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A GIS Analysis of Emergency Medical Services Response in Denver, Colorado

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1. Introduction

Emergency medical services (EMS) exist to ensure a better quality of life. EMS has improved in accessibility and responsiveness since its conception and is responsible for saving countless lives. The increased effectiveness of EMS has provided immediate medical assistance to those who are in need of help. Without EMS, the fatality rate of emergencies, including heart attacks, stroke and car accidents, would be undoubtedly be higher than the observed rate. We seek to explore the geographic variation in accessibility to EMS within the Denver area in order to reveal disparities that may exist as a result of natural, human-made, or socioeconomic barriers. To complete this analysis, we will execute a network analysis to calculate response time patterns and identify underserved areas.

2. Background

The standardized system of emergency medical services that we utilize today, including pre-hospital care and medication, was formalized in the 1960s. In 1966, President Lyndon B. Johnson was presented with a white paper detailing the large number of lives being lost every year to accidental deaths. In 1965 alone, the number of lives lost to accidental death was greater than the number of American lives lost in the Korean War (Edgerly 2013). This white paper lead to the standardization of training for ambulance staff as well as firefighters, police officers, and volunteer rescue squads.

Since the 1970s, the effectiveness of EMS has continuously improved with increased research interests and political efforts. The indicators used to measure effectiveness can be divided into three categories: structure, process, and outcomes (Brodsky 1983). Structure most often refers to the number and location of EMS stations as well as the number of ambulatory vehicles. Measuring effectiveness based on outcomes refers to health outcomes of the patients serviced, which include survival rate and any resulting disabilities (Brodsky 1983). This analysis will focus on the process category, which includes, among other factors, response time.

The National Fire Protection Association's standard response time for a life-threatening emergency is eight minutes and forty-nine seconds. In the case of cardiac arrest, it is vital for a patient to receive medical attention within four minutes (Zaffar 2016). The ability of an ambulance to quickly arrive at a medical emergency site and then continue on to the hospital is key to improving outcomes and saving lives.

Regarding certain types of medical emergencies such as severe asthma attacks, it has been shown that there is a significant difference in service utilization for different demographic groups. One study in Houston revealed that census tracts with higher rates of EMS utilization for asthma attacks had higher percentages of individuals who were low-income, African American, female, and had larger counts of individuals without a high school diploma. The study also showed that certain racial and gender groups are more likely to seek EMS services after regular office hours (when doctor's offices are likely closed) (Raun 2015).

Given the variation of service utilization based on demographics as well as the importance of response time, this analysis will aim to identify census tracts with high travel times. These areas will then be examined further to reveal if there is a correlation between high travel times and certain demographic groups.

3. Conceptualization

While developing the conceptualization diagram, two key concepts were first defined: emergency medical services and demographics. Emergency medical services include four variables: incident point, starting point, end point, and EMS catchment. The incident point is the location of the medical emergency. To determine incident points we will use census tract centroids. The starting point is the location of the nearest EMS station to the specific incident point. The end point is the nearest hospital from the incident point. The EMS catchment will be created by using Voronoi polygons. The EMS catchment area is useful in visualizing an area to distinguish which specific EMS station is closest to the incident point. Demographics includes three variables: age, income, and race. Income will be split into rich and poor, meaning that an income that is greater than or equal to the median income is considered rich. Age will be similarly compared by using the median age as the threshold for young and old. Race will be treated as binary, with white and minority classifications. This will be defined by one- hundred percent less the percentage of white residents for a given census tract.

