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Understanding Delays and Improving Emergency Response with GIS - Evergreen Fire Department in Evergreen, Colorado

Adrien Hoff

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Abstract

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It is expected that both the PSAP and the responders in the field react quickly and arrive on the scene to emergency events as soon as possible. Fire agencies have been held to standards set in place reflective of where the emergency occurs and how quickly responders are expected to reach that location. Calls that experience delays in meeting these standards should be carefully examined and learned from for future events. Utilizing National Fire Protection (NFPA) population zone recommendations, population zones previously established with 2010 census data and unknown methods were recreated for Evergreen Fire Protection District. Then, utilizing SQL data stored within the Computer Aided Dispatch system, delays in response were found for the calendar 2022 year. Statistical GIS methods were applied to find clustering within the delayed responses, spatial autocorrelation, and correlation to CDOT and Jefferson County road data were analyzed. Statistical significance could not be found for either analysis and the null hypothesis' of completely spatial randomness in clustering of delayed response and lack of correlation between pavement condition, width, or road slope was accepted. Examination of multiple Origin-Destination (OD) Cost Matrix analyses revealed complications with using the census data and predetermined, distance derived, areas alone for population zones in the mountainous road network of Evergreen, Colorado. This understanding showcases complications with the initial statistical analyses and suggests additional needs in consideration for uneven terrain road networks.

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Trademarks

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Acronyms and Abbreviations

- AVL - Automatic Vehicle Location
- CAD - Computer Aided Dispatch
- DRCOG - Denver Regional Council of Governments
- DEM - Digital Elevation Model
- EFPD - Evergreen Fire Protection District
- ESRI - Environmental Systems Research Institute
- ETA - Estimated Time of Arrival
- JeffCom911 - Jefferson County Communications Center Authority
- KDE - Kernel Density Estimation
- LiDAR - Light Detection and Ranging
- NFPA- National Fire Protection Association
- NG-911 - Next Generation 911
- OD Cost Matrix - Origin-Destination Cost Matrix
- PCI - Pavement Condition Index
- PPGIS - Personal Perspective GIS
- PSAP - Public Safety Answering Point

Introduction

In 911 emergency response, it is typically thought that the field responders are first on the scene. However, the Public Safety Answering Point (PSAP) is the first notified of the incident and tasked with the responsibility of obtaining the location of the emergency and dispatching responders to the person in need. Of the fundamental questions asked during that initial phase of contact, the most important question is “Where is your emergency?” Therefore, it is no surprise that PSAP centers rely heavily on GIS to locate the incident dependably. Similarly, Emergency responders rely heavily on accurate routing and location information from the dispatcher and the dispatch systems.

It is expected that both the PSAP and the responders in the field react quickly and arrive on the scene as soon as possible. Fire agencies have been held to standards set in place reflective of where the emergency occurs and how quickly responders are expected to reach that location. Calls that experience delays in meeting these standards should be carefully examined and learned from for future events.

This research will attempt to determine the cause for delay in those responses which did not meet the time standard. This research will examine responses to delayed incidents in the Evergreen Fire Protection District (EFPD) dispatched by the Jefferson County Communication Center Authority (Jeffcom911), a local PSAP in the Jefferson County area of Colorado. It will assist with the establishment of population zones based on suggestions provided by the National Fire Protection Association (NFPA), the determination of responses that did not meet the criteria based on these zones, perform analysis to predict why these delays may have occurred, and reassess the fit of the initial population zones suggested for EFPD based on estimated travel time. The null hypothesis for spatial autocorrelation performed assumes delays in response are not significantly dispersed or clustered while the null hypothesis for the regression analysis conducted in this report assumes no definitive conclusion can be assumed to a connection of pavement condition, width, or road slope.

Problem

The most critical question a dispatcher at a 911 operation can ask is “Where is your emergency?” Without this information, emergency services cannot reach the person in trouble. It then becomes highly critical that emergency responders be able to route and locate the caller as quickly as possible. Presently, the Jefferson County Communication Center 911 Authority (Jeffcom911) offers emergency responders verbal routing assistance as well as mobile Computer Aided Dispatch (CAD) with routing integration in the GEO user interface. Current abilities of the CAD routing system limit custom routing to impassible road impedance, tabular speed and direction attributes, and response area polygons. Response areas have been utilized to ensure the station with the shortest travel distance can reach the area of the incident within a set response time to meet accreditation standards. These standards set response time goals according to population density, accounting for residential, rural, and urban areas.

The goal of this research is to analyze a set of calls that suffered poor assistance response times in the Evergreen Fire Protection District of Jefferson County, Colorado. Prior to analyzing the calls, new population zones were determined for Evergreen based on 2020 census block tracts. Previous determination of population zones was performed for the protection district based on 2010 census data and was generalized based on personal perspective GIS (PPGIS) methods, voiding census block boundaries. A cluster analysis of calls with slow response times was evaluated to determine common areas with issues. Road quality, width, and slope were used in a regression analysis to determine how these features play a role in delayed response times. Roads traveled to each incident were determined by studying the Automated Vehicle Location (AVL) data from the CAD Microsoft SQL database. This research answers if there is a correlation between delayed response times and slope or road quality and examines the fit of initial population zones as determined with census data for the Evergreen Fire Protection District in regards to minimum travel times to each census block from the individual stations. OD Cost Matrix analyses were performed to determine areas with minimum travel time estimates using the original CAD routing network and a copy of the same network with added restrictions.

Literature Review

Emergency Management can be defined as "the discipline and profession of applying science, technology, planning, and management to deal with extreme events that can injure or kill large numbers of people, do extensive damage to property, and disrupt community life (Cova, 1999). According to Cova, Emergency Management is inherently spatial in every situation from evacuation planning to analyzing risk. Cova defines risk as a combination of hazard potential and vulnerability. Emergency Management can be divided into three main categories, mitigation, preparedness, and response, and recovery. In the preparedness and response phase, GIS is primarily used to "formulate and execute emergency response plans" (Cova, 1999).

Emergency call-taking and dispatch centers are at the center of this phase in emergency response with decision-making skills focused on hosting response plans in the Computer Aided Dispatch (CAD) system and executing data delivery to field responders at required times. Historically, improvement in caller-automated location data significantly reduced response times compared to the days of tabular address lookup by the call taker. Šterk and Praprotnik note the response time from field agents in Solvania decreased by nearly 30 seconds after the implementation of automated location collection. "After implementation of automated location collection, typically referred to as emergency mobile location, the average ambulance vehicle response time dropped from 469 to 444 seconds" (Šterk and Praprotnik, 2017).

