Exploring factors relating to homeless deaths in Seattle, Washington, 2016

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Abstract: In light of Seattle's current homeless crisis, this paper explores spatial and/or temporal relationships between weather and deaths (n=65) among Seattle's homeless population in 2016; between homeless camp evictions and deaths; and between shelter locations and deaths. We also calculate standardized mortality ratios (SMR) for different age groups and produce a map of homeless-relevant resources in the Seattle area. Overall, our analysis finds no statistically significant and/or reliable relationships beyond the tendency of all events to cluster in the downtown area and the fact that SMRs are highly elevated for the homeless population.

Keywords: homelessness, Seattle, mortality, evictions, weather, spatial analysis

BACKGROUND

In November 2015 press conference, Seattle mayor Ed Murray declared local homelessness a state of emergency (Jaywork, 2015). Despite a subsequent $9.2M (22.5%) increase in annual budget for homelessness (Jaywork, 2016c), local providers have struggled to keep up with demand for services (McNichols, 2016) and the homeless population has grown (Table 1). While the City has officially recognized a few quasi-permanent homeless encampments, it also continues to evict any camps it deems a risk to inhabitants or neighbors, reaching nearly 600 evictions in 2016 despite pressure from journalists, activists, lawyers, and politicians outside the mayor's office (Baker, 2016; Jaywork, 2016a, 2016b, & 2016c).

Although there have been many reports on homelessness in Seattle (e.g., a 2015 summary of homelessness-related investments by the Human Services Department; a 2015 report on services provided by Health Care for the Homeless Network; a 2015 report from the Downtown Emergency Service Center; a 2016 report by Focus Strategies; a 2016 analysis by consultant Barbara Poppe)—and doubtless there have been many unreleased internal analyses conducted by concerned agencies—our review of literature found no investigation of the type we propose. At least 75 homeless people died in Seattle in 2016 (Jaywork, 2016d), prompting us to formulate these questions and hypotheses:

1. **Mortality:**
    a. How does mean age of death for the homeless compare to the regional average? We expect mean age of death to be lower for homeless people.
    b. How do mortality rates for the homeless in Seattle compare to homeless mortality rates in other metropolitan areas? We expect them to be similar.
2. **Weather:** Do deaths among the homeless correlate temporally with windchill temperatures below 32 degrees Fahrenheit and/or amount of precipitation? We expect these weather patterns will increase deaths among the homeless.
3. **Evictions:**
    a. Do deaths among the homeless correlate temporally with camp evictions? We expect deaths to increase as evictions increase.
    b. Do deaths among the homeless correlate spatially with camp evictions? We expect deaths to occur more frequently as distance to evictions decreases.
4. **Resources:**
    a. What is the spatial distribution of Seattle's shelters, public bathrooms, and food banks? (This is a descriptive question, so there are no hypotheses.)
    b. Do deaths among the homeless correlate spatially with shelter locations? We expect deaths to occur more frequently as distance to shelters increases.

Table 1: Estimated number of homeless people in Seattle (SKCCH, 2013 & 2014; All Home, 2015 & 2016). [1] To appreciate scale, these numbers should be contextualized by Seattle's overall population trends, but the raw number of homeless residents in Seattle is also very important in evaluating demand for services. [2] None of the cited reports define the categories of "emergency housing" and "transitional housing".

	Unsheltered	*Emergency housing*	*Transitional housing*
2013	2736	-	-
2014	3123	-	-
2015	3772	3282	2993
2016	4505	3200	2983

METHODS

Data acquisition and description

The dataset for our dependent variable (homeless deaths, n=65) comes from the King County Medical Examiner by way of a *Seattle Weekly* public records request (Jaywork, 2016d). For each individual death in 2016, the dataset includes date of death, address of death, cause of death, age, gender, and race/ethnicity. Descriptive statistics are provided in Appendix 1, and address data was geocoded (assigned latitude and longitude coordinates) by modifying the code presented in Appendix 4.

Data on homeless camp evictions (n=588) comes from the City of Seattle's Human Services Department, also by way of a *Seattle Weekly* public records request (Jaywork, 2016c). This dataset is described in Appendix 2, and was geocoded by modifying the code in Appendix 4.

Daily weather data (n=366) was downloaded from Weather Underground (n.d.). This dataset is described in Appendix 3, and includes daily highs, lows, and averages for temperature, humidity, and wind, as well as daily total precipitation and indications of weather events (rain, fog, snow, etc.).

Data on homeless-relevant resources was obtained from multiple sources. Seattle's open data portal (data.seattle.gov) provides readily downloadable location data for foodbanks (n=36), public toilets (n=5), and park toilets (n=65). Shelter locations (n=134) were scraped from HomelessShelterDirectory.organd ShelterListings.org, then checked for redundancy, geocoded, and mapped (see Appendix 4).

Data cleaning and analysis

To explore mortality, we first conducted a t-test comparing the mean age of death for homeless people in Seattle with the regional mean age of death (King County, 2016), using code presented in Appendix 5, Box A5.1. A more meaningful measure, though, is provided by the standardized mortality ratio (SMR), which compares age-specific mortality rates between a reference population and the study population (NM-IBIS, n.d.). SMR adjusts for the fact that populations may have different age structures, which would affect the mean age of death.

To calculate SMR, we used death tables from the Washington State Department of Health (n.d.) for our reference population, then inferred the age structure of Seattle's 2016 homeless population from the King County One Night Count, an annual count of the homeless (SKCCH, 2016). The One Night count estimates the total number of unsheltered homeless people in the city as well as the number of sheltered homeless people; age demographics are provided for the sheltered subset of the homeless population, which we then generalized to the unsheltered population. Finally, SMR is calculated for each age bracket by comparing observed deaths to expected deaths (as estimated by the reference population).

We used logistic regression to explore the temporal relationship between weather and deaths (Appendix 5, Box A5.2). In order to focus on weather events that posed a plausible risk to health, we first calculated daily low temperatures adjusted for windchill with this formula (USA Today, 2001):

$$35.74 + 0.6215 \cdot \mathtt{daily\_low\_temperature} + 35.75 \cdot \mathtt{daily\_avg\_windspeed}^{0.16} \\ + 0.4275 \cdot \mathtt{daily\_low\_temperature} \cdot \mathtt{daily\_avg\_windspeed}^{0.16}$$

We then created two Boolean variables, one reflecting whether a death or deaths occurred for each day of the year and the other reflecting whether daily low windchill fell below 32 degrees

Fahrenheit (we found no expert consensus on what windchill threshold delineates dangerous weather, so we used 32 degrees Fahrenheit, the threshold at which homeless shelters open up for cold temperatures in Washington). We also explored the possibility of combining both windchill and precipitation into one ‘extreme weather variable’ using various thresholds (32 degrees Fahrenheit, .25” and .5” of precipitation), but that led to too small of a sample size (less than ten days) for days where weather would be categorized as having extreme weather. Ultimately, we regressed deaths on several combinations of weather variables, in most cases introducing one-day lags:

$$(1)\quad \mathbf{death\_boolean}_{t+1} = \beta_0 + \beta_1 \cdot \mathbf{windchill\_boolean}_t$$

$$(2)\quad \mathbf{death\_boolean}_{t} = \beta_0 + \beta_1 \cdot \mathbf{windchill\_boolean}_t$$

$$(3)\quad \mathbf{death\_boolean}_{t+1} = \beta_0 + \beta_1 \cdot \mathbf{windchill\_boolean}_t + \beta_2 \cdot \mathbf{precipitation}_t$$

$$(4)\quad \mathbf{death\_boolean}_{t+1} = \beta_0 + \beta_1 \cdot \mathbf{precipitation}_t$$

We used logistic regression to explore the temporal relationship between deaths and camp evictions (Appendix 5, Box A5.3), and linear regression to explore the temporal and spatial relationship between deaths, evictions and shelters (Appendix 5, Box A5.4). For the linear regression, we tried a variety of different temporal and spatial aggregations, counting shelters and evictions within a range of different bandwidths (0.5-1 mile) and totaling deaths and evictions for different periods (1-3 weeks). Ultimately, the best fitting model came from aggregating into three week periods with a bandwidth of one mile (Appendix 5, Box A5.5):

