating mortality rates after a natural disaster is an important part of understanding the full impact of such an event and guiding effective interventions in public health and policy. Mortality provides a reliable metric to quantify the direct and indirect effects of disasters. The direct effects can be thought of as the 'immediate physical' consequences- injury, drowning-while the indirect effects result from the disruption to healthcare, infrastructure, and social conditions leading to enhanced risks of illness or delayed treatment. One of the best ways to capture the accumulated health effect of disasters is through excess mortality estimation, which refers to the number of deaths over and above what would have been expected based on the recent past. This measure has been widely used in research on everything from Hurricane María to the COVID-19 pandemic (CDC, 2021; Santos-Burgoa et al., 2018).

Usually, excess mortality is estimated with the use of historical data about mortality and statistical models, which take into account the demographic variation, secular trend, and seasonality. All these models need robust baselines from historical data in order to determine deviations during and after a disaster. For example, studies of Hurricane María have demonstrated the utility of such methods in uncovering the large and sustained rise in mortality across vulnerable populations in Puerto Rico (Santos-Burgoa et al., 2018; Kishore et al., 2018). However, existing methods are usually challenged to capture such complex temporal trends, especially in those cases where indirect effects are manifest gradually or show day-to-day variability. Common approaches, such as those based on Poisson regression, often lack the flexibility to model smooth trends and abrupt spikes simultaneously, limiting their effectiveness in characterizing disaster impacts over time(Farrington et al., 1996).

Hurricane María, which struck Puerto Rico in September 2017, provides a compelling case for examining the limitations of existing methodologies and advancing mortality estimation techniques. The hurricane caused widespread destruction, leading to extended power outages, healthcare system failures, and significant disruptions in infrastructure. While prior studies have documented excess mortality following María, discrepancies in datasets and the inability to capture smooth temporal trends have posed challenges for comprehensive analyses (Kishore et al., 2018). These issues highlight the need for methodological improvements to account for both natural variability and demographic-specific vulnerabilities in mortality patterns.

In view of this, our research is designed based on five interconnected tasks: First, we examine the population sizes by age group and sex to identify demographic patterns that may influence mortality risks. Second, we establish baseline mortality estimates using pre-2017 historical data. We compute the weekly expected mortality rates and standard deviations for each age group and sex by aggregating similar groups to enhance the efficiency and reliability of the analysis. Third, we explore the historical data in search of anomalous periods before 2017 exhibiting significant excess mortality unrelated to Hurricane María. These periods would be excluded in order not to affect the baseline mortality estimates. Fourth, we quantify weekly excess deaths for 2017–2018 by comparing the observed mortality rates to the baseline. Finally, we validate our findings by comparing the estimates of mortality with external data extracted from the New York Times report, addressing consistencies and resolving discrepancies, particularly those observed during critical periods like November 2017. These activities together form a comprehensive approach to understanding demographic and temporal patterns of excess mortality associated with Hurricane María.

The specific objectives of this study are the quantification of excess mortality after Hurricane María, assessment of demographic differences in vulnerability, and refinement of statistical methods to improve mortality estimation. Given the replicable framework provided by this research, this work overcomes certain limitations present in existing models informing targeted public health interventions. The findings underline the call for equitable resource allocation and preparedness strategies to protect vulnerable populations in future disasters.

3 Methods (600-700 words)

Task 1

To examine the demographic counts, broken down by age group and sex, the dataset puerto_rico_counts from the R package excessmort was utilized. First, the dataset was grouped by age group and sex to calculate the average population of each pairing of individuals. This was done using the group_by() and summarise() functions in R, with proper handling of missing values, including na.rm = TRUE in the aggregation. The findings were further illustrated using a bar plot created with the ggplot2 package, where the bars for males and females are separated and grouped by each age category. A "dodge" position adjustment is performed in order to make the comparison between gender in the same age group clearer. Such visualization was useful in demographic studies and presents the differences between population proportions in relation to different age groups and sexes.All this has enabled detailed study of population dynamics, laying the ground for basic understanding of demographic distributions necessary for further mortality analyses.

Task2:

We used historical mortality data from Puerto Rico collected before 2017 to estimate weekly expected mortality and standard deviation by age group and sex. The dataset included daily mortality counts, which we filtered for pre-2017 dates. Using the R package, we added variables for the year and ISO week to ensure standard week alignment. We calculated weekly mortality by aggregating daily counts per age group, sex, and week. Baseline statistics, including mean and standard deviation, were computed for each group. For streamlined analysis, age groups were combined based on mortality rate similarities into categories: 0-14, 15-39, 40-59, 60-74, and 75+. Visualization of these patterns was achieved using ggplot2, showing trends in mean weekly mortality by age and sex.