-- Conceptualization Diagram - Denver EMS

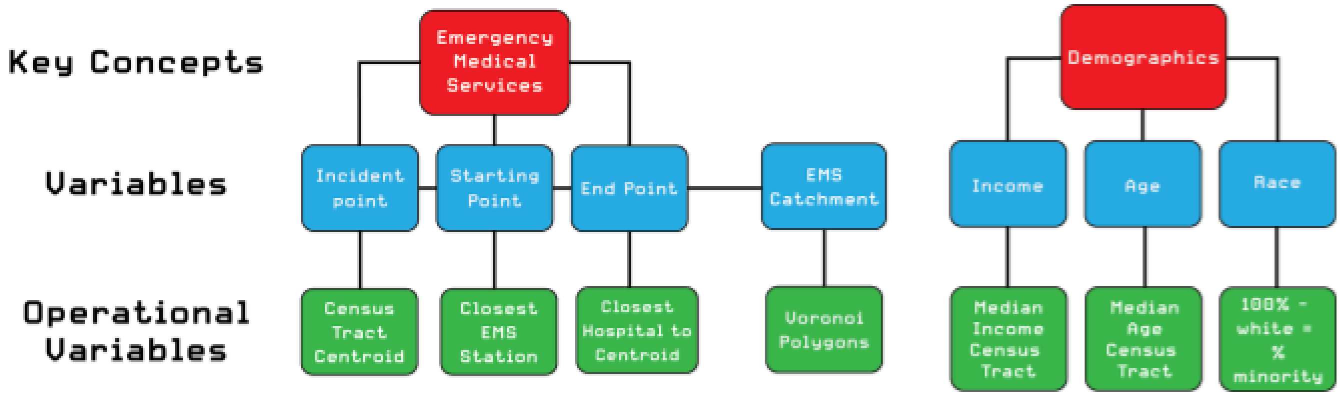


Figure 1

4. Methods

When analyzing emergency medical services, it is important to touch on how each step of the process is being considered in order to highlight assumptions being made as well as to eliminate ambiguity. Our analysis required us to make assumptions that may not have reflected exact situations that would be occurring. For example, we made the assumption that all drive times are calculated with light traffic, i.e., traffic concerns will not be playing a role in our analysis. With additional time and pending how our original analysis process goes, we may be extending our project to better capture the variability in the traffic situations that occur while completing our drive times study. Our methods consist of geocoding, space partitioning, a road network analysis, and lastly finding a correlation between our resulting drive times layer and demographic information.

A. Geocoding

The first step in our analysis was to convert our emergency medical services and hospital layers to usable formats to be used in a geographic information system (GIS).

In order to do this, the address field was geocoded to receive latitude and longitude coordinates. We did this through a python script which made use of the geocoder, pandas, os, time and geopy python packages. The script first takes our list of addresses and searches Bing's location services through its application programming interface (API) to return coordinate positions. Any address not found with Bing's services are then run through Google's location services. If any addresses are still left unfound, they will be manually searched, although we expect this number of locations to be nominal in size.

B. Catchment Areas - Voronoi Polygons

The next step was to create catchment areas for our EMS stations. These catchment areas were formed using Voronoi polygons. Voronoi polygons result from a points data layer. The main idea is that the two-dimensional plane is partitioned around n points given as input (our EMS stations), and any point within each of these convex polygons is understood to be closest to the generating point (again, our EMS stations) (Weisstein 2018). Therefore, any census tract centroids within a given polygon will take the generating point EMS station as the closest emergency medical responder and this will be the station with which we start our drive time calculation.

C. Drive Time Analysis

The bulk of the project's analysis was derived using drive times. We utilized Google Map's Python googlemaps package to calculate drive times. In order to use this package, we first needed to reformat the data. This required nominal changes to the data such as making sure all of the coordinates for each of the census tract centroids, EMS stations, and hospitals were respectively combined (latitude and longitude) as one string. When the data was prepared, we first calculated drive times for each centroid from the closest EMS station. We already knew the associated closest EMS station to each centroid from creating the voronoi polygons layer previously. The second step of the process involved finding the closest hospital to each centroid. We differenced coordinates of centroids and hospitals to find the minimum distance to a hospital and then associated that hospital with the respective centroid point. We then repeated the same process as before with the EMS stations to calculate drive times, only the centroid was now the starting point and the hospital location was now the end point. There was one centroid location that gave the script issues, the Rocky Mountain Arsenal National Wildlife Refuge tract. To deal with this, the centroid's coordinates were changed to the entrance road parking area of the refuge. To create the total drive times field, we then simply summed the two drive times from the EMS station to the census tract centroid, and then from the centroid to the hospital.

D. Demographic Correlation

Our next step was to connect the EMS drive times analysis to the census gathered demographic information. We will be looking to reveal any insights regarding emergency response accessibility to different groups of people. Our characteristics of focus: income, age, and race. We will use the respective median values for income and age given their associated census tracts. Race will be treated as a binary classification between white and non-white. Percent non-white for the census tract will be calculated as one-hundred percent less the percentage of white residents. At this stage, we do not have any bias involved in our search for correlations between drive times and accessibility to different demographics. This is to say, we are not attempting to rebuke or advocate for any noted claims, this project is designed to simply explore the data to reveal if there are patterns of underserved communities within the Denver area.

