Drone Strikes in the Middle East
Pakistan, Somalia, Yemen

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3 June 2022

Contents

Abstract

In this report, we look at drone strike data from 2004 onward (Pakistan) and 2007 onward (Somalia and Yemen). We consider the distribution of civilian casualties by country and president in addition to frequency of strikes by president. Our analyses indicate that Pakistan had a higher percentage of civilian casualties, while Somalia had a civilian casualty rate (as a percent of the total persons killed) distinctly less than expected. Regarding presidents, we find evidence that the lethality of drone strikes differs by president (with Bush having the largest average fatality per strike), but do not find evidence of a significant difference in drone frequency by term length.

Background

Context

Data Introduction

The data contains information on drone strikes in the Middle East, courtesy of The Guardian. We have drone strike data since 2004 for Pakistan and from 2007 for Somalia and Yemen. Within these datasets, each observation corresponds to a single drone strike. We have information on the date and area of the strike along with the number of people, civilians, and children killed and the number of people injured.

From the area and country for each strike, we used a Google Maps API key (within the `ggmap()` package) to geocode the areas into latitude and longitude. The latitude and longitude are for a general area–not a specific strike location–and some observations did not have geocoded locations.
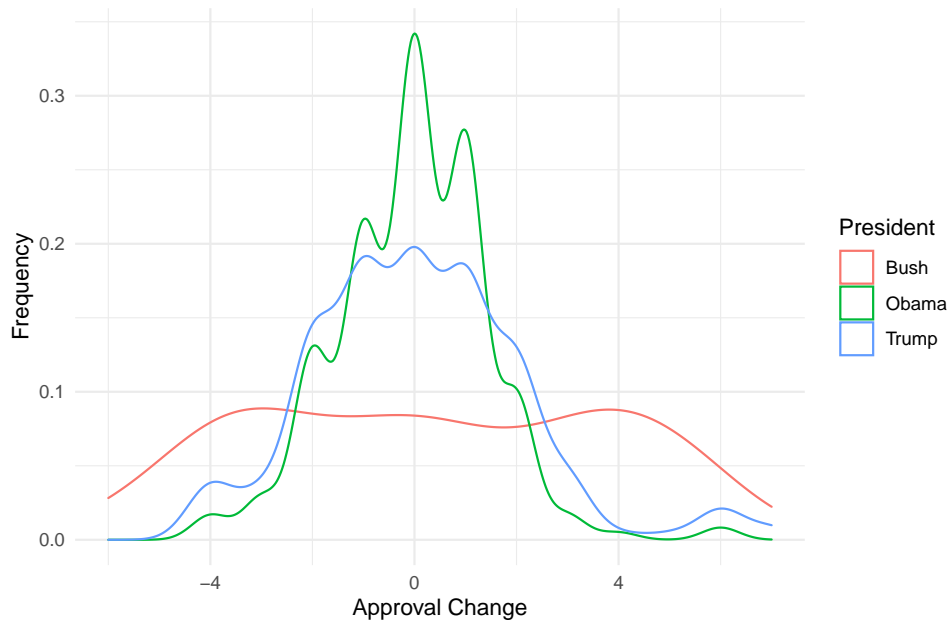
Exploratory Data Analysis
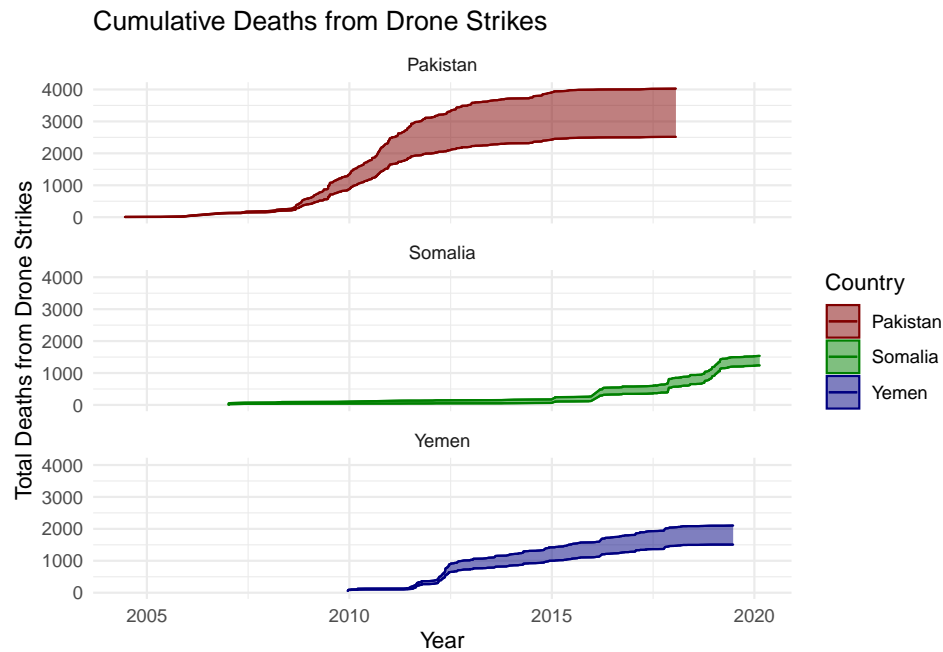
Location of Drone Strikes
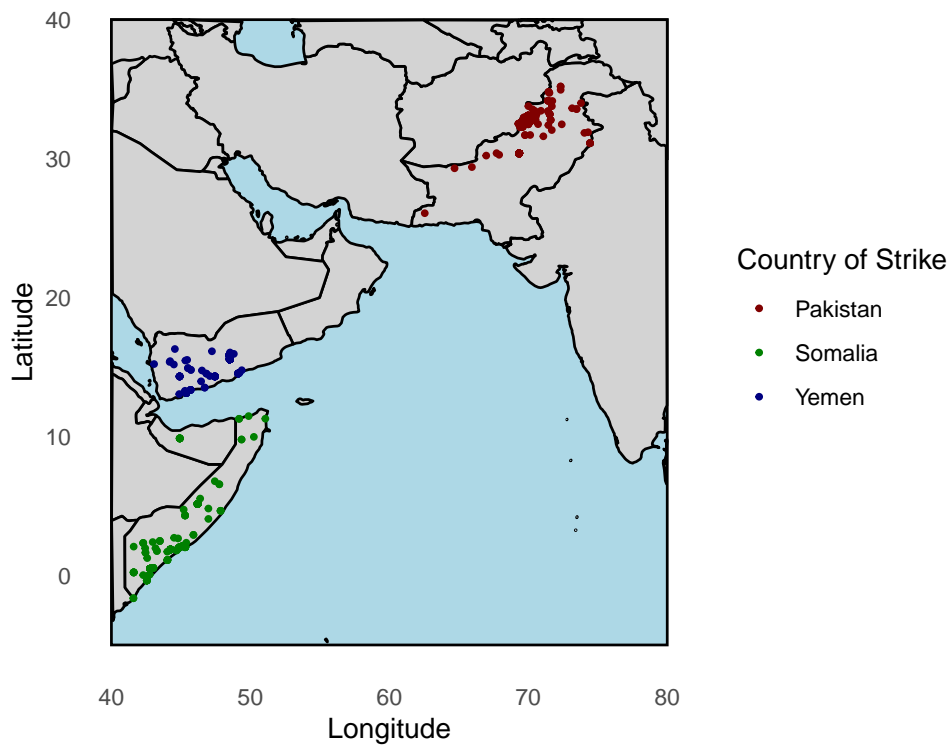
Approval Changes After Drone Strikes by President