Task3:

To explore excess mortality periods in Puerto Rico before 2018 (during or before 2017), we analyzed weekly mortality counts, ensuring inclusion of only complete weeks (seven days). We visualized the data to identify spikes, using thresholds to define excess mortality—700 deaths per week post-1987 and 550 pre-1987—based on historical trends. This baseline allowed us to flag weeks with significantly higher mortality. We then removed these high mortality weeks from the dataset to recalculate expected death rates. This ensured that baseline statistics, such as mean and standard deviation, accurately reflected normal patterns without influence from exceptional events.

Task 4

For task 4, we used the puerto_rico_counts dataset from 2017 to 2018. Weekly outcomes were derived using floor_date() by aggregating the raw daily mortality data to weekly totals, aligning weeks to the day of Hurricane María. Only complete weekly records (7 days) were retained to ensure data consistency and completeness. We also use epiweek() to match weeks of different years. Weekly mortality counts were grouped by date, sex, and agegroup. Historical mortality from pre-2017 data are used to calculate expected mortality (mean_outcome) for each epiweek, age group, and sex. Then, weekly excess deaths from 2017-2018 were calculated by subtracting the expected deaths from the observed weekly deaths for each sex and age group by matching epiweek.

Task 5

The New York Times data was extracted via pdfplumber in Python (ipynb file is provided in directory 'code'). After saving it as an Excel file, we loaded it using the read_excel function in R. The Puerto Rico daily mortality data was filtered to include dates between January 1, 2015, and November 30, 2017, as December was not predicted yet at that point.

The Puerto Rico dataset in excessmort package was grouped by date, and the two datasets were merged using a left join on the Date column. Absolute values of difference between Outcome_NYTimes (from the NY Times dataset) and Outcome_DailyData (from the Puerto Rico dataset) were also calculated and plotted.

4 Results (500-600 words)

Prepare

```r
library(excessmort)
library(dplyr)
library(lubridate)
library(ggplot2)
library(readxl)
data("puerto_rico_counts")
head(puerto_rico_counts)
```

```
  agegroup       date    sex population outcome
1      0-4 1985-01-01 female   158843.0       2
2      0-4 1985-01-01   male   164476.6       0
```

```
3      0-4 1985-01-02 female   158837.8       0
4      0-4 1985-01-02   male   164471.2       0
5      0-4 1985-01-03 female   158832.6       1
6      0-4 1985-01-03   male   164465.9       0
```

Task 1

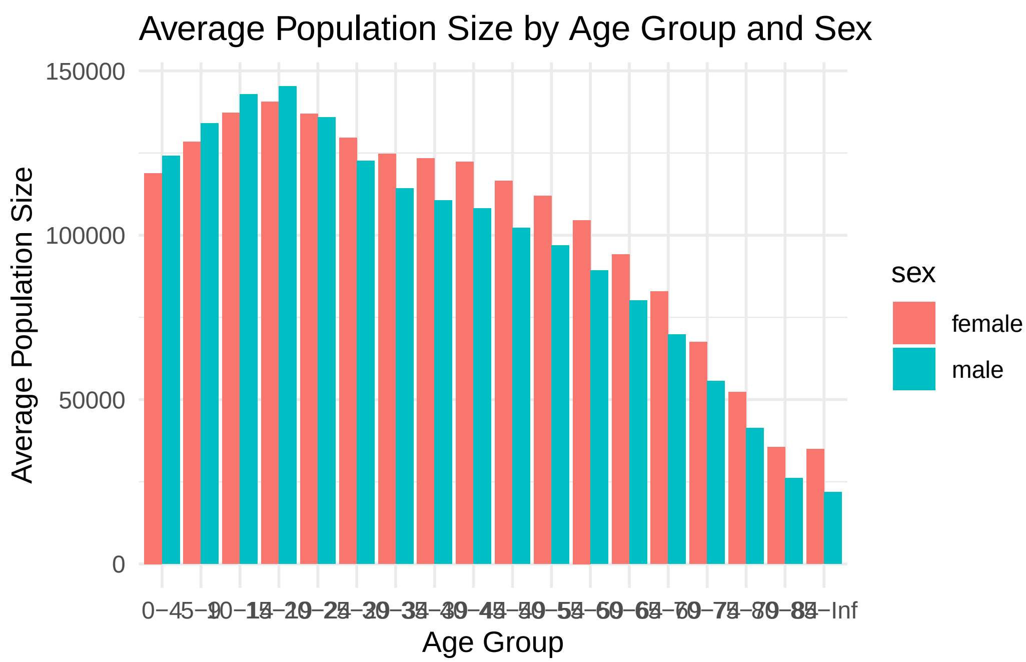
```r
population_summary <- puerto_rico_counts |>
  group_by(agegroup, sex) |>
  summarise(mean_population = mean(population, na.rm = TRUE))
```

```
`summarise()` has grouped output by 'agegroup'. You can override using the
`.groups` argument.
```

```r
print(population_summary)
```

```
# A tibble: 36 x 3
# Groups:   agegroup [18]
   agegroup sex    mean_population
   <fct>    <chr>            <dbl>
 1 0-4      female         118887.
 2 0-4      male           124167.
 3 5-9      female         128338.
 4 5-9      male           134028.
 5 10-14    female         137254.
 6 10-14    male           142835.
 7 15-19    female         140546.
 8 15-19    male           145330.
 9 20-24    female         136901.
10 20-24    male           135803.
# i 26 more rows
```

```r
ggplot(population_summary, aes(x = agegroup, y = mean_population, fill = sex)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Average Population Size by Age Group and Sex",
       x = "Age Group", y = "Average Population Size") +
  theme_minimal()
```