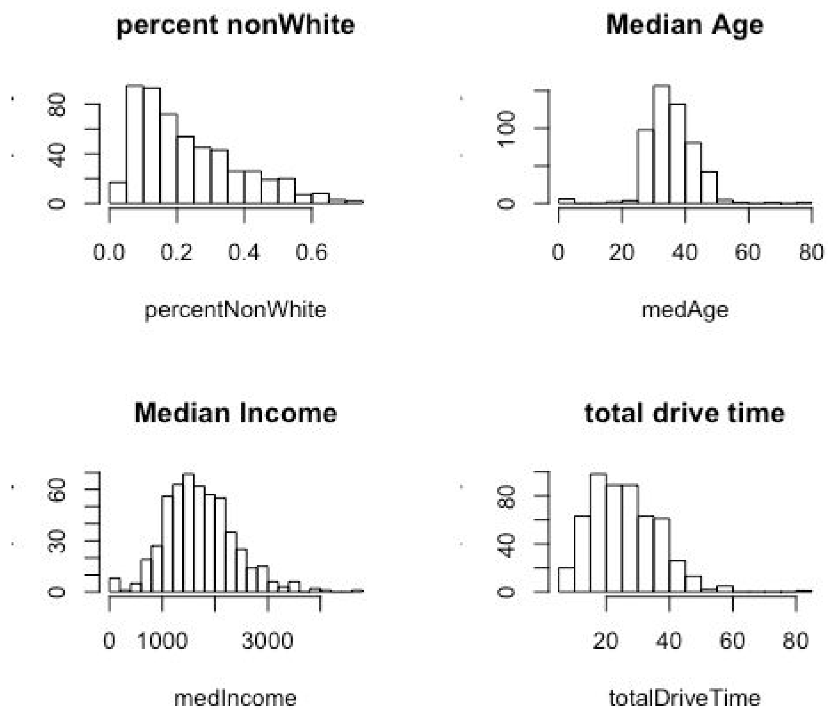
E. Regression

To further explore the relationship between the total drive time and the demographics of different census tracts, a linear model was fit to the data. Total drive time from EMS station to census tract centroid and then to the nearest hospital was treated as the dependent variable. Percent non-white, median age, and median income were used as the independent variables.

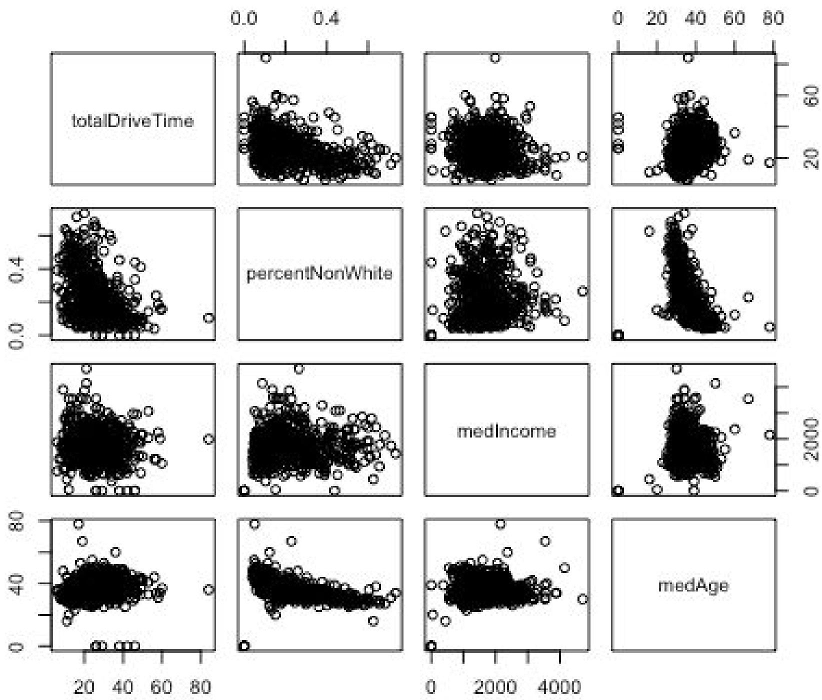
Before fitting a linear model, summary statistics as well as histograms of each variable were created in order to understand the nature of the raw data and to determine whether the data fulfilled the necessary assumptions for fitting a linear model. The entirety of this statistical exploration and regression analysis was carried out using R Studio. The R code that was utilized can be found in Appendix B.