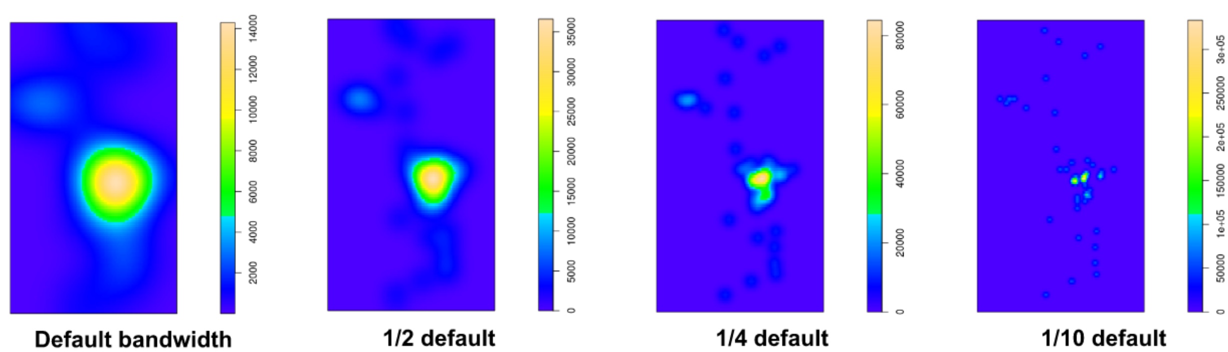
$$(5)\quad \mathbf{death\_boolean}_{t+1} = \beta_0 + \beta_1 \cdot \mathbf{evictions\_boolean}_t$$

$$(6)\quad \mathbf{death\_aggregate}_{t+1} = \beta_0 + \beta_1 \cdot \mathbf{evictions\_aggregate}_t + \beta_1 \cdot \mathbf{shelter\_aggregate}_t$$

Finally, we visualized deaths, homeless-relevant resources, and evictions as point and density maps (Appendix 5, Boxes A5.6 and A5.7). Since our evictions dataset was specific to Seattle while our deaths and shelter datasets covered a larger extent, we restricted our maps to the coordinate boundaries of the evictions dataset.

Density maps (also called heatmaps) are purely data visualization, not statistical analysis. As illustrated in Figure 1, the shape and number of “hotspots” depends on one’s choice of bandwidth. With this in mind, we also tested for spatial clustering with Ripley’s K (Appendix 5, Box A5.8) and—after tallying shelters and evictions within a one mile of each death (Appendix 5, Box A5.5)—for spatial autocorrelation with Moran’s I (Appendix 5, Box A5.9).

Figure 1: Demonstration of how a density map varies with bandwidth.



RESULTS

Mortality analyses

Per our t-test, we are able to reject the null hypothesis that 49.21, the mean age of death for homeless people in Seattle, is statistically equivalent to 72.4, the regional mean age of death for King County ($p < 2.2e-16$; 95% C.I. = 46.19, 52.71). Tables 2 and 3 present our SMR calculations. Consistent with other research conducted in the last 10 years (Nusselder et al., 2013; Morrison, 2009), our local analysis found rates age group-specific mortalities hovering between 3-8 times the average population. Moreover, our results validate Nusselder et al.'s finding (2013) that the effect of homelessness on mortality is at its highest for young to middle aged adults.

Temporal analyses

Logistic regressions of death on lagged windchill (Box 1), on lagged windchill and precipitation (Box 2), and on lagged precipitation (Box 3) failed to identify any statistically significant relationships. Logistic regression of death on windchill with no lag (Box 4) found a statistically significant odds ratio of about 0.25, implying risk of death is lower on days with windchill below 32 °F. Logistic regression of death on evictions (Box 5) and linear regression of death on number of evictions and local shelters within one mile of each death (Box 6) failed to identify statistically significant relationships (see Figures 2 and 3 for best fit lines).

Table 2: Crude death rates by age group for Seattle's homeless population, 2016, based on data from King County's "One Night Count" homeless census (SKCCH, 2016) and the King County Medical Examiner:

Age groups	*Crude death rate*
18-24 years	0.3%
25-49 years	1.9%
50+ years	2.2%

Table 3: Standardized mortality ratio (SMR) by age group for Seattle's homeless population, based on data from King County's "One Night Count" homeless census (SKCCH, 2016), King County Medical Examiner, and Washington State Department of Health (n.d.):

Age groups	*SMR (95% CI)*	*P value*
18-24 years	**3.04** (0.15-14.95)	0.32
25-49 years	**8.29** (5.65-11.74)	<0.001
50+ years	**1.15** (0.75-1.69)	0.49

Box 1: Output for logistic regression of homeless deaths on windchill, lagged one day.

```
Deviance Residuals:
        Min         1Q          Median      3Q          Max
        -0.6815     -0.6815     -0.6815     -0.4551     2.1536
Coefficients:
                    Estimate    Std. Error  z value     Pr(>|z|)
(Intercept)         -1.3417     0.1415      -9.482      <2e-16 ***
bool.windchill.lagged -0.8739   0.4526      -1.931      0.0535 .

Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Null deviance: 353.93  on 364  degrees of freedom
Residual deviance: 349.46  on 363  degrees of freedom
AIC: 353.46
```

Box 2: Output for logistic regression of homeless deaths on windchill and precipitation, lagged one day.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.7058	-0.7058	-0.6901	-0.3699	2.3382

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.2627	0.1534	-8.232	<2e-16 ***
wind_chill_boolean	-1.3791	0.5357	-2.574	0.010 *
precip	-0.3511	0.5940	-0.591	0.554

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Null deviance: 354.34 on 365 degrees of freedom

Residual deviance: 344.82 on 363 degrees of freedom

AIC: 350.82

Box 3: Output for logistic regression of homeless deaths on precipitation, lagged one day.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.6863	-0.6459	-0.6444	-0.6444	1.8297

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.46635	0.14827	-9.89	<2e-16 ***
precip.lagged	0.08662	0.54298	0.16	0.873

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Null deviance: 353.93 on 364 degrees of freedom

Residual deviance: 353.90 on 363 degrees of freedom

AIC: 357.9

Box 4: Output for logistic regression of homeless deaths on windchill, no lag.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.6936	-0.6936	-0.6936	-0.3652	2.3413

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.3021	0.1399	-9.308	<2e-16 ***
windchill_bool	-1.3721	0.5355	-2.562	0.0104 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Null deviance: 354.34 on 365 degrees of freedom

Residual deviance: 345.20 on 364 degrees of freedom

AIC: 349.2

Box 5: Output for logistic regression of homeless deaths on homeless encampment sweeps.

Deviance Residuals:

Min	1Q	Median	3Q	Max
-0.6900	-0.6900	-0.5915	-0.5915	1.9128

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-1.3140	0.1718	-7.650	2.02e-14 ***
bool.sweeps.lagged	-0.3406	0.2744	-1.241	0.215

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Null deviance: 353.93 on 364 degrees of freedom

Residual deviance: 352.36 on 363 degrees of freedom

AIC: 356.36

Box 6: Output for linear regression of homeless deaths on number of homeless encampment sweeps and number of shelters within one mile of each death, aggregated into three week periods.

Deviance Residuals:

	Min	1Q	Median	3Q	Max
	-1.0370	-0.7427	-0.3013	-0.0124	7.9385

Coefficients:

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	2.06149	0.55614	3.707	0.000999 ***
plotdt$SweepCount	-0.03133	0.18628	-0.168	0.867756
plotdt$ShelterCount	-0.02452	0.02778	-0.883	0.385489

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1.724 on 26 degrees of freedom
Multiple R-squared: 0.04785, Adjusted R-squared: -0.0254
F-statistic: 0.6533 on 2 and 26 DF, p-value: 0.5287

Figure 2: Best fit line for deaths versus windchill.