In the younger age group, under 14 years, male has higher proportion than female. This might be because of the notion that some of the family willingly prefer having boy baby than girl. Besides, the sex ratio at born is around 105-107 boys versus 100 girls globally.

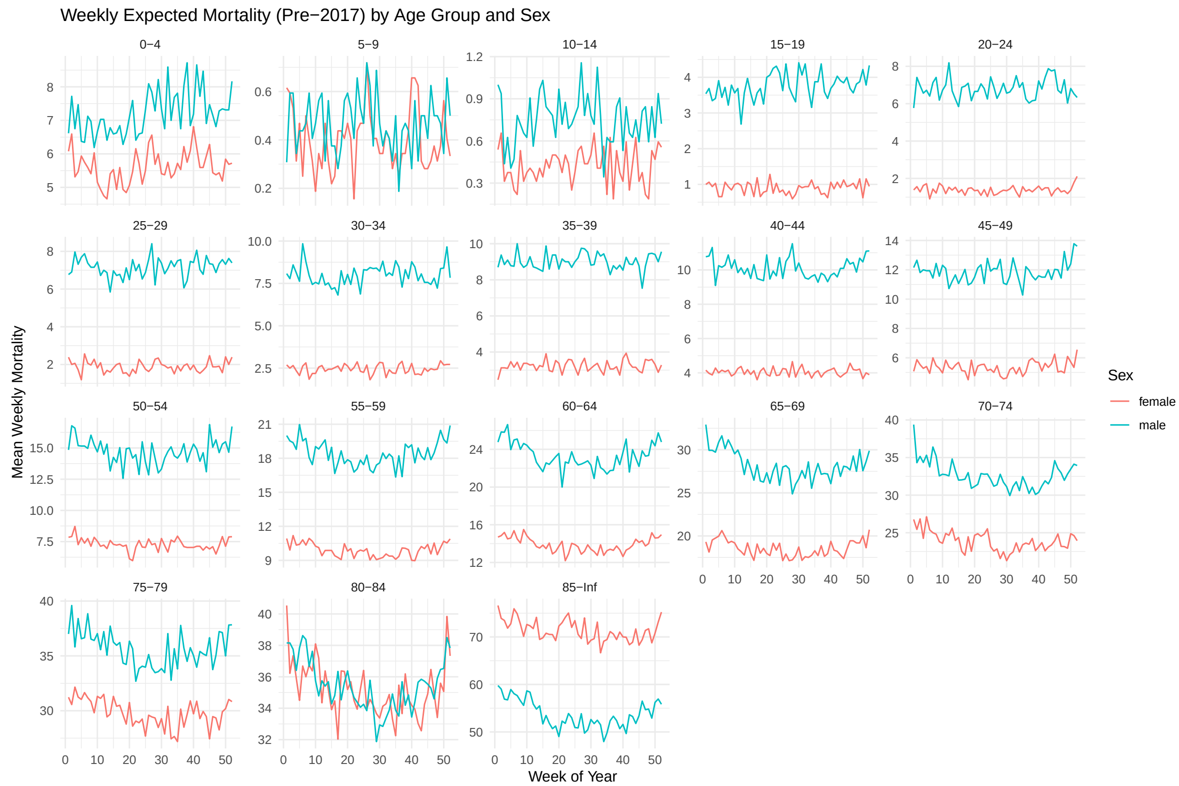
In the working age group, 20-49, female has higher proportion than male. This might be because male moving out for work or moving out for immigration.

During the elder group, the proportion of female is still higher than that of male. This might be because the average age of female is higher than that of male.