One of Cova's key elements in utilizing GIS for preparedness and response answers the best route available for emergency deployment (Cova, 1999). In a case study to improve the emergency response of Gaza, City, Eljamassi conducts routing analysis for the emergency vehicles based on weight classifications of the navigability of the roads. By applying weights and delays to the road network, better decision-making can be made by the Computer Aided Dispatch system in suggesting routes and time estimates for the responders to the emergency. Width, one-way accessibility, and pavement condition all impact the speed at which an emergency vehicle can access the scene of an event (Eljamassi, 2012). The pavement condition index (PCI) is ranked on a scale of zero to 100 degrees with zero indicating the worse road conditions. PCI can have a great effect on emergency vehicle response as poor road conditions often slow the vehicle's speed dramatically (Eljamassi, 2012). Pennino's examination of response delays from Largo Fire Rescue highlights that the CAD and AVL data observed the greatest cause for the delay due to the time of day and road congestion (as noted by Eljamassi, 2012), road impedance, and availability of the closest unit (Pennino, 2015).

Similarly, in a study conducted by Puji Adiatna Nadi and Abdul Kader Murad GIS statistical methods are used for modeling the performance of Sustainable Urban Transport (SUT) in the Jakarta city Region. Nadi and Murad examine the existing performance of SUT in Jakarta city and explore the relationships between indicators of SUT. Five basic indicators of sustainable urban transport data were selected as independent variables against the SUT performance: traffic congestion, traffic accident, traffic air pollution, traffic noise pollution, and land consumption for transport infrastructure. Each indicator was classified into five weighted categories: High = 1 (lowest problems), Medium–High = 2, Medium = 3, Medium–Low = 4, and Low (highest problems) = 5 (Nadi and Murad, 2019). Ordinary Least Squares and Geographically Weighted Regression methods were used to understand correlations between the chosen indicator values and SUT performance (Nadi and Murad, 2019). Residuals were then checked for clustering behavior using spatial autocorrelation techniques and checked for biases. Additional regression analysis techniques were utilized to determine the relationship between variables including descriptive statistical analysis and scatter plot analysis, Results from the regression scatter plot on SUT Performance Index and Traffic Congestion Indicator, Traffic Accident, and

Traffic Air Pollution show a significantly positive relationship, with *p*-values less than 0.05. Nadi and Murad found no multi-collinearity problem with the Variance Inflation Factor (VIF) under 7.5 (Nadi and Murad, 2019). The adjusted R-square of the transformed model was 0.855, indicating 85.5% variability in SUT Performance Index value could be explained by these variables. Additionally, a Moran's I analysis showed residuals as not significantly distributed (Nadi and Murad, 2019).

This research pulls from a variety of sources to gain insight into the need for emergency response routing. Zhan highlights the original issue with network routing and analyzes the shortest path distance in real-time. Zhan compares shortest path algorithm functionality for real-time analysis on road networks (Zhan, 1998).

Research conducted by Daniel, et al analyzed population density and road connectivity utilizing a correlation matrix using SPSS. This research examined the correlation of accessibility to individual wards, Estimated Time of Arrival (ETA) indices regarding length per network segment, and network density in correlation to the population growth of Kerala, India. Observed on a 0.05 level of significance, road network density appeared to be greatly correlated to population density and accessibility was greater at the central locations of the individual wards. ETA indices were found to have a negative correlation and no effect on the accessibility of the road network (Daniel, et al. 2019). Similar methods to those used in this research can be applied to understanding the correlation between response accessibility and time delays using multivariate regression to model the relationship.

Requirements for the NFPA 1720 standards are placed according to population density. In an analysis by Stilley, population zones for response time analysis were created in similar methods to redistricting of Tompkins County, New York in which gerrymandering practices are applied. This method involves shortest-split line methods to divide the county and calculating the census population blocks against the divided zones (Stilley, Thomas E., Jr. 2019). The beginnings of this research will reassess the 1720 population zones within Evergreen Fire Protection District with 2020 census data, which will enable a clear analysis of which responses did not meet the criteria based on population zones where the calls occurred.

The research following this literature review will determine where to perform routing analysis based on cluster analysis of geo-verified calls where the response was delayed. Cluster analysis methods are commonly applied in a wide variety of applications including emergency planning for rescue services and risk assessment. "Kernel Density Estimation (KDE) is specifically useful in detecting hot spots due to the series of estimations which are made over a grid placed on the entire point pattern" (Kalinic and Krisp, 2018). Kalinic and Krisp apply Kernel Density Estimation in determining patterns of San Fransico crime based on location density. Kalinic and Krisp describe the resulting pattern of KDE as follows: "The surface value is highest at point location and diminishes as the distance from the point increases. It becomes zero at the search radius (bandwidth) distance from the point" (Kalinic and Krisp, 2018). The authors note the lack of confidence values provided by the KDE analysis on crime density and suggest performing signifigance calculations in future analysis to determine randomness. "The local sum for a feature and its neighbors is compared proportionally to the sum of all features; when the local sum is very different from the expected local sum, and that difference is too large to be the result of random choice, a statistically significant z-score results…we suggest that KDE should be used in conjunction with hot spot analysis to increase efficiency and efficacy in results interpretation” (Kalinic and Krisp, 2018).

Levine reviews spatial autocorrelations with respect to crime pattern analysis. In his review of the Getis-Ord “G” statistic method, he highlights the method clusters data with a provided p- and z-score to determine significance. Levine describes the Getis-Ord “G” statistic as having an advantage over Moran’s I and Geary’s C in that it can distinguish between hot and cold spots of clustering. Getis-Ord “G” determines positive spatial autocorrelation where neighbors have similar values and can determine differences in positive spatial autocorrelation with neighboring raster cells which have high values compared to areas with low values (Levine, 2013).