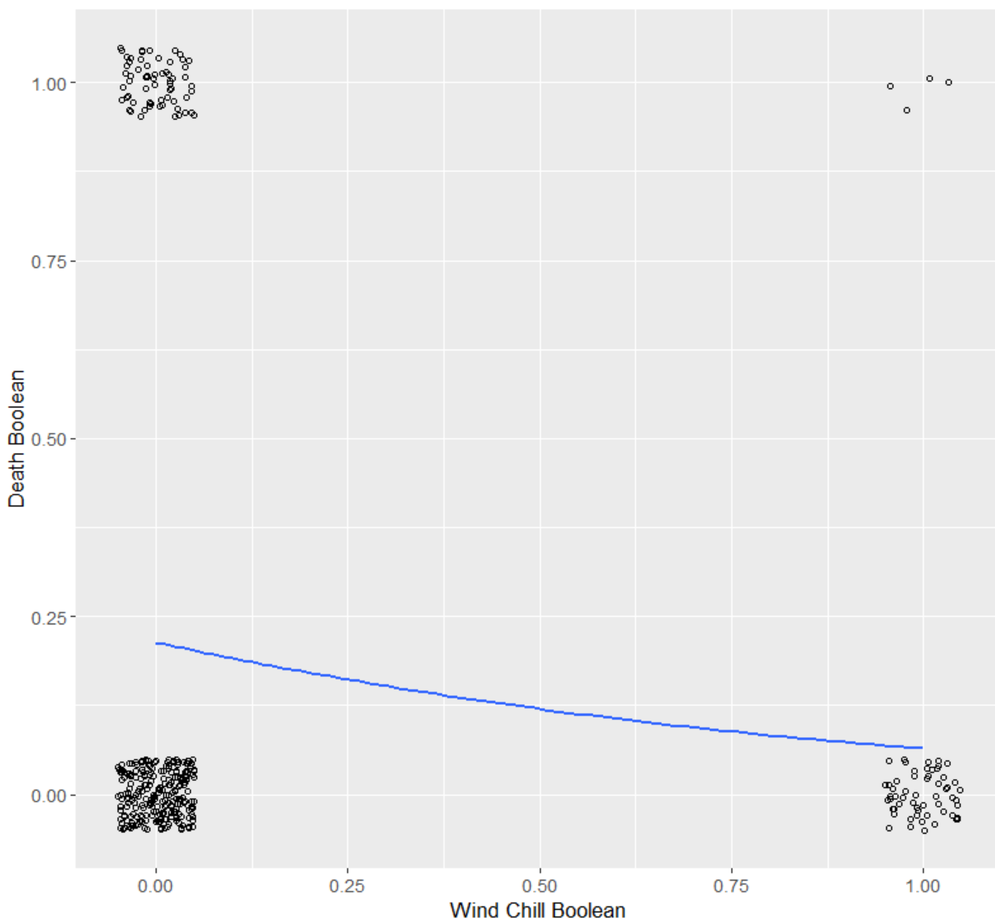
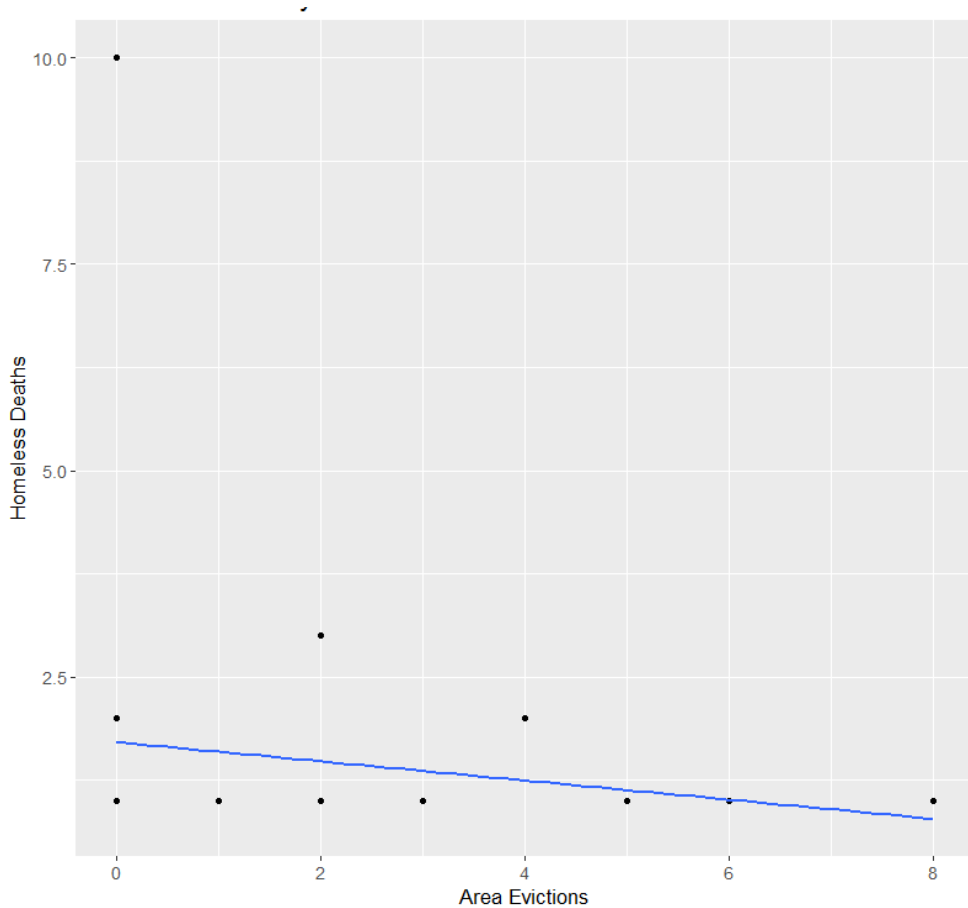


Figure 3: Best fit line for deaths by aggregate evictions, controlling for aggregate shelters.



Spatial analyses

The spatial distribution of resources is presented in Figure 5. Shelters cluster heavily downtown; foodbanks also cluster downtown, but seem to do so over a larger area than shelters. The limited number of public toilets (five) and the dispersion of public park bathrooms relative to other resources likely mean that homeless people rely on non-public bathroom access, perhaps obtained by purchasing items like coffee.

Figure 6 presents a density map of deaths, evictions, and shelters. These datasets all appear to center on the downtown area, with a few minor hotspots elsewhere in the case of shelters and deaths. Ripley's K is a descriptive statistic for spatial data; Figure 7 shows how Ripley's K would be distributed if the data generation process were random (Poisson) versus how Ripley's K (calculated by several different estimators) is actually distributed for the given deaths dataset. The graph indicates that the spatial clustering in the deaths data is statistically significant, and the same is true for the evictions and shelters datasets (which produced graphs so qualitatively similar they are not included here).

Finally, Moran's I showed moderately positive spatial autocorrelation (0.43) for number of shelters within a half mile of each death (p-value <0.0001) and slightly positive spatial autocorrelation (0.12) for number of sweeps within a half mile of each death (p-value ≈ 0.014). This indicates that clustering in our data is somewhat aligned across datasets.

Figure 5: Distribution of homeless-relevant resources in Seattle, WA, 2016.