The initial summary statistics showed that the standard deviation and variance of each variable varied by more than two orders of magnitude. This is due to the fact that the median income data was on a much larger scale than the race and age data. Because of the difference in scale, it was determined that the data would need to be standardized in order to fit a linear model.

Histograms for each variable were also created in order to establish the normal distribution of the data. The histograms reveal that the data for percent non-white, median income, and total drive time all show a rightward skew. Because of this, it was determined that some kind of transformation would be necessary for a linear model.



Next, a matrix of scatterplots was created in order to determine if collinearity could arise as an issue. The relationship between median age and percent non-white showed strong potential for collinearity. To explore this relationship further, correlation and covariance matrices were produced to check for problematic collinearity.

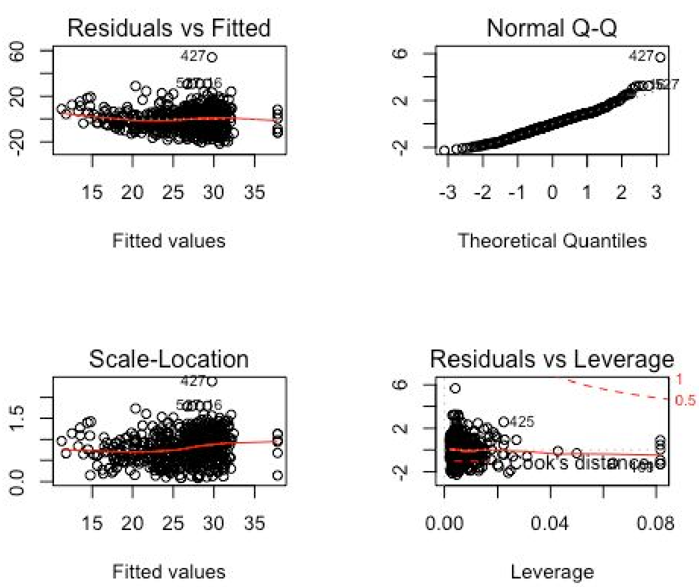


The covariance matrix below shows that there are values close to 0 -- which would indicate perfect independence; however, none of the variables show perfect linear independence. The correlation matrix shows that none of the variable pairs have a correlation value close to the absolute value of one, which would indicate a high correlation. The highest correlation was between the percent non-white and median age. The relationship between percent non-white and drive time showed a moderate amount of correlation. A variance inflation factor was calculated, which confirmed we did not have to remove any of the variables due to collinearity; however, after this exploration of the data, it was determined that standardization would be needed. The scale function in r would be used to achieve this.

```
> cov(drivetimes)
              medIncome     med_age  per_nonWhi         Tot
medIncome  453211.627007 495.1735207  4.12917510 -690.733474
med_age       495.173521  57.7409316 -0.52123766   11.368531
per_nonWhi      4.129175  -0.5212377  0.02311528   -0.677246
Tot          -690.733474  11.3685309 -0.67724603  111.912576
```

```
> cor(drivetimes)
             medIncome     med_age  per_nonWhi         Tot
medIncome   1.00000000  0.09679769  0.04034253 -0.09698857
med_age     0.09679769  1.00000000 -0.45117421  0.14142396
per_nonWhi  0.04034253 -0.45117421  1.00000000 -0.42107301
Tot        -0.09698857  0.14142396 -0.42107301  1.00000000
```

Finally, a linear model was fit to the unstandardized and untransformed data in order to check for heteroscedasticity. After a linear model was fit, the following summary plots show that there is a slight megaphone shape to the residual plot as well as some potential outliers. The outlier test function was used to confirm the outliers that should be removed from the model and those observations were removed from the data. The shape of the residual plot also confirmed that the data should be transformed.