Study Area

Jeffcom911’s dispatch boundary extends just beyond the Jefferson County boundary in Colorado. For purposes of this research, this paper will examine the calls and response times within the Evergreen Fire Protection Boundary. Evergreen is a Census Designated Area in Unincorporated Jefferson County and not a recognized city or town. The Fire Protection District extends beyond the Evergreen Boundary for a total coverage area of 115.64 square miles. The district encompasses 320.7 square miles of road with 197.4 square miles of paved and 123.3 unpaved surface. The Fire Protection District contains a population of 26,933. Therefore, census blocks used in this study will be recalculated to fit within the boundary. This region was chosen based on time limitations and the ability to clearly display the slope factor of routing challenges.

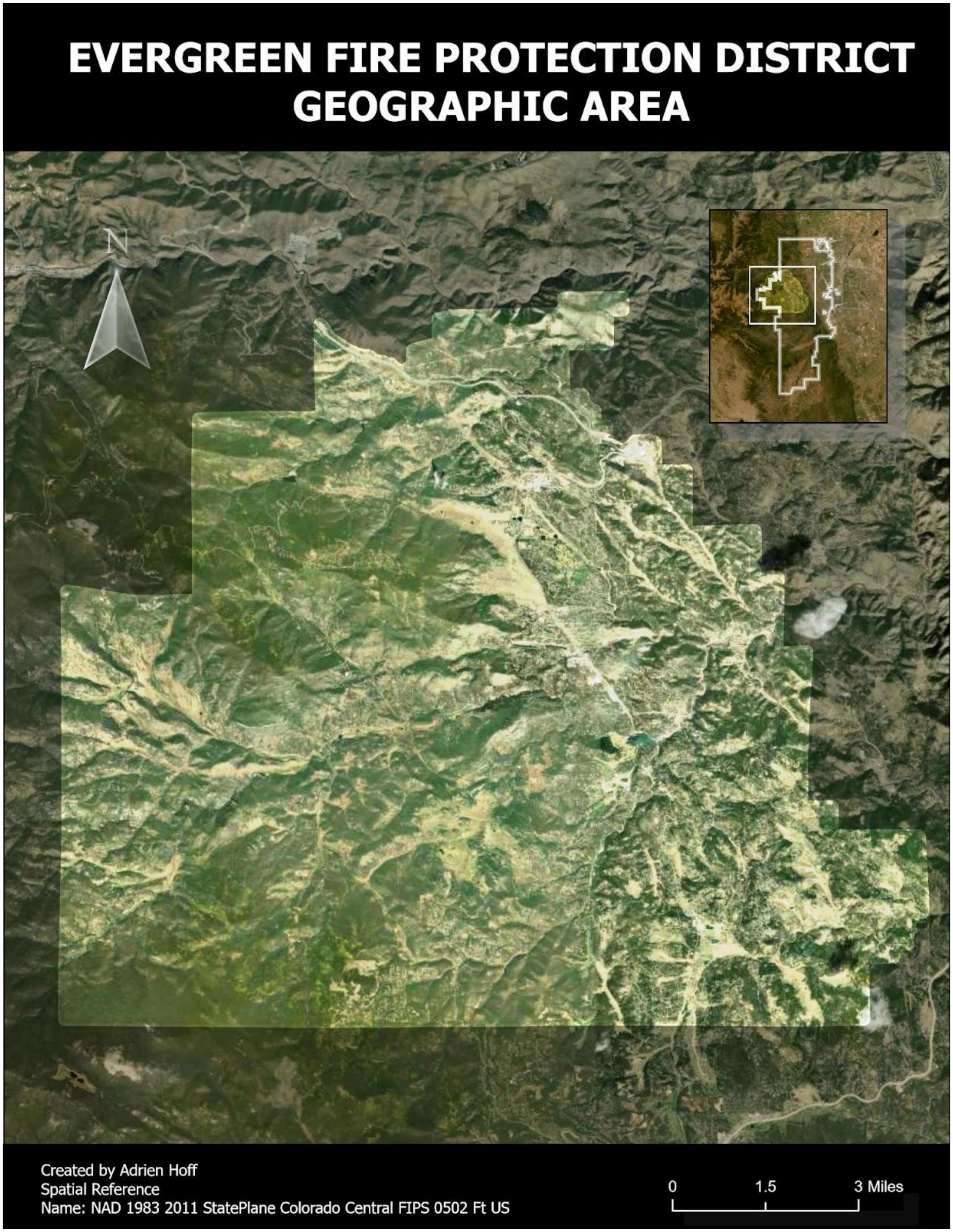


Figure 1: Study Area - Evergreen Fire Protection District

Data Sources

Data for this research is sourced from the Jefferson County Communication Authority Microsoft SQL CAD Database, Jefferson County Road and Bridge Maintained Roads GIS data, CDOT Highway Pavement and Driveability GIS data, Denver Regional Council of Governments (DRCOG), and the IPUMS National and Historical GIS dataset. The CAD AVL data is a primary data source and provides clear details from the time the first unit was assigned to the first unit on the scene, which is used in calculating the total response time. Jefferson County and Colorado Department of Transportation (CDOT) GIS data is utilized as a secondary data source for road width and pavement condition. Census data is derived as a secondary source to establish zones as determined by the NFPA. One-way accessibility is derived from the already available CAD services and GIS data. The Slope will be calculated from Jeffcom's existing Digital Elevation Model (DEM) dataset provided by the Denver Regional Council of Governments (DRCOG). The DRCOG DEM is derived through Light Detection and Ranging (LiDAR) methods utilized in the Regional LiDAR Project (DRCOG, Regional LiDAR Project).

Design and Implementation

Population Zones

Response standards are determined by the National Fire Protection Association (NFPA) which provides research, training, education, codes, and maintains standards for fire services. The NFPA 1720 Standard recommends calls made in Urban Zones receive a response time of 9 minutes or less, Suburban Zones of 10 minutes or less, Rural Zones in 14 minutes or less, and Remote Zones in 14 minutes or less than 80-90% of the time. As these zones are not specifically defined by the US Census, the NFPA has provided qualifications for each zone (NFPA, 2022):

- **Urban Zones** with >1000 people/sq. miles.
- **Suburban Zones** with 500-1000 people/sq. miles.
- **Rural Zones** with <500 people/sq. miles.
- **Remote Zones** with a travel distance of 8 miles or over.