Statistical Analysis

After performing exploratory data analysis, we had three main interests in the dataset: (1) the accuracy/effectiveness of the drone strikes (in terms of casualties), (2) the strike lethality for each president, and (3) the frequency of drone strikes for each president's term.

Drone Accuracy Rate

For this statistical analysis, we compared the three countries (Pakistan, Somalia, and Yemen) with respect to the percentage of civilian casualties. For the purposes of the analysis, we define the total and civilian number of casualties as the average of the minimum and maximum deaths for people and civilians, respectively.

We conducted the analysis as a Chi-squared test to look at the distribution of civilian deaths across the three countries. Our null hypothesis would assume that the distribution of civilian deaths matched the distribution of noncivilian deaths, calculated by total deaths − civilian deaths. The reason we set the null distribution as the number of noncivilians killed–and not just a pure equality–is because the number of deaths does not remain consistent across countries, so we wanted to account for that distribution. We can summarize our null and alternative hypotheses as follows:

$$H_0 : \text{Civilian deaths follow the same distribution as noncivilian deaths}$$
$$H_a : \text{Civilian deaths do not follow the same distribution as noncivilian deaths}$$

After conducting the Chi-squared test, we obtained a test statistic of $\chi^2 \approx 217.53$, which corresponds to a p-value of $p < 2.2 \times 10^{-16} \approx 0$. Thus, we reject our null hypothesis that civilian deaths by country follow the same distribution as noncivilian deaths, implying that the countries differed in the accuracy of their strikes with respect to civilian deaths as a fraction of total deaths. Moreover, a posthoc analysis of the test demonstrated the stark differences on the country level:

Table 1: Posthoc Summary of Civilian Deaths by Country

Country	Civilians Killed	Total Killed	Civilian Percent of Deaths	Pearson Residual
Pakistan	696	3,270	21.3%	9.3
Somalia	72	1,390	5.2%	-11.3
Yemen	266	1,811	14.7%	-1.6

From the above posthoc analysis, we see that Pakistan had a decided higher civilian death rate, while Somalia had a relatively low civilian death rate. While we cannot make any causal inference from these results, it appears that Pakistan–which does have data from an earlier timeframe (since 2004)–has a less deliberate approach while Somalia had greater accuracy in eliminating hostiles.