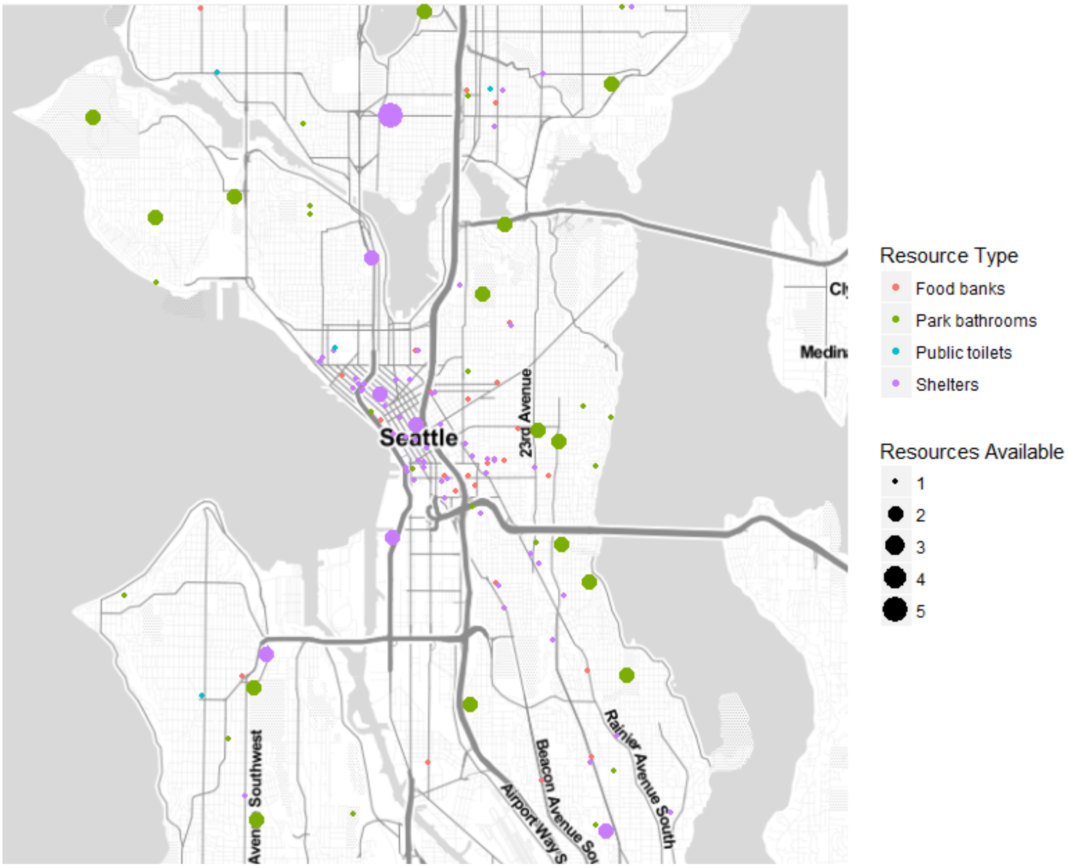


Figure 6: Density maps of deaths, evictions, and shelters, visualizing the intensity of events in space.

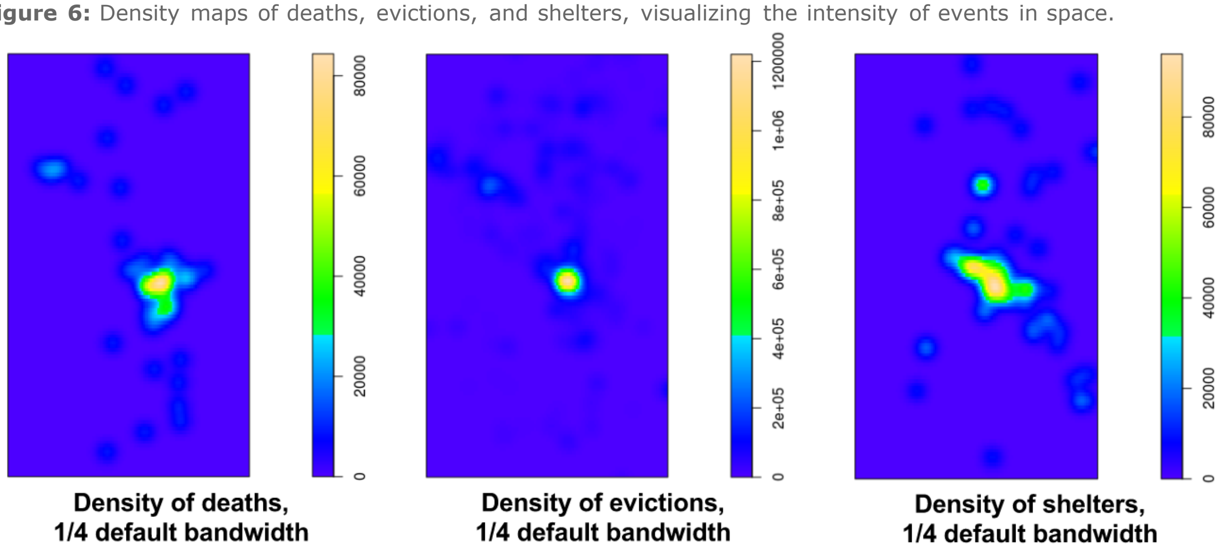
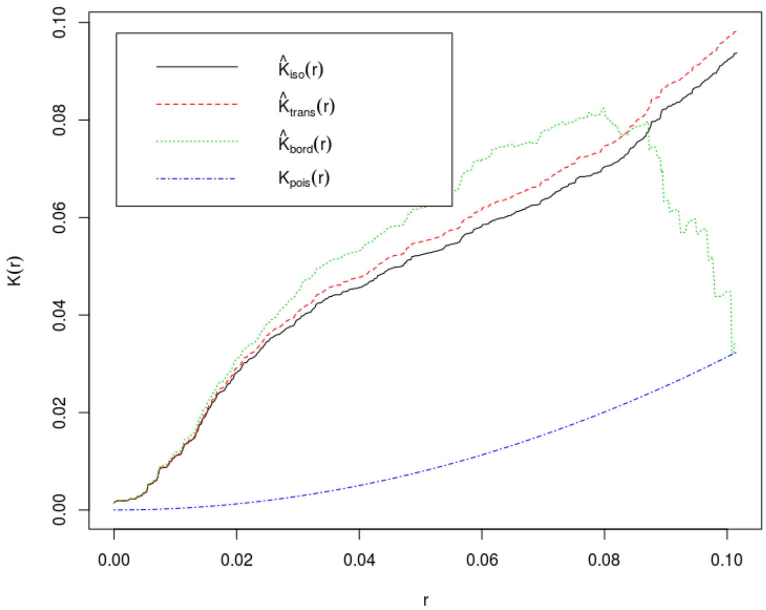


Figure 7: Ripley's K for deaths data. Evictions and shelters data showed qualitatively similar patterns.



DISCUSSION

We are confident in rejecting the null hypothesis that mean age of death is the same for Seattle's homeless population as it is for the general population. Although it requires generalizing the age distribution of Seattle's sheltered homeless population to its unsheltered homeless population, we are also fairly confident in concluding that the standardized mortality rate for Seattle's homeless is extremely high (especially for young adults) and consistent with other studies of homeless mortality.

After fitting various weather models, we note that most failed to produce statistical significance and that our one statistically significant result should be viewed skeptically. It is mostly likely a reflection of limitations in our data and modeling process—for instance, our choice of dangerous weather threshold, or the fact that the effect of an extreme weather event could be immediate (freezing) or delayed by days, weeks, or months; lagging by one day is probably the wrong time scale, but there is also perhaps not a consistent time scale available. Treating our counterintuitive result as reliable only for discussion's sake, it is possible that an inverse relationship could arise from homeless people making behavioral adaptations to obviously dangerous weather, but then underestimating the risk of slightly warmer weather.

Logistic regression also failed to identify a statistically significant temporal relationship between deaths and camp evictions. Moran's I somewhat corroborates this, in that spatial autocorrelation for number of evictions within a half mile of each death is notably smaller than spatial autocorrelation for number of shelters within a half mile of each death (i.e., there is a weaker overlap of clustering between deaths and evictions than between deaths and shelters).

Our finding of positive spatial autocorrelation for number of shelters within a half mile of each death is contrary to our hypothesis that deaths will occur more frequently as distance to shelter increases. On the other hand, the common clustering of deaths, evictions, and (to a lesser extent) sweeps is not too surprising given the overall tendency of our data to overwhelmingly cluster in the city center. This likely says more about infrastructural, economic, social or legal factors shaping the mobility of the homeless population and the location of public resources than it does about a direct relationship between deaths, evictions, and/or shelters. In other words, there are likely many factors that cause deaths and evictions and shelter in the same area of the city, and these factors probably overwhelm any direct relationship between our variables of interest.

CONCLUSION

Data for in-depth analysis of homeless populations are definitionally difficult to obtain. Most published literature has either used estimations based on death certificate data (which can be misleading as most jurisdictions will note the last place of residence), or use a sample size to project onto the estimated population. Seattle has fairly robust data by comparison to most major cities, but without basic demographic information associated with the homeless population it will be difficult to tailor resources and services. Furthermore, when collecting the data for our analysis, we realized that there does not exist a centralized online database of public resources pertinent to our homeless population. We recommend that the City of Seattle consider creating and hosting such a resource in collaboration with area nonprofits.