Lastly, we used the box cox method to determine the most appropriate transformation. After using the boxcox function in r, it was determined that a power of .5 or square root transformation would be most appropriate. A new model was created with the scaled data that included the new transformation. Finally, a backwards step function was applied in order to decide which variables should be included in the model. The final model:

sqrt(drive time) = 5.88900 - 0.00013(Median Income) - 2.83479 (Percent Non-White)

5. Results

A. Age

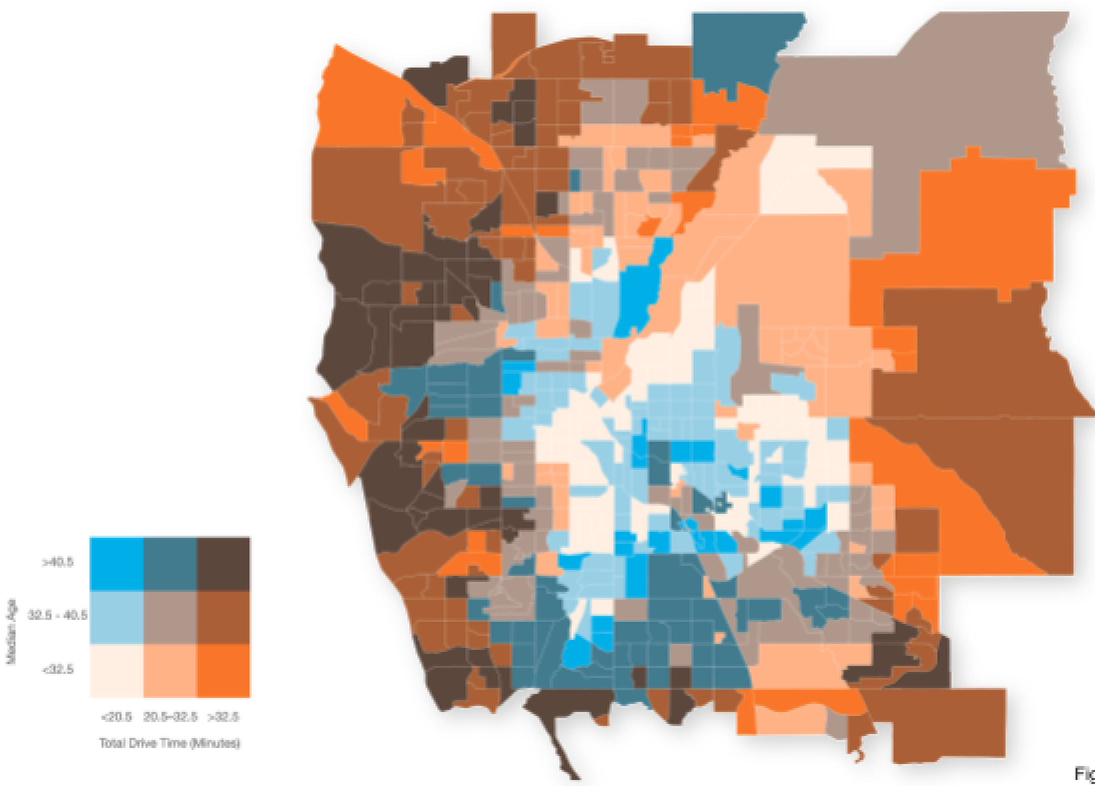


Figure 2

B. Income

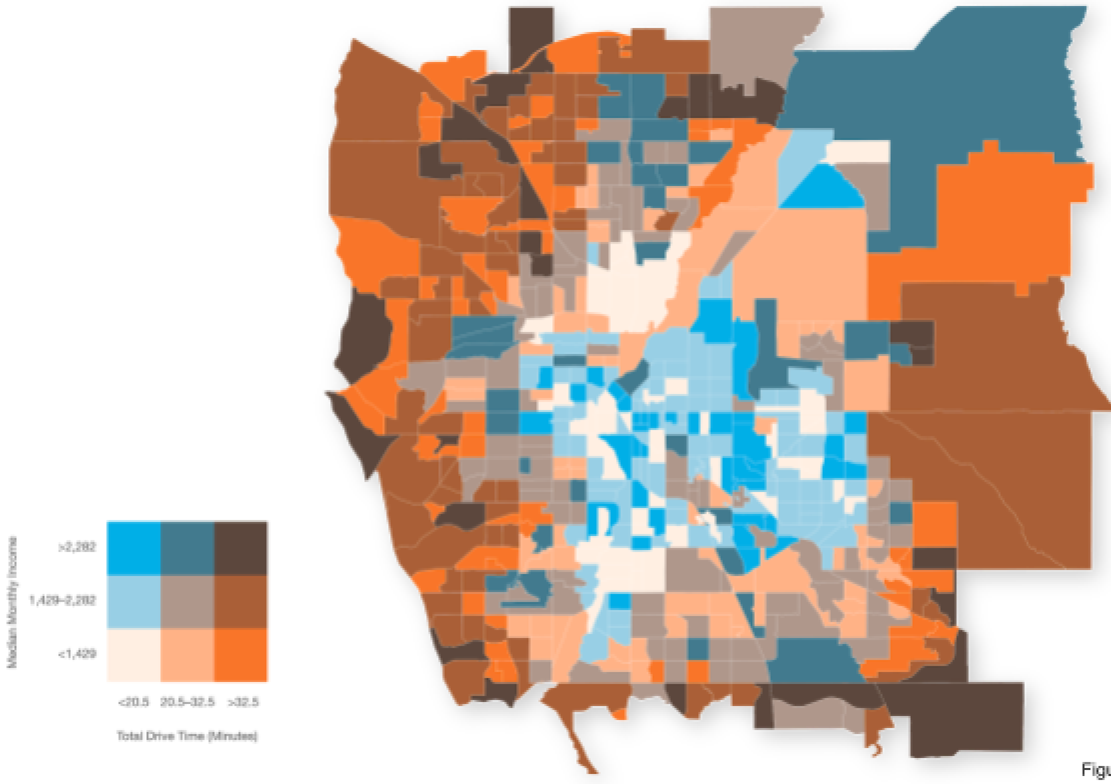


Figure 3

C. Race

While analyzing the connection between percent non-white and drive time we found that there was a slight inverse relationship between the two. There was a coefficient value of -0.15 for the respective constant fitting the drive time and percent non-white relationship. This was the largest value found between drive time and any of the three operationalized demographic variables. Using a bivariate map (see figure 4 below) of drive times and percent non-white we can begin to find spatially where this relationship might be found. The center of the city bolsters the census tracts with the highest percent non-white demographic. We see particularly low drive times for most of the tracts in the downtown (near center) area both connected to high and low percent non-white tracts.This is mainly because the hospital and ems locations are concentrated in the downtown area. As we move out from the center of the city, we see the drive times increase as we would expect, and we also see the percentage of white residents within census tracts increase. This phenomena best captures the slight inverse relationship between non-white residents and drive times. With the highest values of non-white residents centered in the Denver area, they are prone to have lower drive times associated while the majority of the tracts surrounding the city center are mainly white.