To determine population zones within Evergreen Fire Protection District, census blocks with 2020 population data were obtained and clipped to the Evergreen Fire protection district boundary. Evergreen, Colorado is a census-designated place located in unincorporated Jefferson and Clear Creek Counties. The Evergreen Fire Protection District boundary includes this area and extends beyond. Given the unincorporated nature of the study area, census blocks did not fit perfectly within the Evergreen Fire Protection District, and intersecting blocks were divided by the boundary line. This spilt required adjusting the population data to accommodate the change in block area provided by the following:

Adjusted Population = (Population of the Split Block / Total Area of the Split Block) x Area of the portion of the Split Block within the boundary

Population zones are then derived by applying the following formula to the table:

Population density = Total population / Area

Predetermined remote areas were requested by the fire department to remain intact based on the prior analysis. This prior analysis found the northwest and southeast regions to be considered remote areas, consistently exceeding the 14-

minute response time, and using PPGIS methods with local knowledge of the general area, these areas were drawn into the original population zones. These remote areas were confirmed through a service area analysis using the original network dataset from the CAD system with a maximum service distance of eight network-based miles from each station, although initial drawings displayed these areas in aggregated polygons. The Service Area Analysis leverages the network dataset to determine serviceable areas based on time and distance perimeters (GIS Geography, 2022).

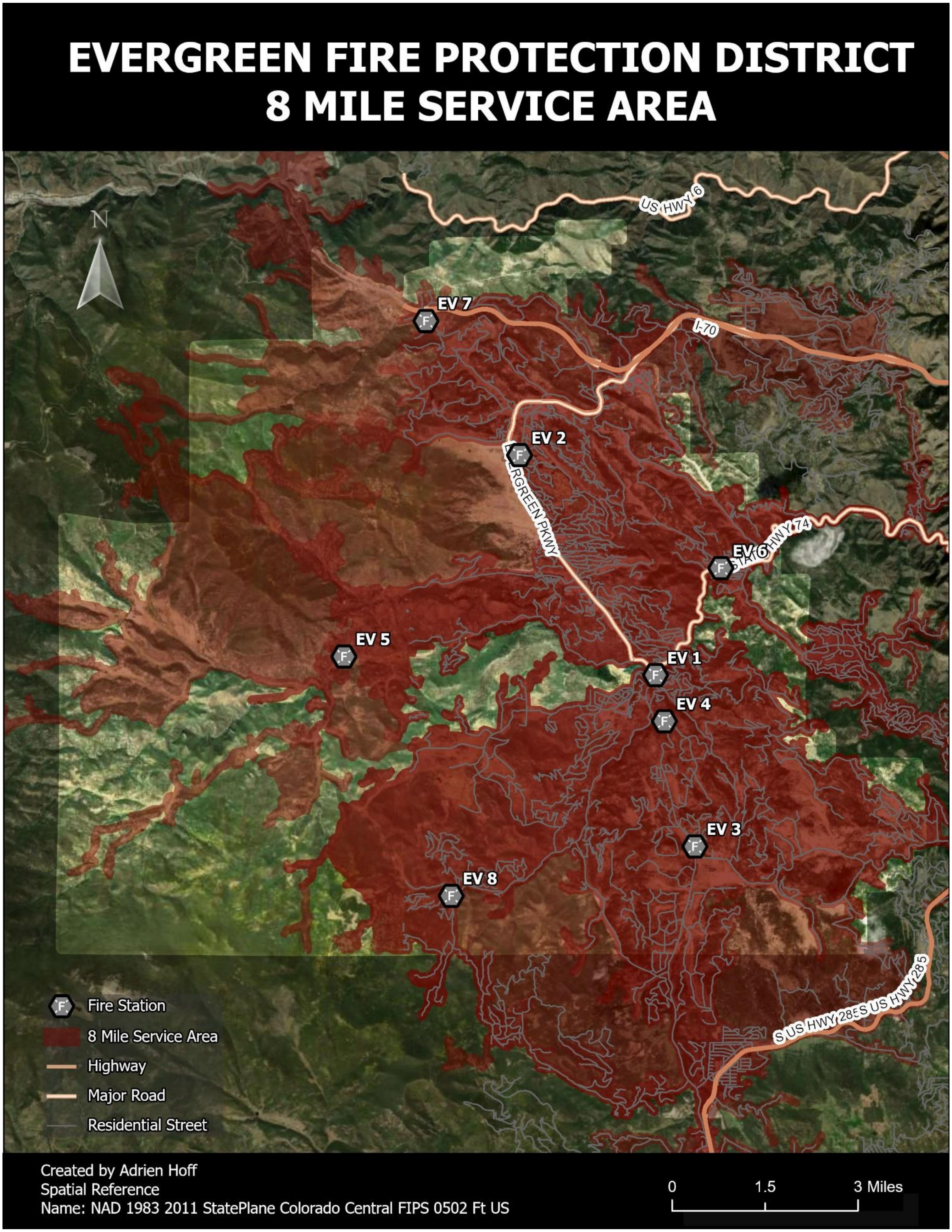


Figure 2: 8 mile service area coverage from each Evergreen Fire Station

Spatial Autocorrelation

Once population zones were achieved, SQL annual response data for Evergreen Fire Protection District could be derived from the CAD database table, dbo.response, and the GPS data was spatially joined to the population zones with ArcGIS Pro. Each record was then determined if it met the NFPA standard based on population zone.

Response records, classified by Master Incident Number, which were determined to be over the 1720 benchmark were retrieved for an annual response delay cluster analysis. Moran's I is a measurement of spatial correlation, used to find clustering of patterns across a study area. Counts of individual points are aggregated into a grid or polygons and observed for density clustering. Census blocks were retained for the cluster analysis. Moran's I suggest data are clustered when the average distance of neighboring clusters is less than the distance between the observed features (Levine, 2013). Moran's I is represented in Figure 1 (ESRI, "How Spatial Autocorrelation (Global Moran's I) works"):

The Moran's I statistic for spatial autocorrelation is given as:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} z_i z_j}{\sum_{i=1}^{n} z_i^2} \qquad (1)$$

where z_i is the deviation of an attribute for feature i from its mean $(x_i - \bar{X})$, $w_{i,j}$ is the spatial weight between feature i and j, n is equal to the total number of features, and S_0 is the aggregate of all the spatial weights:

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} \qquad (2)$$

The z_I-score for the statistic is computed as:

$$z_I = \frac{I - \mathrm{E}[I]}{\sqrt{\mathrm{V}[I]}} \qquad (3)$$

where:

$$\mathrm{E}[I] = -1/(n-1) \qquad (4)$$

$$\mathrm{V}[I] = \mathrm{E}[I^2] - \mathrm{E}[I]^2 \qquad (5)$$

Figure 3: Moran's I equation

Regression Analysis

Results of the cluster analysis narrowed the focus for regression analysis based on areas with the greatest clustering significance or “hot spots”. Annual Response Delay points represented by their destination coordinates were selected from the greatest clustered blocks. Automated Vehicle Location (AVL) data was then pulled from the SQL database.