Task 2

```
pre_2017_data <- puerto_rico_counts |>
  filter(date < as.Date("2017-01-01")) |>
  mutate(
    year = year(date),
    week_of_year = epiweek(date)
  )

# Aggregate by year, week_of_year, agegroup, and sex, and ensure full weeks (7 distinct da
weekly_data <- pre_2017_data |>
  group_by(year, week_of_year, agegroup, sex) |>
```

```r
  summarise(
    weekly_outcome = sum(outcome, na.rm = TRUE),
    ndays = n_distinct(date),  # Count distinct days in this week-group
    .groups = 'drop'
  ) |>
  filter(ndays == 7)  # Keep only full weeks

# Compute baseline statistics across all pre-2017 years
baseline_stats <- weekly_data |>
  group_by(agegroup, sex, week_of_year) |>
  summarise(
    mean_outcome = mean(weekly_outcome, na.rm = TRUE),
    sd_outcome = sd(weekly_outcome, na.rm = TRUE),
    .groups = 'drop'
  )

# Plot: Facet by age group, color by sex on the same plot
ggplot(baseline_stats, aes(x = week_of_year, y = mean_outcome, color = sex)) +
  geom_line() +
  facet_wrap(~ agegroup, scales = "free_y") +
  labs(
    title = "Weekly Expected Mortality (Pre-2017) by Age Group and Sex",
    x = "Week of Year",
    y = "Mean Weekly Mortality",
    color = "Sex"
  ) +
  theme_minimal()
```



The analysis shows clear mortality patterns by age and sex. Males generally exhibited higher mortality rates than females across most age groups. Mortality rates increased with age, particularly in the 75+ category. Over the weeks, mortality rates remained relatively stable, with minor fluctuations in younger groups. Combining age groups allowed us to maintain trend visibility while simplifying analysis. The visualizations highlighted these trends effectively, showing greater variability in older age groups. These patterns reflect demographic expectations, confirming the consistency and reliability of the estimated mortality statistics.

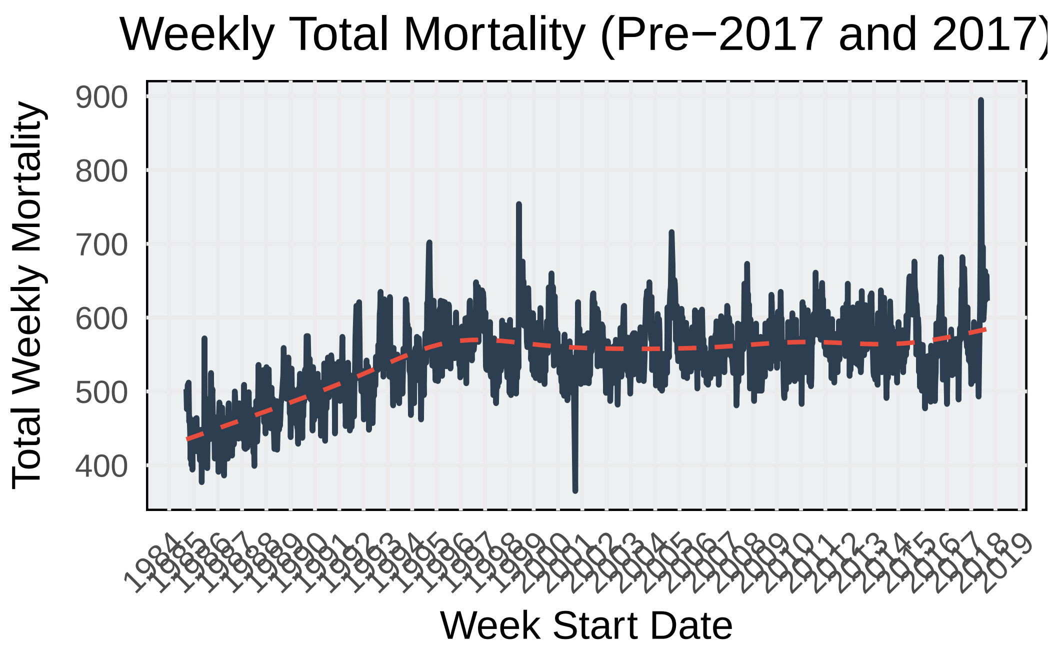
Task 3

```
# Filter for pre-2017 and 2017 data, assign year and week_of_year
pre_and_during_2017 <- puerto_rico_counts |>
  filter(date < as.Date("2018-01-01")) |>  # Include all data before 2018
  mutate(
    year = year(date),
    week_of_year = epiweek(date)
  ) |>
  group_by(year, week_of_year) |>
```

```r
    summarise(
      total_outcome = sum(outcome, na.rm = TRUE),  # Sum weekly outcomes
      ndays = n_distinct(date),                    # Ensure full weeks (7 days)
      .groups = "drop"
    ) |>
    filter(ndays == 7) |>  # Keep only full weeks
    mutate(
      week_start = as.Date(paste(year, week_of_year, 1, sep = "-"), "%Y-%U-%u")  # Start of
    )

  # Visualization: Weekly total mortality over time
  # Add a new date column to represent the start of each week
  pre_and_during_2017 <- pre_and_during_2017 |>
    mutate(week_start = as.Date(paste(year, week_of_year, 1, sep = "-"), "%Y-%U-%u"))

  ggplot(pre_and_during_2017, aes(x = week_start, y = total_outcome)) +
    geom_line(color = "#2C3E50", size = 1) +
    geom_smooth(se = FALSE, color = "#E74C3C", linetype = "dashed", size = 0.8) +
    labs(
      title = "Weekly Total Mortality (Pre-2017 and 2017)",
      x = "Week Start Date",
      y = "Total Weekly Mortality"
    ) +
    scale_x_date(date_labels = "%Y", date_breaks = "12 months") +
    theme_minimal(base_size = 15) +
    theme(
      plot.title = element_text(hjust = 0.5),
      plot.subtitle = element_text(hjust = 0.5, face = "italic"),
      axis.text.x = element_text(angle = 45, vjust = 1, hjust = 1),
      axis.title.y = element_text(margin = margin(r = 10)),
      panel.grid.minor = element_blank(),
      panel.background = element_rect(fill = "#ECF0F1")
    )
```

```
Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.
i Please use `linewidth` instead.
```

```
`geom_smooth()` using method = 'gam' and formula = 'y ~ s(x, bs = "cs")'
```




```
# Identify weeks with mortality >= 700 for year > 1987 and < 2017
weeks_high_mortality_post_1987 <- pre_and_during_2017 |>
  filter(year > 1987 & year <= 2017, total_outcome >= 700) |>
  select(year, week_of_year, total_outcome, week_start)

# Identify weeks with mortality > 550 for year <= 1987
weeks_high_mortality_pre_1987 <- pre_and_during_2017 |>
  filter(year <= 1987, total_outcome > 550) |>
  select(year, week_of_year, total_outcome, week_start)

# Combine high mortality weeks
high_mortality_weeks <- bind_rows(
  weeks_high_mortality_post_1987 |> select(year, week_of_year),
  weeks_high_mortality_pre_1987 |> select(year, week_of_year)
)

#### Remove high mortality weeks from baseline computation
# Filter pre-2017 data and define epiweek and year
pre_2017_data <- puerto_rico_counts |>
  filter(date < as.Date("2017-01-01")) |>
  mutate(
    year = year(date),
```