REFERENCES

All Home. (2015). King County One Night Count: Summary of 2015 data [PDF file]. Retrieved from http://allhomekc.org/wp-content/uploads/2016/11/2015-KC-ONC-numbers.pdf

All Home. (2016). King County One Night Count: Summary of 2016 data [PDF file]. Retrieved from http://allhomekc.org/wp-content/uploads/2015/09/2016-KC-ONC-numbers.pdf

Baker, M. (2016, August 19). Chaos, trash and tears: Inside Seattle's flawed homeless sweeps. *The Seattle Times*. Retrieved from http://www.seattletimes.com/seattle-news/chaos-trash-and-tears-inside-seattles-flawed-homeless-sweeps/

Downtown Emergency Service Center. (2015). 2015 annual report [PDF file]. Retrieved from http://desc.org/documents/Annual_Reports/DESC_2015_Annual_Report.pdf

Focus Strategies. (2016, September). Seattle/King County: Homeless system performance assessment and recommendations with particular emphasis on single adults [PDF file]. Retrieved from http://allhomekc.org/wp-content/uploads/2016/01/System-Performance- Analysis-Final-Report.pdf

Healthcare for the Homeless Network. (2015). 2015 annual report [PDF file]. Retrieved from http://www.kingcounty.gov/depts/health/locations/homeless-health/~/media/depts/health/homeless-health/healthcare-for-the-homeless/documents/HCHN-2015-annual-report.ashx

HomelessShelterDirectory.org.(2017, February 19). Seattle homeless shelters & services for the needy. Retrieved from http://www.homelessshelterdirectory.org/cgi-bin/id/city.cgi?city=Seattle&state=WA

Human Services Department, City of Seattle. (2015). Homelessness investment analysis [PDF file]. Retrieved from https://www.seattle.gov/Documents/Departments/HumanServices/Reports/HomelessInvestmentAnalysis.pdf

Jaywork, C. (2015, November 2). Murray declares civil emergency on homelessness. *Seattle Weekly*. Retrieved from http://archive.seattleweekly.com/home/961570-129/murray-declares-civil-emergency-on-homelessness

Jaywork, C. (2016a, August 1). City and county councilmembers ask Murray not to clear homeless encampment. *Seattle Weekly.* Retrieved from http://www.seattle weekly.com/news/city-and-county-councilmembers-ask-murry-not-to-clear-homeless-encampment/

Jaywork, C. (2016b, August 24). Advocates propose sweeping reforms to homeless sweeps. *Seattle Weekly.* Retrieved from http://www.seattleweekly.com/news/advocates-propose-sweeping-reforms-to-homeless-sweeps/

Jaywork, C. (2016c, November 2). A year of emergency. *Seattle Weekly.* Retrieved from http://www.seattleweekly.com/news/a-year-of-emergency/

Jaywork, C. (2016d, December 21). The homeless people who died in King County in 2016. *Seattle Weekly.* Retrieved from http://www.seattleweekly.com/news/the-homeless-people-who-died-in-king-county-in-2016/

King County. (2016, August 25). Community health indicators. Retrieved from http://www.kingcounty.gov/depts/health/data/community-health-indicators.aspx

McNichols, J. (2016, May 22). Seattle shelters are so crowded some people sleep in chairs. *KUOW.* Retrieved from http://kuow.org/post/seattle-shelters-are-so-crowded-some-People-sleep-chairs

Morrison, D. S. (2009). Homelessness as an independent risk factor for mortality: Results from a retrospective cohort study. *International Journal of Epidemiology 38(*3): 877–883.

New Mexico Indicator-Based Information System (NM-IBIS). (n.d.) Standardized mortality ratio. Retrieved from https://ibis.health.state.nm.us/resource/SMR_ISR.html

Nusselder, W. J., Slockers, M. T., Krol, L., Slockers, C. T., Looman, C. W. N., & van Beeck, E. F. (2013). Mortality and life expectancy in homeless men and women in Rotterdam: 2001-2010. *PLoS ONE, 8*(10), e73979. http://doi.org/10.1371/journal.pone.0073979

Poppe, B. (2016, August 15). [PDF file]. Recommendations for the City of Seattle's homeless investment policy: The path forward [PDF file]. Retrieved from http://www.seattle.gov/Documents/Departments/pathwayshome/BPA.pdf

Seattle/King County Coalition on Homelessness (SKCCH). (2013). Summary of the 2013 unsheltered homeless count in selected areas of King County [PDF file]. Retrieved fromhttp://www.homelessinfo.org/resources/one_night_count/2013_ONC_Street_Count_Summary.pdf

Seattle/King County Coalition on Homelessness (SKCCH). (2014). Summary of the 2014 unsheltered homeless count in selected areas of King County [PDF file]. Retrieved from http://www.homelessinfo.org/resources/one_night_count/2014_ONC_Street_Count_Summary.pdf

Seattle/King County Coalition on Homelessness (SKCCH). (2016). 2016 results. Retrieved from http://www.homelessinfo.org/what_we_do/one_night_count/2016_results.php

ShelterListings.org. (2017, February 19). Seattle WA homeless shelters, halfway houses. Retrieved from http://www.shelterlistings.org/city/seattle-wa.html

USA Today. (2001, October 30). Formula used to calculate windchill. Retrieved from http://usatoday30.usatoday.com/weather/winter/windchill/wind-chill-formulas.htm

Washington State Department of Health. (n.d.). All death tables by year. Retrieved from http://www.doh.wa.gov/DataandStatisticalReports/VitalStatisticsData/Death/DeathTablesbyYear

Weather Underground. (n.d.). Weather history for Seattle Boeing, WA [Dataset]. Retrieved from https://www.wunderground.com/history/airport/KBFI/2017/3/4/CustomHistory.html?req_city=Seattle&req_state=WA&reqdb.zip=98101&reqdb.magic=1&reqdb.wmo=99999

APPENDIX 1: Description of deaths dataset

Figure A1.1: Spatial distribution of homeless deaths, 2016.

Table A1.1: Racial demographics of decedents.

White	57
Black	8
Native American	7
Asian	2
Other	1
Unknown	1

Table A1.2: Hispanic ethnicity of decedents (unclear whether NULL value means not Hispanic, unknown value, or both).

NULL	73
Hispanic	3

Table A1.3: Sex of decedents.

Male	56
Female	20

Table A1.4: Age of decedents.

Min	24
1st quarter	39.75
Median	49
Mean	49.21
3rd quarter	58.25
Max	83

Table A1.5: Manner of death of decedents.

Natural	32
Accident	28
Homicide	6
Undetermined	5
NULL	3
Suicide	2

APPENDIX 2: Description of evictions dataset

Figure A2.1: Temporal distribution of homeless camp evictions.