Drone Lethality

Our second analysis considered the lethality of drone strikes, by president. Initially, when performing EDA, we noticed that the distribution of deaths from drone strikes was heavily right-skewed. To correct for this (and meet the assumptions for the ANOVA we wished to conduct), we log-transformed the deaths after adding 1 to all deaths. This ensured that we did not have to remove strikes with 0 deaths from our analysis.

Once we ensured that we met the assumptions of our ANOVA, we could construct our null and alternative hypotheses and conduct the analysis. Our null hypothesis would be that the average number of deaths per strike would be the same across all presidents; our alternative would be that at least one president had a significantly different average number of deaths.

$$H_0 : \mu_{\text{Bush}} = \mu_{\text{Obama}} = \mu_{\text{Trump}}$$
$$H_a : \text{At least one } \mu \text{ is not equal}$$
$$\mu_{\text{President}} \text{ represents the average number of deaths per strike, after transformation}$$

Table 2: ANOVA Results for Strike Lethality

	df	SS	MS	F	p-value
President	2	53.89	26.94	44.93	0
Residuals	941	564.31	0.60		

Table 3: TukeyHSD Pairwise Posthoc

Pairwise Comparison	Adjusted p-value
Obama-Bush	0.0245
Trump-Bush	0.0000
Trump-Obama	0.0000

Table 4: Lethality Statistics by President

President	Average Deaths per Strike	Median Deaths per Strike
Bush	9.75	7.50
Obama	7.03	5.00
Trump	5.54	2.25

People Killed per Drone Strike by President
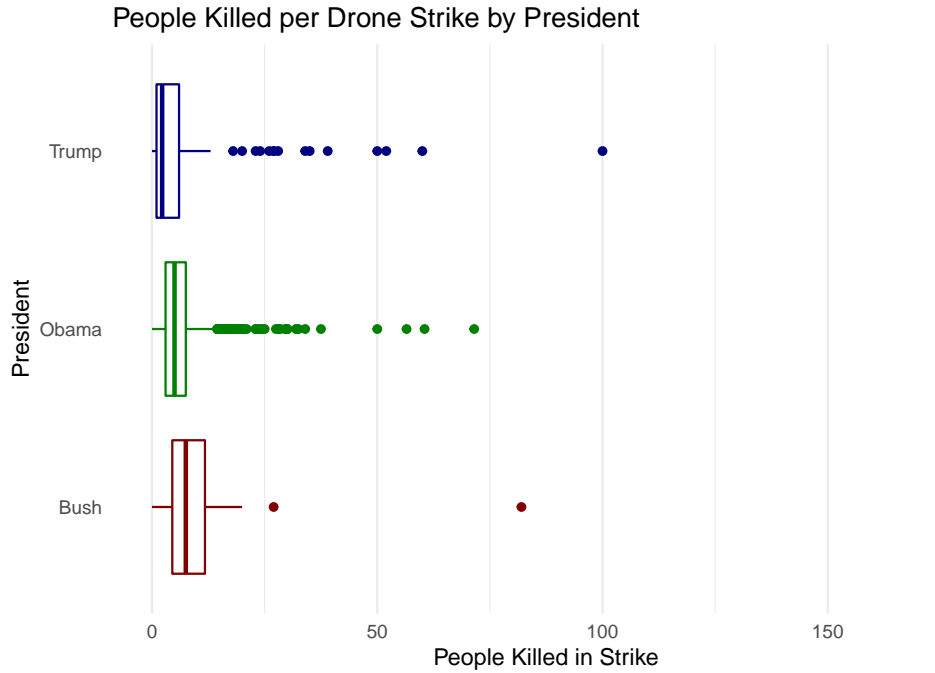
Drone Usage

Our third statistical analysis focused on the frequency of drone strike usage by each president. However, this analysis had a much greater limitation than our first analysis, due to the time frames for each country. Thus, to accommodate for data discrepanies across countries, we limited the date range to the overlapping date range across all three datasets. After filtering the data, we had strikes from December 18, 2009 (2009-12-18)

to January 18, 2018 (`2018-01-18`). Because of this, our analysis for how frequently presidents utilized drone only applies to Presidents Obama and Bush.