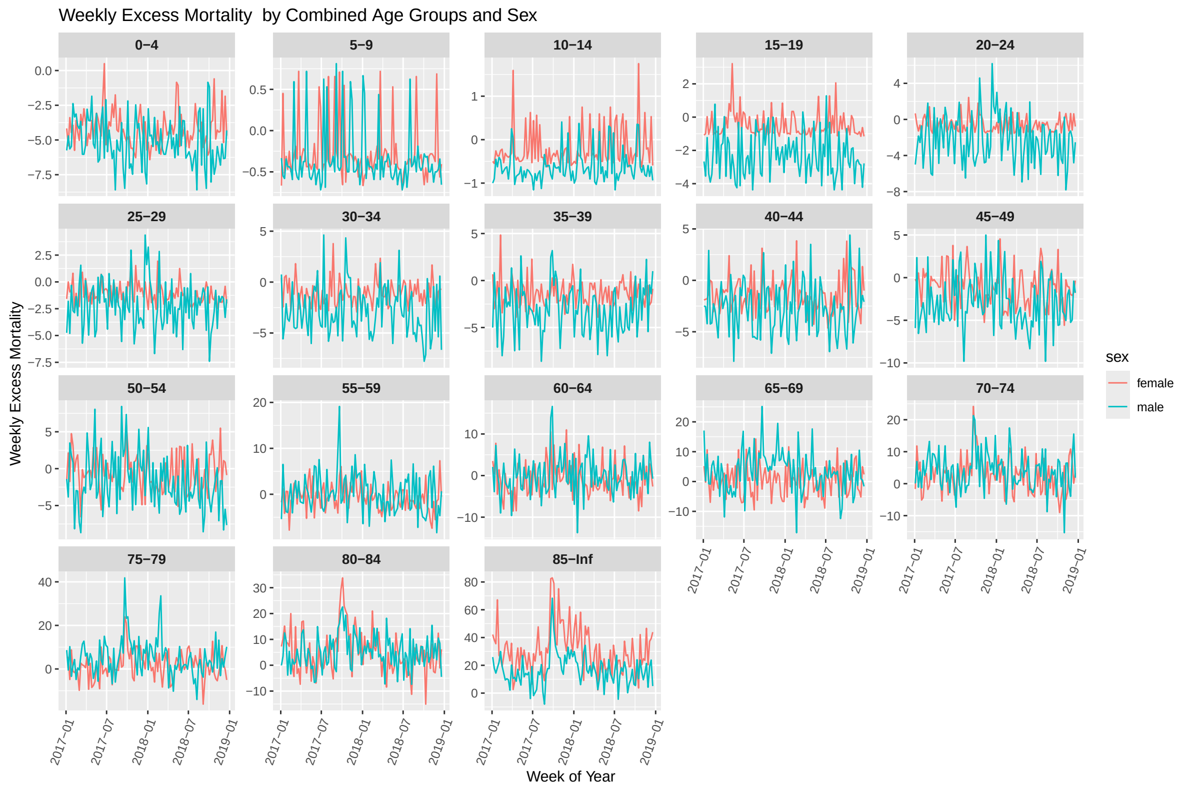
```
    week_of_year = epiweek(date)
  )

# Aggregate by year, week_of_year, agegroup, and sex, and ensure full weeks (7 distinct da
weekly_data <- pre_2017_data |>
  group_by(year, week_of_year, agegroup, sex) |>
  summarise(
    weekly_outcome = sum(outcome, na.rm = TRUE),
    ndays = n_distinct(date),  # Count distinct days in this week-group
    .groups = 'drop'
  ) |>
  filter(ndays == 7)  # Keep only full weeks

# Remove weeks with high mortality
filtered_weekly_data <- weekly_data |>
  anti_join(high_mortality_weeks, by = c("year", "week_of_year"))

# Compute baseline statistics across all pre-2017 years, excluding high mortality weeks
baseline_stats <- filtered_weekly_data |>
  group_by(agegroup, sex, week_of_year) |>
  summarise(
    mean_outcome = mean(weekly_outcome, na.rm = TRUE),
    sd_outcome = sd(weekly_outcome, na.rm = TRUE),
    .groups = 'drop'
  )
```