AVL data records vehicle location in GPS coordinates around every 100 meters of the moving target. The Department of Homeland Security reports AVL accuracy between 15-20 feet on differential-GPS compatible systems (Department of Homeland Security, 2009). AVL data was used to select road data from Jefferson County Road and Bridge Maintained Roads GIS data and Colorado Department Of Transportation (CDOT) Highway Pavement and Driveability GIS data by a 5-meter buffer of each point. These road sources provide Pavement Condition Indexes and width data for all public roads within the unincorporated Jefferson County portions of Evergreen, Colorado.

CDOT determines pavement conditions based on road fatigue, longitudinal and traverse cracking, road roughness, and pavement rutting. The conditionals are then normalized into pavement condition indices ranging from a scale of 0 in the road segments' worst state and 100 in its best (Colorado Department of Transportation, 2021). Similarly, Jefferson County pavement conditions were classified by scores from 0-100 with breaks of 20 per quality ranging from failing to excellent. These scores were merged into a single scoring system for consistency.

Roads selected by intersecting AVL data were sorted by Master Incident Number and merged to single features with averaged condition indices and widths. The slope was then calculated from DRCOG DEM and the degree of slope per path of response was found by extracting slope values to vertices and finding the mean. Delay in response from the 1720 standard was calculated over the distance traveled to maintain consistency within the data.

Utilizing multivariate regression methods, linear analysis was conducted to observe the correlation, significance, and collinearity of the dependent delay over distance traveled variable as it is tested against the independent variables of slope, pavement condition, and road width. Of the 100 selected responses from the cluster analysis, 37 had recorded AVL data which was retrieved. The 37 paths were then used as the units for observation and sample size. Data for the independent variables was not normally distributed so a log transformation was applied.

Original observations of the correlation matrix suggest that pavement condition, width, and slope all had a negative linear relationship to the delay in response. None of the variables were statistically significant at the 0.1 statistical level.

A factor analysis was performed to observe if there was a need for redundancy reduction between the time delay data. Results of the KMO and Bartlett's test produced a significance score of <0.001 indicating a small need for a reduction but the KMO value of 0.588 landed between miserable and mediocre indicating not worth the reduction factor analysis.

Origin-Destination Cost Matrix

An Origin-Destination (OD) Cost Matrix was created to determine predicted travel times in minutes from each originating station in Evergreen Fire Protection District and the centers of each census block using the original CAD network dataset where impassible road impedance, tabular speed, and travel direction were honored as restrictions and the ESRI traffic layer was incorporated. “The OD cost matrix finds and measures the least-cost paths along the network from multiple origins to multiple destinations.” (ESRI, “OD Cost Matrix”). The results from this analysis were then summarized by census block for the minimum travel time to determine the average drive time from each station.

A second OD Cost Matrix was performed with slope, width, and pavement condition indices added in conjunction with the original road network restrictions. Per CDOT’s Maximum Grade for Design Speed, the maximum grade for mountainous rural areas is suggested to be no greater than 16% for local rural roads (Colorado Department of Transportation, 2018). This percentage was factored in for the slope restriction. Using NFPA standards for fire apparatus access road specifications, a minimum restriction of 20ft in width was applied as a second restriction (NFPA, 2021). Pavement condition indices were applied with a minimum restriction based on qualifying failed to poor conditions from the merged datasets. As in the first analysis, minimum travel time was determined through field calculations and applied to each census block.

Flowcharts

The following tasks were generated in ArcGIS Pro Model Builder for enhanced workflow. The first model displays the process for determining population zones from the Census derived data and generation of the Moran's I autocorrelation statistic. The second model displays the workflow for obtaining multiple street dataset sources, merging them, and joining the independent variables within that data to the AVL derived delayed response paths. The result of this process is a table prepared for use in SPSS for regression analysis. The final is the workflow for creating the network dataset and generating the OD cost matrices with and without restrictions.

Figure 4: Flowchart for finding population zones and creating Moran's I autocorrelation statistic.