From here, we conducted another Chi-squared test to see if the frequency of strikes aligned with the term length for each president over the restricted time frame. Therefore, we can summarize our null and alternative hypothesis as:

$$H_0 : \text{The number of drone strikes follow the distribution of term length}$$
$$H_a : \text{The number of drone strikes do not follow the distribution of term length}$$

After running the analysis, we obtained a Chi-squared statistic of 0.1316, which has a p-value of 0.7168. Thus, at the $\alpha = 0.05$ significance level, we fail to reject the null hypothesis–we do not have sufficient evidence that the frequency of drone strikes differed between Presidents Obama and Trump. However, as we noted earlier, this analysis was severely constrained due to the shorter time frame that overlapped across all three countries.

Dashboard

We expanded upon the basic graphics made in our exploratory data analysis and added more complex visualizations for the RShiny dashboard.

Specifically, we borrowed the visualizations for the cumulative deaths over time overall and by country. From these base plots, we added filters for each country–and each president–so that an end user could select which countries and presidential terms to highlight.

We also created a tab with an interactive timeline to visualize the strikes locations over time. This visualization shows strikes over time at their impact point (found through geocoding), with the size and color correlating to the number of deaths caused by that strike.

The interactive timeline map presented itself as the most intensive element of the dashboard–and the project.

Conclusions

Suggestions for Future Research

Additional research into these drone strikes include looking at the relationship to terrorism attacks, including whether or not U.S. citizens or affiliates were affected by the attack. One strong data source would be the Global Terrorism Database (GTD); we chose not to use this dataset because we wanted to make our analysis and dashboard public, which would have required payment (the data is only free for private research).

Another sector to investigate would be the impact of drone strikes–either count, death rates, or injuries–on presidential approval rating. From my high-level exploration, there appeared to be limited-to-no relationship between approval change and various drone statistics, but a deeper dive into these two elements could glean previously undiscovered insights.

Limitations

The original dataset contained data on drone strikes from Pakistan, Somalia, and Yemen. For Pakistan, the data begins in 2004; for Somalia and Yemen, we do not have drone strike data before 2007. Therefore, any temporal analysis may not be wholly accurate if comparing across presidential terms or countries. This became an issue when comparing the frequency of drone strikes for each president; in my analysis, I limited the date range of interest between December 17, 2009 and January 24, 2018 because this was the range of

dates for which all three countries had drone strikes. Therefore, I could only compare the strike frequency between Presidents Obama and Trump.

Additionally, for geocoding the areas and countries to derive a latitude and longitude, we used a Google Maps API. While useful, we remained unable to geocode some locations due to undefined areas or incorrectly mapped locations. To verify that the geocoded location was correct, we redetermined the spatial country location from the latitude and longitude. If the spatial country and the original country did not match, we assigned the latitude and longitude to `NA` and dropped those strikes from map visualizations. In total, we removed 109 of 944 drone strikes (11.55%) for the map visualizations. However, we still included these strikes in subsequent analyses.

In the analyses, we encountered a big limitation in the date range for the individual countries. To avoid issues that may arise due to missing/unaccounted data, we decided to bound the range of interest. However, when doing this, we constricted Trump's term to approximately one year and completely eliminated Bush, presenting a clear drawback of that analysis.

Sources

Data

- The Guardian (via Professor Vivian Lew, UCLA Department of Statistics)

  - `us-pakistan-strikes-from-2004.xlsx`
  - `us-somalia-strikes-from-2007.xlsx`
  - `us-yemen-strikes-from-2007.xlsx`

- Gallup (via UCSB)

  - `bush-ratings.csv`
  - `obama-ratings.csv`
  - `trump-ratings.csv`

Help Websites

- Creating spatial mapping in R from coordinates
- Creating an RShiny map timeline

R Packages

- `ggmap`: D. Kahle and H. Wickham. ggmap: Spatial Visualization with ggplot2. The R Journal, 5(1), 144-161. URL http://journal.r-project.org/archive/2013-1/kahle-wickham.pdf
- `lubridate`: Garrett Grolemund, Hadley Wickham (2011). Dates and Times Made Easy with lubridate. Journal of Statistical Software, 40(3), 1-25. URL https://www.jstatsoft.org/v40/i03/.
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- `rvest`: Hadley Wickham (2021). rvest: Easily Harvest (Scrape) Web Pages. R package version 1.0.2. https://CRAN.R-project.org/package=rvest
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- `sp`: Pebesma, E.J., R.S. Bivand, 2005. Classes and methods for spatial data in R. R News 5 (2), https://cran.r-project.org/doc/Rnews/.
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