The weekly total mortality plot reveals several periods with significant spikes in mortality between the years 1985 and 2017. As you can see from the graph, it shows fluctuations with some significant spikes, particularly around the mid-1990s, late 1990s, early 2000s, and 2017. The identified weeks exhibiting high mortality include weeks 2 and 3 of 1995, week 38 of 1998, week 1 of 2005, weeks 39 and 40 of 2017, and week 41 of 1985. After identifying and isolating these high mortality weeks, we excluded them from the dataset and recomputed expected death rates. The refined data is documented in the Supplementary Methods, supporting a more accurate understanding of mortality trends absent of those identified anomalies.

Task 4

```
maria <- make_date(2017, 9, 20)

q4_data <- puerto_rico_counts |>
  filter(between(year(date), 2017, 2018)) |>
```

```r
  mutate(date = floor_date(date, week_start = wday(maria)-1, unit = "week"))

weekly_counts <- q4_data |>
  group_by(date, sex, agegroup) |>
  summarize(outcome = sum(outcome,na.rm = TRUE),n = n(),
            .groups = "drop")|>
  filter(n == 7) |>
  select(-n)|>
  mutate(week_of_year=epiweek(date))

excess_counts <- weekly_counts %>%
  left_join(baseline_stats, by = c('sex', 'agegroup','week_of_year'))|>
  mutate(excess_deaths=outcome-mean_outcome)

# Plot the combined groups
ggplot(excess_counts, aes(x = date, y = excess_deaths, color = sex)) +
  geom_line() +
  facet_wrap(~ agegroup, scales = "free_y") +
  labs(
    title = "Weekly Excess Mortality  by Combined Age Groups and Sex",
    x = "Week of Year",
    y = "Weekly Excess Mortality"
  ) +
    theme(
    axis.text.x = element_text(angle = 70, hjust = 1),  # Rotate week labels for better re
    strip.text = element_text(size = 10, face = "bold") # Adjust facet label
  )
```