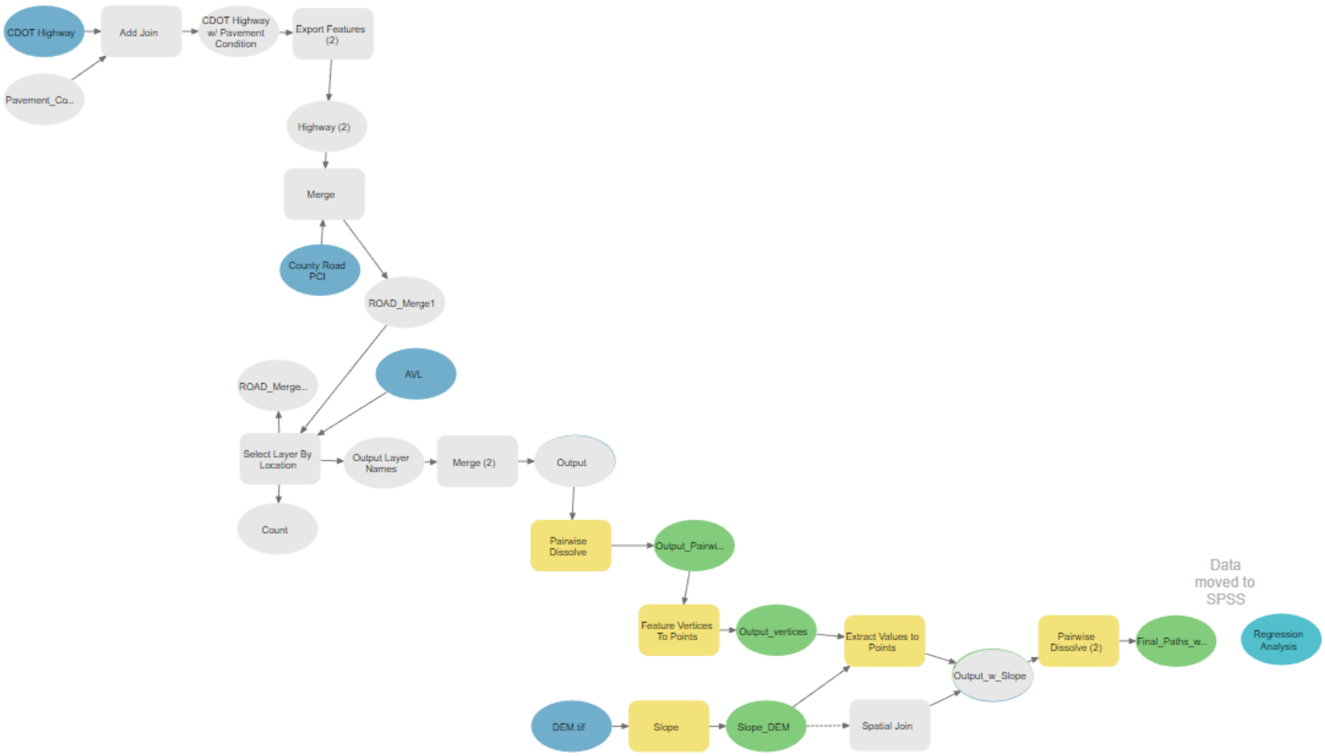


Figure 5: Flowchart for finding response delay paths, joining independent values, and preparing for SPSS.

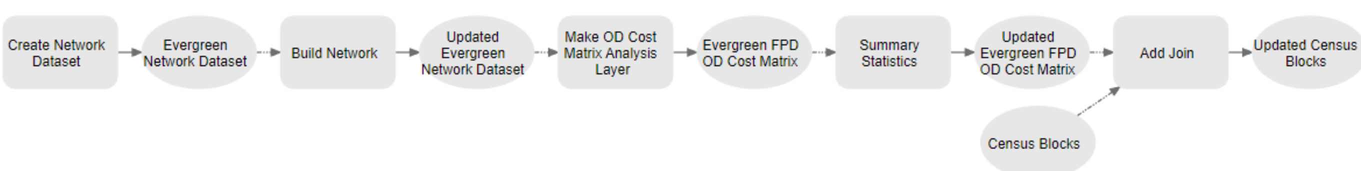


Figure 6: Flowchart for creating OD Cost Matrix and determining the least time traveled to each census block

Results

Population Zones

Evergreen Fire Protection District was found to have higher concentrations of population near highways and population centers. Suburban and Urban areas occur along highways and major county roads, predominantly in the East of Jefferson County. The Suburban areas contain 20% of the population with a total of 3.5 square miles in area coverage. 