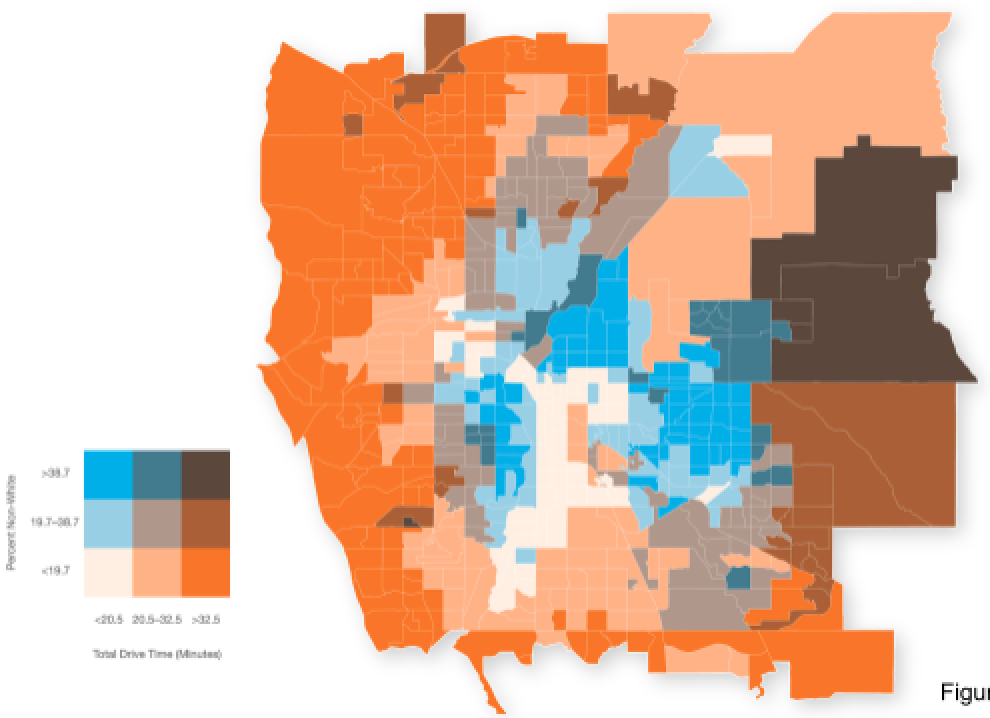


Figure 4

6. Discussion

In order to start our analysis, we had to make certain assumptions. Our study area was essentially the Denver area encompassed by Highway 470. This was an arbitrary way to define our study area, and we acknowledge that there could be hospitals or EMS stations just outside the boundary that could lead to different results. Secondly, we calculated drive times using light traffic conditions. This is not always going to be the case, and EMS are allowed to exceed speed limits, so drive times will not be exactly representative of raw values. From the incident point, we decided that the EMS will always drive to the closest hospital, which is not always the case. Lastly, all of our operationalized variables were defined in a manner we saw best fit, but this does not necessarily mean that this is the only way to study accessibility to emergency medical services.

We ended this analysis with a new original data layer. This layer contains EMS locations around the Denver area with the following associated information (given they are serving census tract centroid locations): locations (census tract centroid locations) that they will serve, the distance there, the drive time to get there, the closest hospital, its distance, and the drive time to get there. Having information like this on hand can allow EMS to better prepare for arriving at an incident because they can connect the type of accident and what state the situation will be in given the amount of time it will take them to drive there. This information would also be valuable to governing bodies looking to expand EMS and hospital locations in the future.

7. Conclusion

The focus of this GIS analysis was to explore the geographic variation in accessibility to EMS within the Denver area and to reveal if there were any shortcomings regarding accessibility across different demographics. Because it was an exploratory analysis, we were not specifically biased towards finding a particular result. After running a regression function for drive times associated with each demographic, we found low levels of significance. The only usable coefficient was is that of drive times slightly inversely associated with the non-percent white field. With this, we also found that census tracts with higher percentages of non-white residents tended to be located near the center of the city, which is also where the majority of the hospitals are clustered. Through different Python and R scripts as well as using a GIS system, we were able to fully implement this analysis. With the exception of the creation of the map visuals, which required unique cartographic attention, this project contained steps and scripts that should allow the work to be reproducible for new studies in different cities given new data sets. We have been able to reveal trends about the city and how they are connected to drive times regarding medical attention. However, at this stage we do not have any recommendations to the respective EMS governing bodies of Denver for new locations or adjustments to increase accessibility to these services.

Works Cited

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APPENDIX

A. Sample of drive times script

```
ems_cent_drive = []
cent_hosp_drive = []
total_drive_time = []

for row in data:
    # centroid coords row[12]
    # hospital coords row[13]
    # ems station coords row[14]

    now = datetime.now()

    # generates results
    ems_cent_result = gmaps.directions(row[14],
                                       row[12],
                                       mode="driving",
                                       avoid="ferries",
                                       departure_time=now
                                      )
    cent_hospital_result = gmaps.directions(row[12],
                                            row[13],
                                            mode="driving",
                                            avoid="ferries",
                                            departure_time=now
                                           )

    # append the results' drive times to lists
    try:
        ems_cent_drive.append(ems_cent_result[0]['legs'][0]['duration']['text'])
        cent_hosp_drive.append(cent_hospital_result[0]['legs'][0]['duration']['text'])

        # convert drive times to usable numbers
        if len(ems_cent_result[0]['legs'][0]['duration']['text']) == 5:
            ems_drive_time = float(ems_cent_result[0]['legs'][0]['duration']['text'][:-4])
        else:
            ems_drive_time = float(ems_cent_result[0]['legs'][0]['duration']['text'][:-5])
        if len(cent_hospital_result[0]['legs'][0]['duration']['text']) == 5:
            hosp_drive_time = float(cent_hospital_result[0]['legs'][0]['duration']['text'][:-4])
        else:
            hosp_drive_time = float(cent_hospital_result[0]['legs'][0]['duration']['text'][:-5])

        # calculate total drive time
```

```
        total_time = ems_drive_time + hosp_drive_time
        total_drive_time.append(total_time)

    except:
        ems_cent_drive.append('X')
        cent_hosp_drive.append('X')
        total_drive_time.append('X')

    # DISTANCE
    # ems_cent_result[0]['legs'][0]['distance']['text']

    # DURATION
    # ems_cent_result[0]['legs'][0]['duration']['text']
```