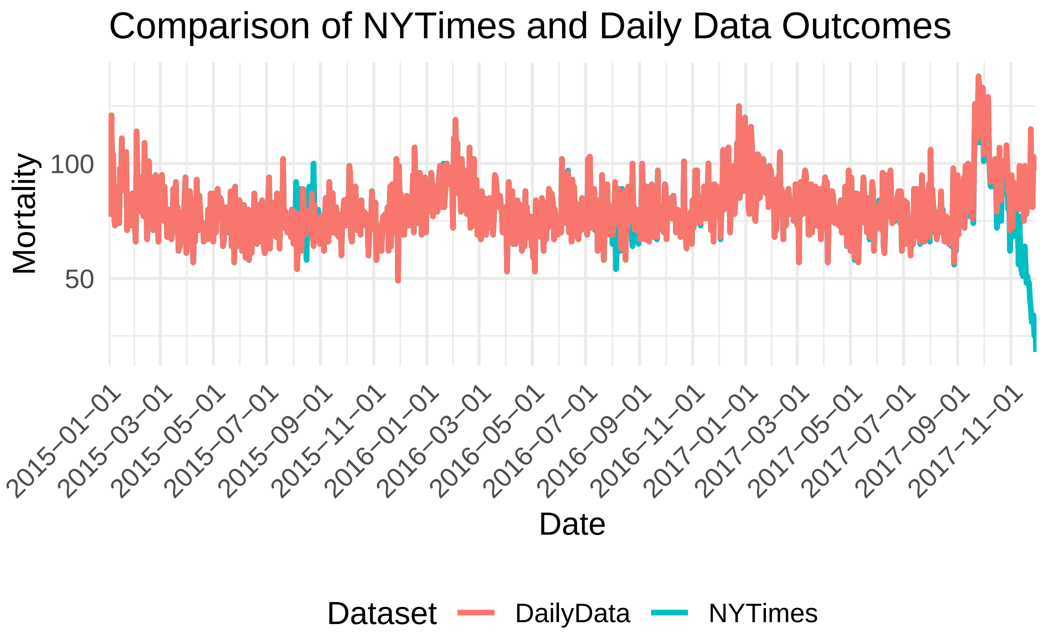
Weekly excess deaths were plotted for each age group, separated by sex using facet grids. Axes were scaled independently (free_y) to accommodate varying ranges of mortality across age groups. Weekly excess deaths varied significantly by age group and sex. Older age groups (e.g., 85+) exhibited the highest excess mortality (roughly range from -10 to 85), particularly among females. Younger age groups (e.g., 0–4) showed minimal to no significant excess deaths. Generally, across most age groups, females experienced slightly higher excess deaths than males, particularly in the elderly cohorts, while mortality in male is more fluctuated than mortality in female. Excess mortality peaked in the weeks immediately following Hurricane María(2017/09/20), with continued elevated mortality into early 2018. Mortality trends normalized for most age groups by mid-2018.

Task 5

```
# Read and prepare NYTimes data
ny_times <- read_excel("../data/ny_times_data.xlsx") %>%
  arrange(Date) %>%
  mutate(Date = as.Date(Date))  # Ensure Date column is in Date format
```

```r
# Prepare Puerto Rico daily data
daily_data <- puerto_rico_counts %>%
  filter(date >= as.Date("2015-01-01") & date <= as.Date("2017-11-30")) %>%  # Filter date
  group_by(date) %>%
  summarize(Outcome = sum(outcome, na.rm = TRUE), .groups = "drop") %>%
  rename(Date = date) %>%  # Rename `date` to `Date` for consistency
  arrange(Date)

# Join datasets and calculate the difference
compared_data <- ny_times %>%
  left_join(daily_data, by = "Date") %>%
  rename(Outcome_NYTimes = Outcome.x, Outcome_DailyData = Outcome.y) %>%
  mutate(Difference = Outcome_NYTimes - Outcome_DailyData)  # Add Difference column
```

```r
# Plot the data
ggplot(compared_data, aes(x = Date)) +
  geom_line(aes(y = Outcome_NYTimes, color = "NYTimes"), size = 1) +
  geom_line(aes(y = Outcome_DailyData, color = "DailyData"), size = 1) +
  labs(
    title = "Comparison of NYTimes and Daily Data Outcomes",
    x = "Date",
    y = "Mortality",
    color = "Dataset"
  ) +
  scale_x_date(
    breaks = "2 months",              # Add breaks every 2 months
    date_labels = "%Y-%m-%d",         # Format labels as "Year-Month-Day"
    expand = c(0, 0)                  # Remove extra space on the x-axis
  ) +
  theme_minimal(base_size = 12) +
  theme(
    axis.text.x = element_text(angle = 45, hjust = 1),  # Rotate x-axis labels for readabi
    legend.position = "bottom"                          # Move legend to the bottom
  )
```



The plot shows the trends of daily mortality counts from both the New York Times and the Puerto Rico daily dataset. Overall, the two datasets align closely for most of the time period (2015–2017), but notable divergences occur: The NY Times data exhibits a sharp drop toward the end of 2017. The absolute difference plot in Task 5 section of supplementary.qmd highlights the absolute differences in mortality counts between the two datasets. Significant spikes in differences are observed around November 2017, and noticeable spikes occur in August 2015 and 2016.

Discussion (600-700 words)

Our study analyzed excess mortality in Puerto Rico following Hurricane María using a structured framework of demographic analysis, historical baselines, and external validation. The findings illuminate key demographic patterns, disaster-related mortality trends, and the broader implications of natural disasters on public health.