32% of the population belongs to the Urban areas which cover 6.4 square miles of the district. Rural areas were found scattered throughout the district, predominantly in Clear Creek County and further from main access roads. These areas contain 48% of the district population and 91.5 square miles of the district. Remote areas were kept intact by request with known accessibility issues as suggested by the protection district, totaling 14.3 square miles.

OBJECTID *	Shape *	PopZone	SqMi	Acres
2	Polygon	Remote	14.290727	9146.324496
3	Polygon	Rural	91.552869	58596.721364
4	Polygon	Suburban	3.527915	2257.960555
5	Polygon	Urban	6.448722	4127.354593

Figure 7: Population Zone Area.

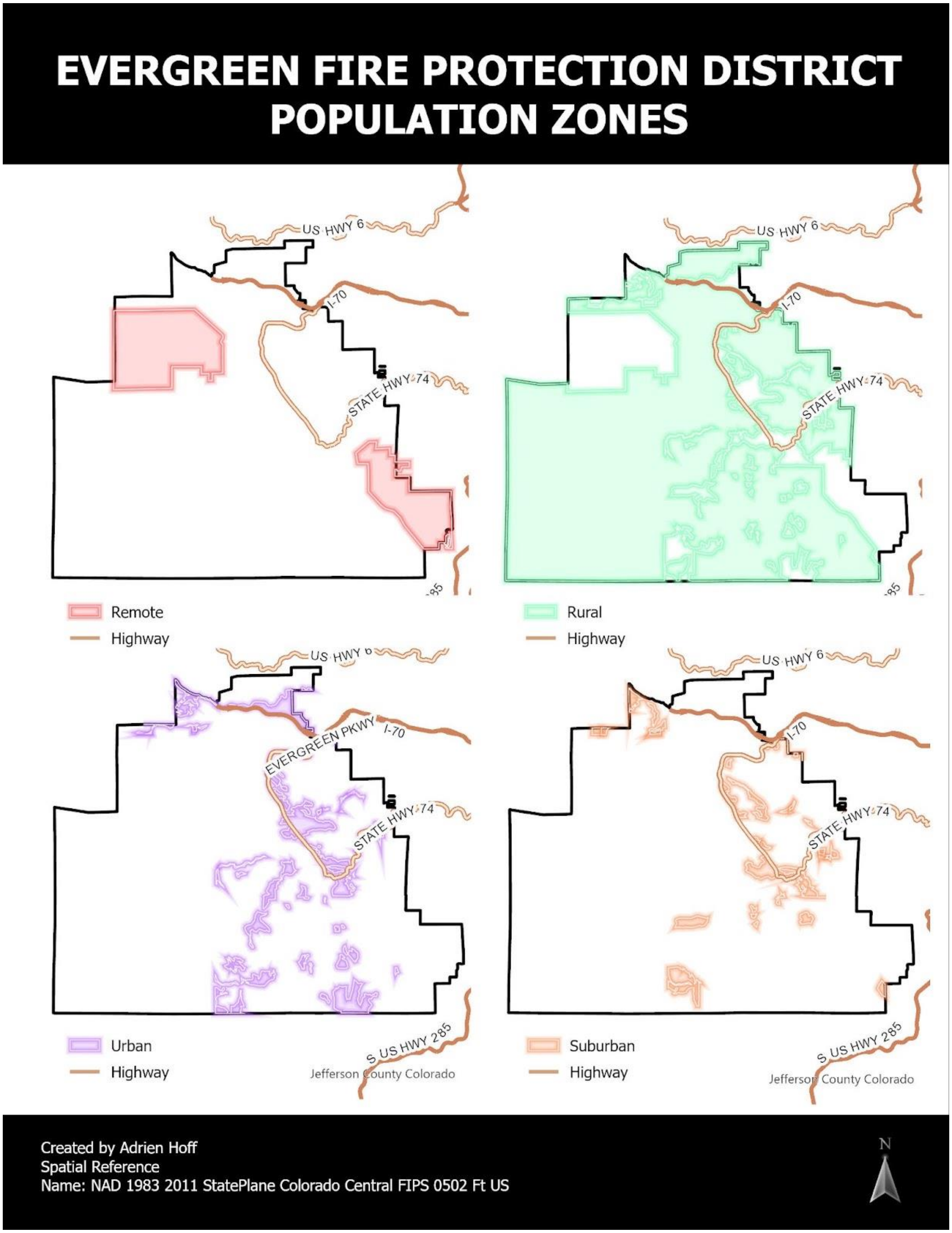
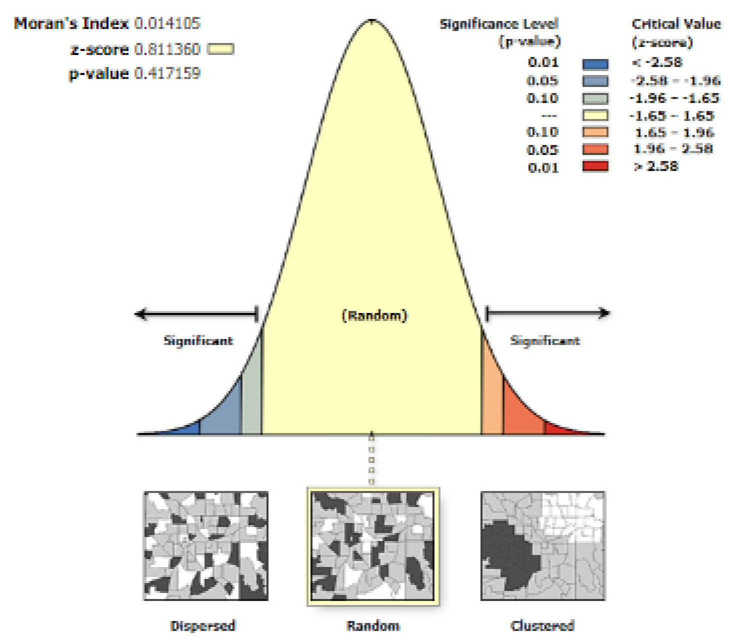