B. R Code for Linear Regression

```
getwd()
setwd("/Users/caseykalman/desktop")

file.exists('drivetimeData_.csv')

##read in csv with drive times and demographic data
drivetimes <- read.csv('drivetimeData_.csv', header=TRUE, stringsAsFactors = FALSE)
colnames(drivetimes)

##rename each field for easy recall
percentNonWhite <-drivetimes$per_nonWhi
medAge <- drivetimes$med_age
medIncome <- drivetimes$medIncome
totalDriveTime <- drivetimes$Tot

##explore
summary(percentNonWhite)
summary(medAge)
summary(medIncome)
summary(totalDriveTime)

var(percentNonWhite)
var(medAge)
var(medIncome)
var(totalDriveTime)
##Variance of vary by more than one order of magnitude (income). Will need to scale
data

sd(percentNonWhite)
```

```
sd(medAge)
sd(medIncome)
sd(totalDriveTime)

par(mfrow=c(2,2))
hist(percentNonWhite, main="percent nonWhite", breaks=20)
hist(medAge, main="Median Age", breaks=20)
hist(medIncome, main="Median Income", breaks=20)
hist(totalDriveTime, main="total drive time", breaks=20)
##All data are skewed except the median age. Will need to transform

##Check potential for colinearity
pairs(~totalDriveTime+percentNonWhite+medIncome+medAge)
pairs(drivetimes)
##potential collinearity between percentNonWhite and median age. Nothing else looks
super strong

##Calculate correlation matrix
cor(drivetimes)

##Calculate covariance matrix
cov(drivetimes)

##fit a linear model to "raw" data. not scaled. not transformed
model1 <- lm(totalDriveTime~percentNonWhite+medIncome+medAge)
model1

##plot the model
par(mfrow=c(2,2))
plot(model1)
##nonconstant variance, potentially non normal distribution, one potential outlier

##outlier test
library(car)
outlierTest(model1)
##p value is less than .05, potentially significant

##remove obsrvation 427
drivetimes2 <- drivetimes[-427,]

##standarize the dataset
drivetimes2 <-scale(drivetimes2)
drivetimes2 <-as.data.frame(drivetimes2)

##rename variables within new table without outlier
```

```
totalDriveTime2 <- drivetimes2$Tot
percentNonWhite2 <- drivetimes2$per_nonWhi
medIncome2 <- drivetimes2$medIncome
medAge2 <- drivetimes2$med_age

##fit a new model
model2 <-lm(totalDriveTime2~percentNonWhite2+medIncome2+medAge2)

##fit new linear model without the outlier and create summary plots
par(mfrow=c(2,2))
plot(model2, main="model 2")

outlierTest(model2)
##Potential outlier: Observation 526. Bonferonni p value greater than .05. No need to
delete the observation

##test for variance inflation factor to determine if collinearity is an issue
vif(model2)

##Still seeing a cone shape on the residual v. fitted graph. Will use boxcox method to
transform
library(MASS)
model.bc <- boxcox(model2, lambda = seq(0,1, by=.1))
lambda <- model.bc$x[which.max(model.bc$y)] ##max lambda is .474747474747475.
Will round to .5

##create and name the new model
model3 <- lm(sqrt(totalDriveTime2)~medAge2+medIncome2+percentNonWhite2)

##use stepwise function to determine what variables should be included in the final
model
step(model3, direction="backward")

finalmodel <- lm(sqrt(totalDriveTime2)~medAge2+percentNonWhite2)
finalmodel

par(mfrow=c(2,2))
plot(finalmodel, main="final model")
```