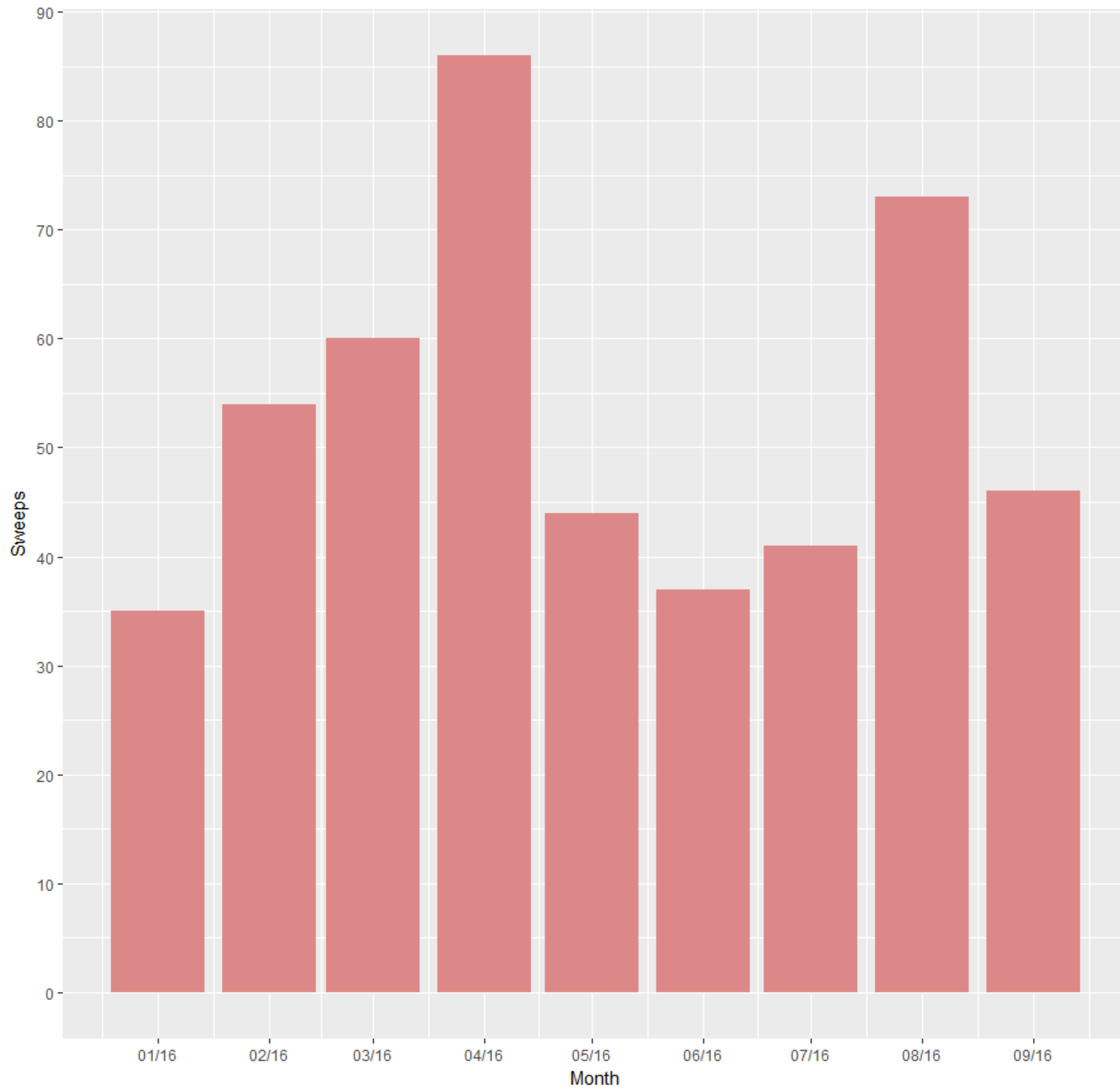
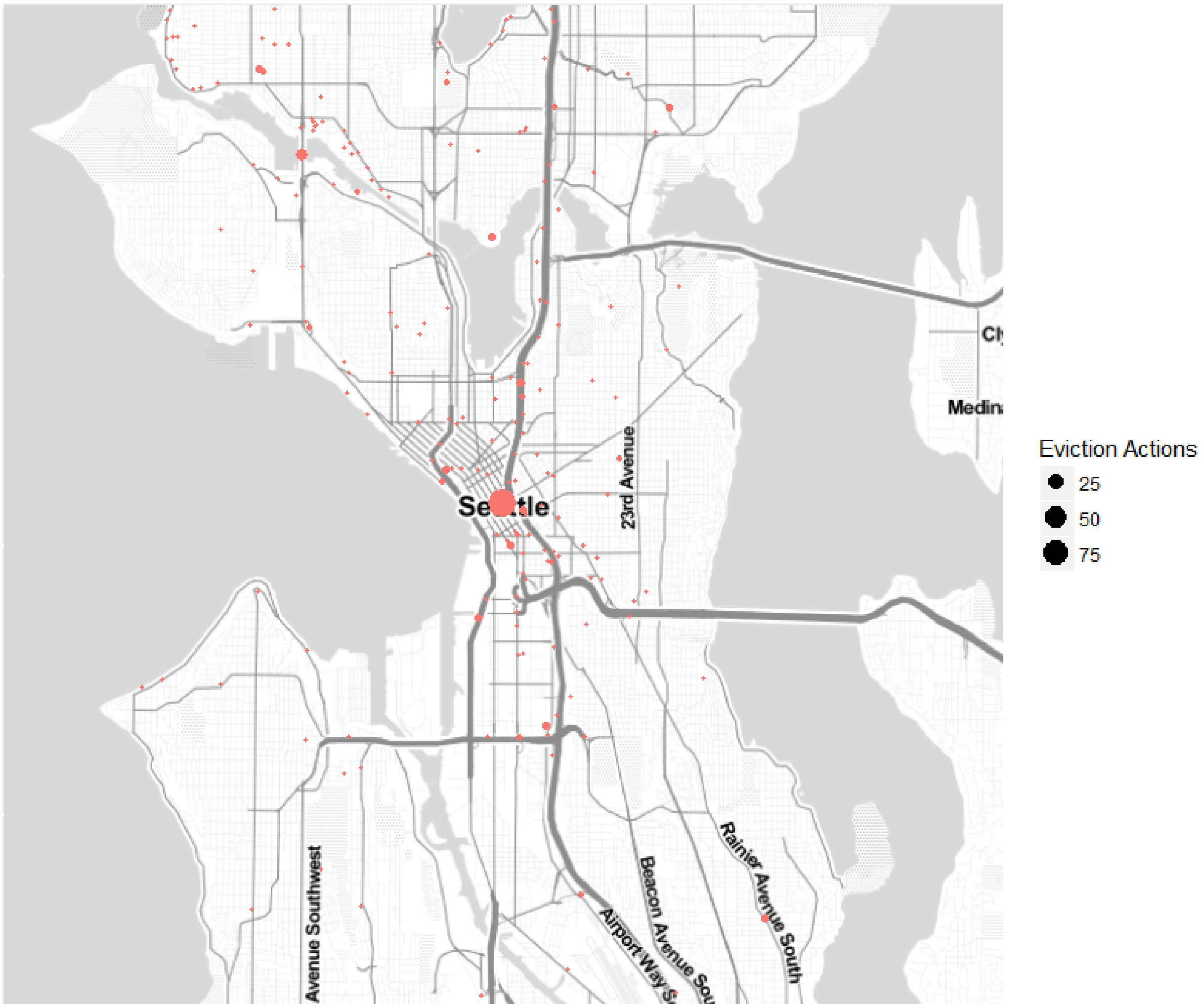


Figure A2.2: Spatial distribution of homeless camp evictions.



APPENDIX 3: Description of weather dataset

Table A3.1: Weather event counts by type for 2016.

None	175
Rain	172
Fog	7
Fog, Rain	4
Rain, Snow	4
Rain, Thunderstorm	2
Snow	1
Fog, Rain, Snow	1

Figure A3.1: Distribution of daily total precipitation (inches) for 2016.

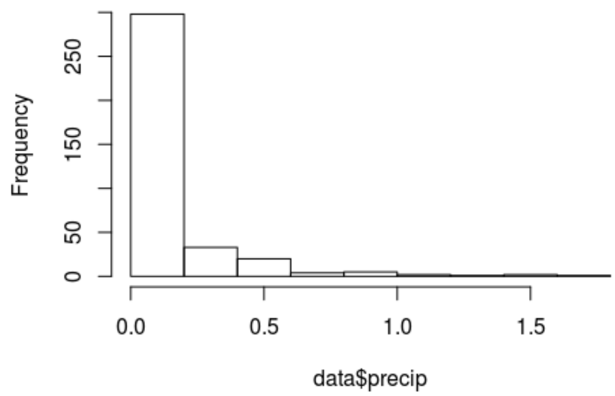


Figure A3.2: Time series of daily total precipitation (inches) for 2016.