The demographic analysis (Task 1) revealed notable patterns across age groups and sexes. In the youngest age group, 0–14 years, males consistently outnumbered females in this age group, which may be explained by the global biological norm of higher male birth ratio. This pattern does not influence mortality directly; however, it points out underlying population dynamics. Working-age adults (20–49 years) showed a higher proportion of females, likely due to male emigration for employment, which may shift local mortality risks. Among the elderly (65+ years), females were significantly outnumbering males, reflecting higher female life expectancy.

This disparity signals the importance of consideration of disaster response strategies in light of elderly women's particular vulnerabilities, including access to medications and mobility aids during post-disaster recovery.

Baseline mortality estimates (Task 2) confirmed that mortality rates increase with age and are higher among males, aligning with global trends attributed to biological vulnerabilities and lifestyle factors (World Health Organization, 2021). Weekly mortality rates exhibited seasonal stability but fluctuated significantly in older age groups (85+ years), likely driven by seasonal illnesses and extreme weather events. These findings really emphasize the role and contribution of public health measures addressing vulnerabilities at specific times of the year, such as vaccination campaigns and early warnings among vulnerable populations. Further examination beyond 2017 might reveal how these trends have been influenced by improved healthcare.

Identifying and excluding anomalous pre-2017 periods (Task 3) was an important step in refining baseline estimates. Large deviations, such as those occurring during flu seasons, were removed to provide more accurate mortality estimates. This ensured that the mortality trends were not influenced by unrelated events, thus enhancing the reliability of baseline models and supporting more accurate post-disaster analysis. Such removal of outliers is considered a best practice in disaster-related mortality studies (Spagat & van Weezel, 2020).

The quantification of excess deaths on a weekly basis for 2017-2018 (Task 4) showed a sharp increase in mortality following Hurricane María, with marked effects among the elderly (85+ years). This finding underscores systemic healthcare vulnerabilities and difficulties in managing chronic conditions amid protracted infrastructure disruptions. Higher excess mortality among elderly females would suggest disparities in healthcare access or pre-existing health conditions that were accentuated in the post-hurricane period. In contrast, very low excess mortality among younger age groups, such as 0–4, speaks to their relative resilience. Temporally aligning the analysis to María's landfall provided rich temporal insights that allowed for specific policy recommendations to protect vulnerable groups in future disasters.

The validation process (Task 5) compared our mortality estimates with data from the New York Times. While alignment was strong for most periods, discrepancies in November 2017 likely resulted from delayed death registrations, reflecting known reporting challenges during disasters (Kishore et al., 2018). Variances in earlier periods, such as August 2015 and 2016, may be attributed to localized events inconsistently captured across datasets. These findings emphasize the importance of cross-referencing multiple datasets to improve the accuracy of mortality assessments.

This study further develops the methodological approach by incorporating demographic trends, refined baselines, and validation of datasets for estimating excess mortality. In contrast to the traditional methods, which often face difficulties with temporal trends or daily variability, this framework provides a robust model that can be applied to other disasters and public health crises, such as pandemics or extreme weather events (CDC, 2021). The fact that this approach is reproducible enhances its usefulness for both policymakers and researchers.

Yet, it also has limitations. Small daily counts led to challenges, particularly after stratification by demographic groups; these were reduced by the smoothing technique. Events may also have overlapped, such as flu seasons occurring with Hurricane María, which complicates the disentanglement of the individual impacts. Future research should focus on refining methods to decouple overlapping effects and incorporate granular data on healthcare access and socioeconomic factors to enhance disaster response strategies. Refining statistical methods and embedding demographic knowledge, the findings provide a solid basis for the development of equitable disaster response strategies and enhanced public health preparedness. As climate change increases the risks of disasters, this research underlines the urgent need for the protection of vulnerable populations through targeted interventions and resilient healthcare systems.

Reference:

Centers for Disease Control and Prevention (CDC). (2021). Excess deaths associated with COVID-19. CDC Excess Deaths Associated with COVID-19. Retrieved from https://www.cdc.gov/nchs/nvss/vsrr/covid19/excess_deaths.htm

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Kishore, N., Marqués, D., Mahmud, A., Kiang, M. V., Rodriguez, I., Fuller, A., ... & Buckee, C. O. (2018). Mortality in Puerto Rico after Hurricane Maria. New England Journal of Medicine, 379(2), 162-170. Retrieved from https://doi.org/10.1056/NEJMsa1803972

Santos-Burgoa, C., Sandberg, J., Suárez, E., Colón-Ramos, U., Nazario, C. M., Rios-Gonzalez, C. M., & Goldman, A. (2018). Differential and persistent risk of excess mortality from Hurricane Maria in Puerto Rico: A time-series analysis. The Lancet Planetary Health, 2(11), e478-e488. Retrieved from https://doi.org/10.1016/S2542-5196(18)30209-2

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