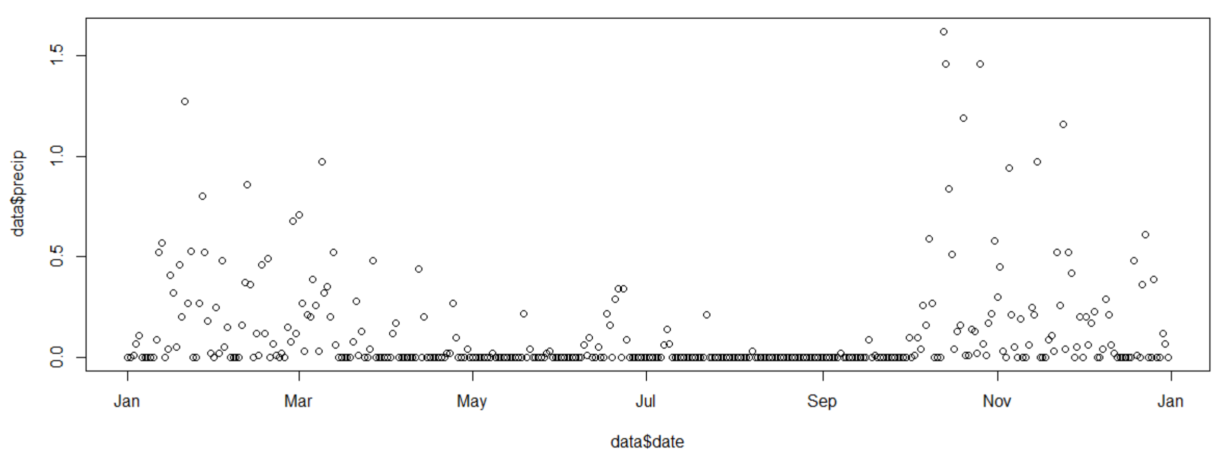
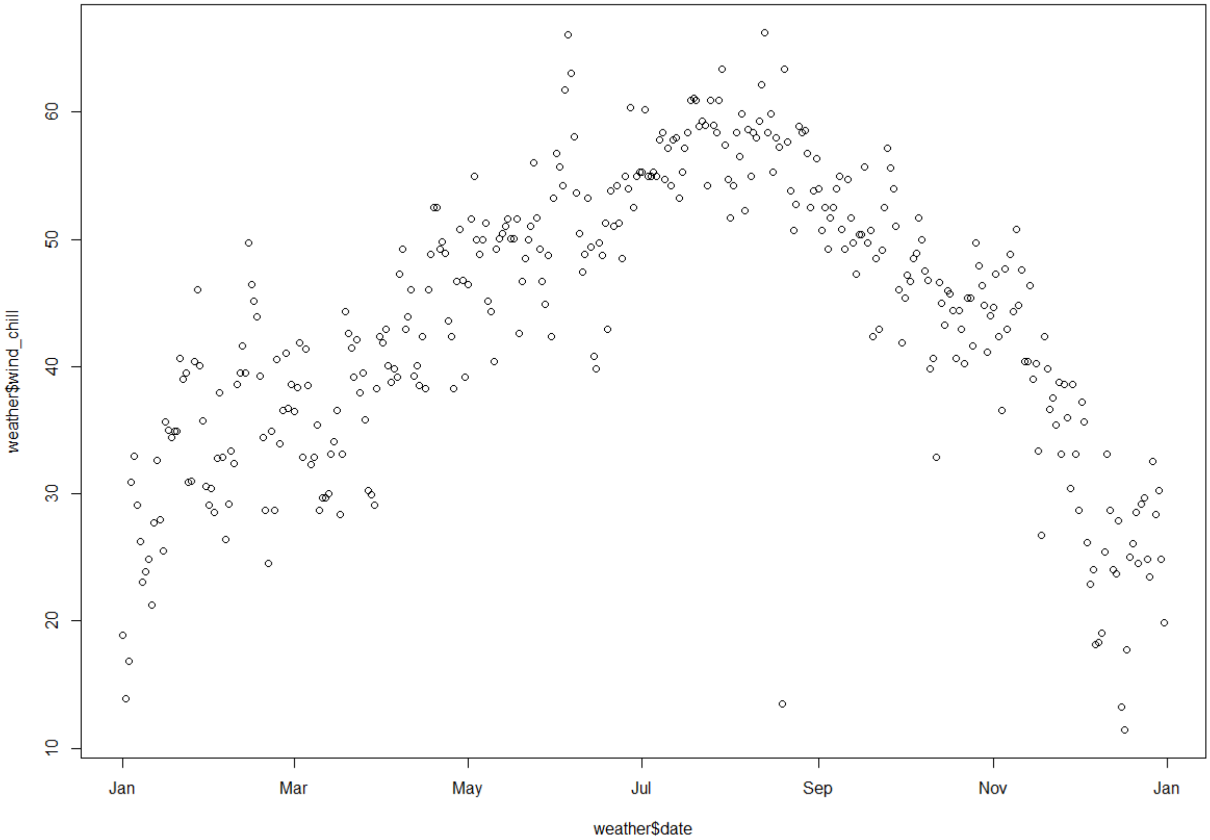


Figure A3.3: Time series of daily low temperatures for 2016, adjusted for windchill.



APPENDIX 4: Python code for obtaining shelter data

Box A4.1: Python code for scraping shelter data from HomelessShelterDirectory.organd ShelterListings.org. After scraping these two sources and combining them into one dataset, the data was checked manually in Excel and redundant shelters were deleted.

```
# load libraries
from bs4 import BeautifulSoup
import urllib.request
import csv

# open URLs
HSD = urllib.request.urlopen('http://www.homelessshelterdirectory.org/cgi-bin/id/city.cgi?city=
        Seattle&state=WA').read()
SL = urllib.request.urlopen('http://www.shelterlistings.org/city/seattle-wa.html').read()

# create BeautifulSoup objects from HTML
HSD_soup = BeautifulSoup(HSD, "html.parser")
SL_soup = BeautifulSoup(SL, "html.parser")

# extract shelter names from HSD data
HSD_divs = HSD_soup.find_all("div", class_="item_content")
HSD_shelters = list()
for em in HSD_divs:
        try:
                HSD_shelters.append(["HSD", em.a.get_text()])
        except:
                pass
HSD_shelters_final = HSD_shelters[0:-18]

# extract shelter names from SL data
SL_divs = SL_soup.find_all("td")
SL_shelters = list()
for em in SL_divs:
        try:
                tx = em.a.get_text()
                if len(tx) > 1:
                        SL_shelters.append(["SL", tx])
        except:
                pass

# combine and export to CSV
all_shelters = HSD_shelters_final + SL_shelters
filename = 'shelters_raw.csv'
with open(filename, 'w', newline='') as tsvfile:
        my_writer = csv.writer(tsvfile, delimiter='\t', quotechar='|', quoting=csv.QUOTE_MINIMAL)
        for em in all_shelters:
                my_writer.writerow(em)
```

Box A4.2: Python code for geocoding shelters using the Google Places API Web Service (https://developers.google.com/places/web-service/intro)which performs better than the Google Maps API when fed messy address data.

```
# load libraries
import csv
import urllib.request
import json

# open CSV file
my_file = 'shelters_raw.csv'
my_list = list()
with open(my_file, newline='') as my_csv:
        my_reader = csv.reader(my_csv, delimiter='\t')
```

```
		for row in my_reader:
		my_list.append(row)

# send HTTP request
places_key = 'paste your Places API key here'
my_results = list()
for em in my_list:
	address_str = em[6]
	my_url = 'https://maps.googleapis.com/maps/api/place/textsearch/json?query='+
		# turns an address string like "123 East Place" into 123+East+Place
		'+'.join(address_str.split(' '))+'&key='+places_key+'
		# sets search area to Seattle region
		&location=47.604752,-122.329963&radius=50000'
	try:
		with urllib.request.urlopen(my_url) as response:
			my_json = response.read()
		my_data = json.loads(my_json.decode('utf-8'))
		my_lng = my_data['results'][0]['geometry']['location']['lng']
		my_lat = my_data['results'][0]['geometry']['location']['lat']
		my_results.append([address_str, my_lng, my_lat])
	except:
		print(address_str)
		print(my_data)  # error message from web service

# export to CSV
filename = 'shelters_geocoded.csv'
header = ['SiteName', 'Long', 'Lat']
with open(filename, 'w', newline='\n') as tsvfile:
	my_writer = csv.writer(tsvfile, delimiter=',', quotechar='|', quoting=csv.QUOTE_MINIMAL)
	my_writer.writerow(header)
	for em in my_results:
		my_writer.writerow(em)
```

APPENDIX 5: R code for analyses

Box A5.1: R code for testing whether the mean age upon death for Seattle's homeless is statistically equivalent to the region's mean age upon death (King County, 2016).

```
deaths <- read.csv("deaths_cleaned_geocoded.csv", sep="\t")
regional.mean <- 72.4
t.test(deaths$age, alternative="two.sided", mu=regional.mean, conf.level = 0.95)
```

Box A5.2: R code for logistic regression of deaths on windchill-adjusted daily low temperatures and/or amount of precipitation.

```
# load data
weather <- read.csv("data/weather_coded.csv", sep = "\t")

# add 1-day lag
end <- length(weather$death_boolean)
bool.deaths.lagged <- weather$death_boolean[2:end]
precip.lagged <- weather$precip[1:end-1]
bool.windchill.lagged <- weather$wind_chill_boolean[1:end-1]

# fit models
mod1 <- glm(formula = bool.deaths.lagged ~ bool.windchill.lagged, family = 'binomial')
summary(mod1)
mod2 <- glm(formula = bool.deaths.lagged ~ bool.windchill.lagged + precip.lagged, family = 'binomial')
summary(mod2)
mod3 <- glm(formula = bool.deaths.lagged ~ precip.lagged, family = 'binomial')
summary(mod3)
```

Box A5.3: R code for logistic regression of deaths on homeless camp evictions.

```
# load data
evictions <- read.csv("data/evictions_cleaned_geocoded.csv", sep = "\t")
deaths <- read.csv("data/weather_coded.csv", sep = "\t")

# make Boolean for evictions
all.dates <- seq(as.Date("2016-01-01"), as.Date("2016-12-31"), by="days")
sweep.dates <- as.Date(unique(evictions$SweepDate), format = "%m/%d/%Y")
sweeps.boolean <- as.numeric(all.dates %in% sweep.dates)

# add 1-day lag
bool.deaths.lagged <- deaths$death_boolean[2:end]
bool.sweeps.lagged <- sweeps.boolean[1:end-1]

# fit model
mod7 <- glm(bool.deaths.lagged ~ bool.sweeps.lagged, family = 'binomial')
summary(mod7)
```

Box A5.4: R code for logistic regression of aggregate deaths, evictions and shelters.

```
# load library
library(data.table)

# Using the data frame created from the code in Box A5.5, a data table is created
# then cross-tabbed to create an aggregate table which was used for the linear model
DT<-data.table(combinedset)
PlotDT<-[, sum(deaths), by=list(ShelterCount, SweepCount)]
lm(plotDT$V1~plotdt$ShelterCount+plotdt$SweepCount)
```

Box A5.5: R code for aggregating by geographic distance and a date range.

```
# Create two empty counters for the loop and an empty dataframe for the results
counter<-0
nacount<-0
resultsdf2<-data.frame()

# First loop iterates through the deaths data looking for associated rows in the eviction dataset
# that have an eviction date range of at or before 21 days of the date of death
for(i in 1:nrow(resultsdf)){
  row <- resultsdf[i,]
  eresultsdf<-subset.data.frame(subevict,  subevict$SweepDate  >= row$`subdeaths$DOD  - 21` &
subevict$SweepDate  <= row$`subdeaths$DOD`)

# Second loop then runs through the recent evictions data and looks for evictions that
# happen within one mile of the incident location
  for (i in 1:nrow(eresultsdf)){
    erow <- eresultsdf[i,]
    chkdist<-distHaversine(unlist(c(erow[2],erow[3])),   unlist(c(row[4],row[3])))/1609.344
    if (chkdist  <= 1){counter  <- counter + 1}
      else{nacount<-nacount+1}

# If matches exist it reports the sum of matches as a column value back into a
# new dataframe associated with the death data
    if (i == nrow(eresultsdf)){
      newrow<-as.data.frame(c(row,counter))
    colnames(newrow)<-c('startdate','DOD','lat','lon','count')
    resultsdf2<-rbind(resultsdf2,newrow)}
  }
  counter<-0
}

# Similar to above but simplified: only one loop looking for geographic proximity within a mile
# this was run iteratively over each resource data set and appended to the results of the
# data frame created from the code above
resultsdf3<-as.data.frame(subdeaths$DOD)
resultsdf3<-cbind.data.frame(resultsdf3,subdeaths$Lat)
resultsdf3<-cbind.data.frame(resultsdf3,subdeaths$Long)
counter<-0
nacount<-0
resultsdf4<-data.frame()
for(i in 1:nrow(resultsdf3)){
  row <- resultsdf3[i,]
  for (i in 1:nrow(sresources)){
    rrow <- sresources[i,]
    chkdist<-distHaversine(unlist(c(rrow[1],rrow[2])),   unlist(c(row[3],row[2])))/1609.344
    if (chkdist  <= 1){counter  <- counter + 1}
    else{nacount<-nacount+1}
    if (i == nrow(sresources)){
      newrow<-as.data.frame(c(row,counter))
      colnames(newrow)<-c('DOD','lat','lon','scount')
      resultsdf4<-rbind(resultsdf4,newrow)}
  }
  counter<-0
}
```

Box A5.6: R code for mapping resources (shelters, food banks, public and park toilets).

```
# load library
library(ggmap)

# load datasets
food.banks  <- read.csv("resources_food_banks_raw.csv")
park.bathrooms  <- read.csv("resources_park_bathrooms_cleaned.csv")
```

```
public.toilets <- read.csv("resources_public_toilets_raw.csv")
shelters <- read.csv("resources_shelters_cleaned_geocoded.csv")

# create child datasets
food.banks.simple <- data.frame(food.banks$Longitude, food.banks$Latitude, rep("Food banks",
        length(food.banks$Longitude)))
colnames(food.banks.simple) <- c("Longitude", "Latitude", "Type")
park.bathrooms.simple <- data.frame(park.bathrooms$xPos, park.bathrooms$yPos, rep("Park
        bathrooms", length(park.bathrooms$xPos)))
colnames(park.bathrooms.simple) <- c("Longitude", "Latitude", "Type")
public.toilets.simple <- data.frame(public.toilets$Longitude, public.toilets$Latitude, rep("Public toilets",
        length(public.toilets$Latitude)))
colnames(public.toilets.simple) <- c("Longitude", "Latitude", "Type")
shelters.simple <- data.frame(shelters$Long, shelters$Lat, rep("Shelters", length(shelters$Lat)))
colnames(shelters.simple) <- c("Longitude", "Latitude", "Type")

# combine into parent dataset
resources <- rbind(food.banks.simple, park.bathrooms.simple, public.toilets.simple, shelters.simple)

# map
SeaMap <- get_map(location="Seattle", maptype="toner-lite", zoom=12)
ggmap(SeaMap) + geom_count(aes(Longitude, Latitude, color=Type), data= resources)
```

Box A5.7: R code for density maps of homeless deaths, shelter locations, and evictions.

```
# load library
library(spatstat)

# load datasets
shelters <- read.csv('data/resources_shelters_cleaned_geocoded.csv')
evictions <- read.csv('data/evictions_cleaned_geocoded.csv', sep='\t')
deaths <- read.csv('data/deaths_cleaned_geocoded.csv', sep='\t')

# set boundaries based on evictions dataset and convert to ppp objects
min.long <- min(evictions$Long)
max.long <- max(evictions$Long)
min.lat <- min(evictions$Lat)
max.lat <- max(evictions$Lat)
shelters.ppp <- ppp(shelters$Long, shelters$Lat, c(min.long, max.long), c(min.lat, max.lat))
evictions.ppp <- ppp(evictions$Long, evictions$Lat, c(min.long, max.long), c(min.lat, max.lat))
deaths.ppp <- ppp(deaths$Long, deaths$Lat, c(min.long, max.long), c(min.lat, max.lat))

# create density plots
plot(density(deaths.ppp, adjust=.25))
plot(density(evictions.ppp, adjust=.25))
plot(density(shelters.ppp, adjust=.25))
```

Box A5.8: R code for calculating Ripley's K for deaths, shelters, and evictions.

```
# using ppp objects created with Box A5.7 code
plot(Kest(shelters.ppp))
plot(Kest((evictions.ppp)))
plot(Kest(deaths.ppp))
```

Box A5.9: R code for calculating Moran's I for (1) number of shelters within a half mile of each death and (2) number of evictions within a half mile of each death.

```
# load library
library(spatstat)
```

```
# load data
proximities <- read.csv('data/proximity_counts.csv', sep='\t')

# calculate weights matrix
death.dists <- as.matrix(dist(cbind(proximities$lon, proximities$lat)))
death.dists.inv <- 1/death.dists
death.dists.inv[is.infinite(death.dists.inv)] <- 0
diag(death.dists.inv) <- 0

# calculate Moran's I
Moran.I(proximities$ShelterCount, death.dists.inv)
Moran.I(proximities$SweepCount, death.dists.inv)
```