Figure 8: Population Zones for Evergreen Fire Protection District

Spatial Autocorrelation

Moran’s I was chosen to observe cluster patterning of point density in comparison to neighboring census blocks. Results of Moran’s I Analysis for response delay activity returned a greatest Z-score of 0.811 and a P-value of 0.417. A Z-score of 0.811 falls between -1.65 and 1.65 indicating random patterning of clustering results. Similarly, the p-value also indicates a lack of significance in clustering. The greatest clustering was found between station one and station three in each population zone classification. In an attempt to discover the reasoning for delays in these areas, the regression analysis was generated.

Spatial Autocorrelation Report



Given the z-score of 0.81136, the pattern does not appear to be significantly different than random.

Global Moran's I Summary

Moran's Index	0.014105
Expected Index	-0.001876
Variance	0.000388
z-score	0.811360
p-value	0.417159

Dataset Information

Input Feature Class:	Block_Data_Cli_ExportFeature
Input Field:	CALL_DELAY
Conceptualization:	K_NEAREST_NEIGHBORS
Distance Method:	EUCLIDEAN
Row Standardization:	True

Figure 9: Spatial Autocorrelation Results

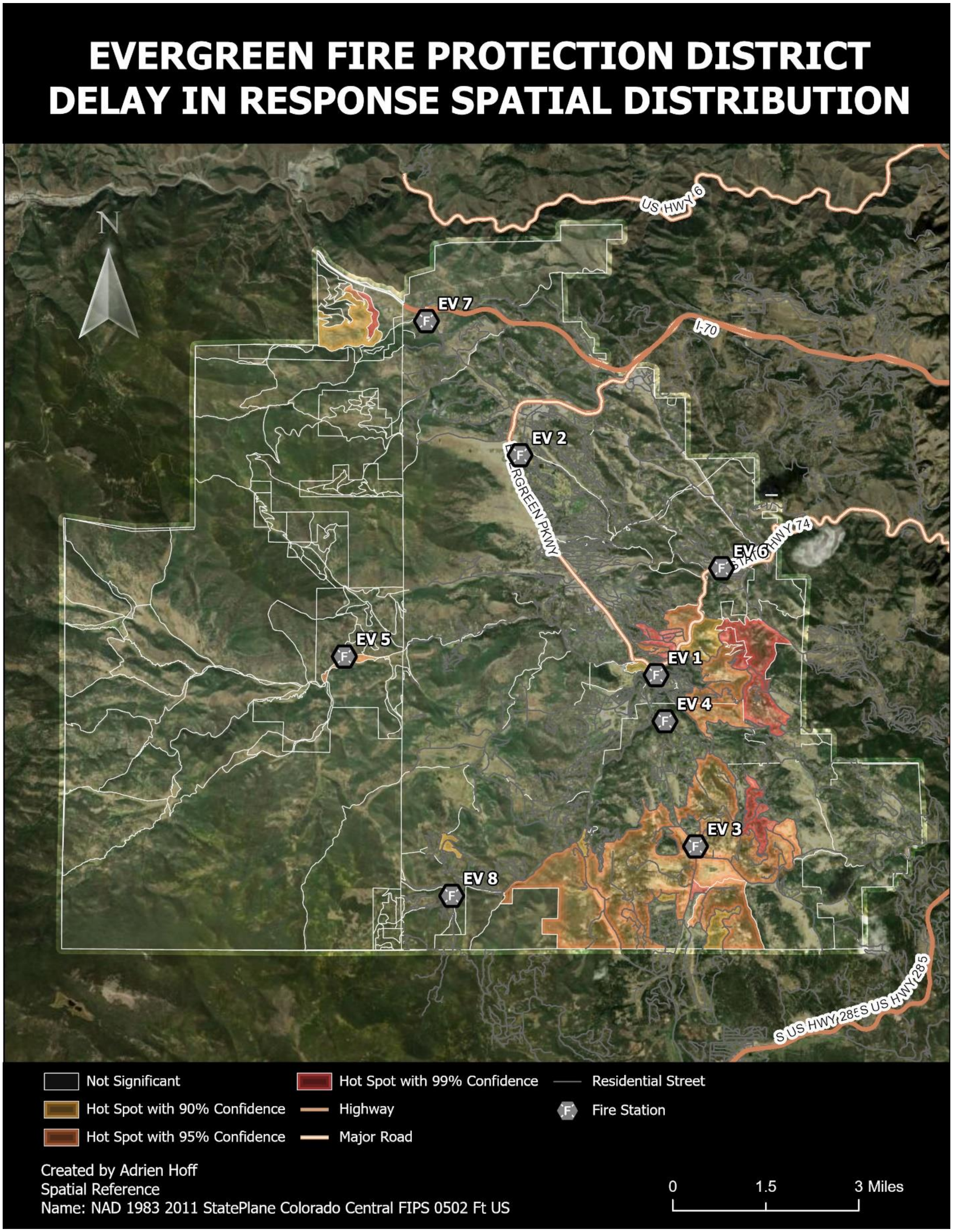


Figure 10: Moran's I Clustering Hot Spots for Delays in Response

Regression Analysis

Of the 100 response delays intersecting hot spots found by the Moran's I analysis, only 37 AVL records were able to be retrieved from the SQL database. Regression analysis in SPSS returned the absolute value of the Beta coefficient and the partial coefficients with lower values than the Zero-Order values for the Log of Width, suggesting a lack of suppression for the hypothesized variables' effect on response delay (Nadi and Murad, 2019). However, the Log of Pavement Condition and Log of Slope returned partial coefficients greater than the zero-order value with Beta coefficients less than the zero-order value, suggesting suppression with this variable. Each variable returned a significance value over the 0.05 confidence level suggesting no sign of significance in explaining response delay. The beta coefficients returned negative correlation values for all independent variables. This was expected of width and pavement condition.

The final equation for the log-transformed variables resulted as:

$$Yp = 490.430 - 173.391 \log PavementCondition - 83.034 \log Width - 51.958 \log Slope$$

Normality of residuals was returned closest to a heteroscedastic and unbiased pattern (figure 6).

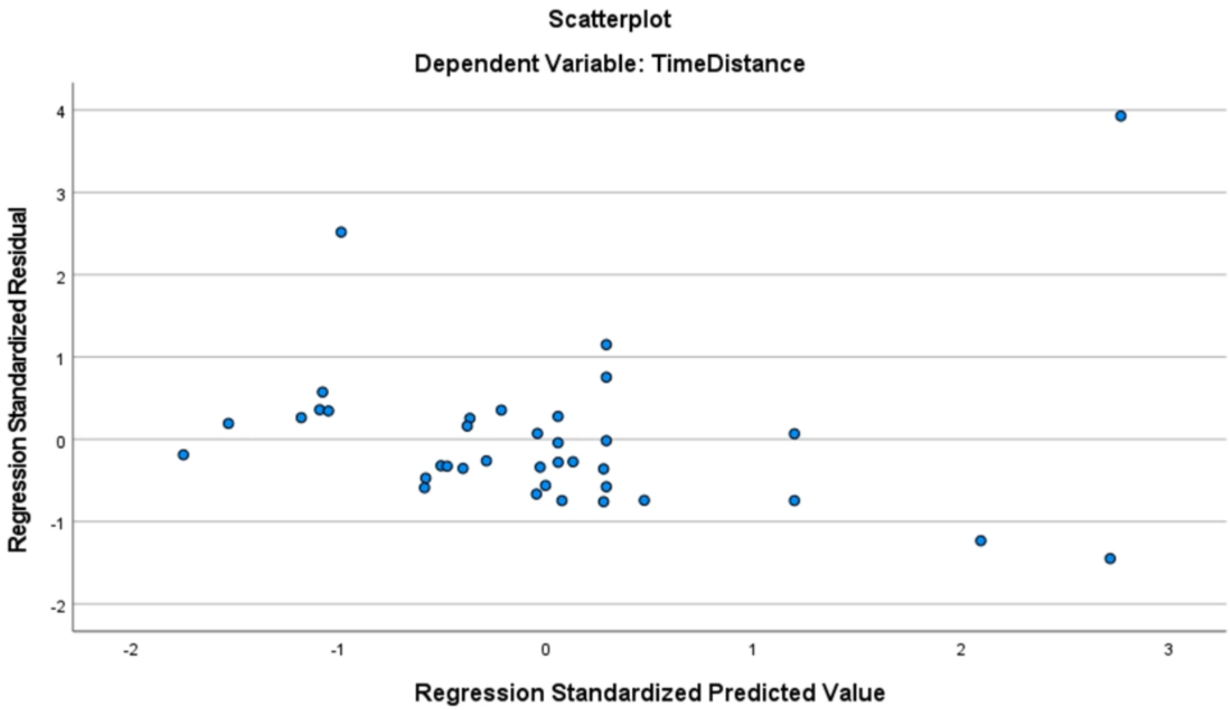


Figure 11: Residual Regression Scatterplot for Log Transformed Variables

Origin-Destination Cost Matrix Results

Two OD Cost Matrices were generated to understand predicted travel times from each station to each census block centeroid as they exist within the CAD system. Although a lack of significance in clustering and a lack of significance with independent variables was determined, independent variables were considered in the creation of the second network dataset along with elements of the first, including impassible road impedance, tabular speed, and travel direction restrictions and ESRI’s current traffic layer. The results of the initial OD Cost Matrix suggest areas that were predetermined as Urban or Suburban with nine to 10-minute response requirements should be reconsidered as rural or remote with allowances of 14-minute response times, with some blocks suggesting minimum travel time to over an hour. Many areas determined to have expected minimum travel times over 14 minutes intersect the service area and fall under the eight-mile distance suggested response area for remote zones. Conversely, many areas considered rural had minimum travel times within the range of under nine minutes. The second analysis suggested elements of slope, width, and PCI would include additional areas with greater travel times which should be included in the remote and rural categories.

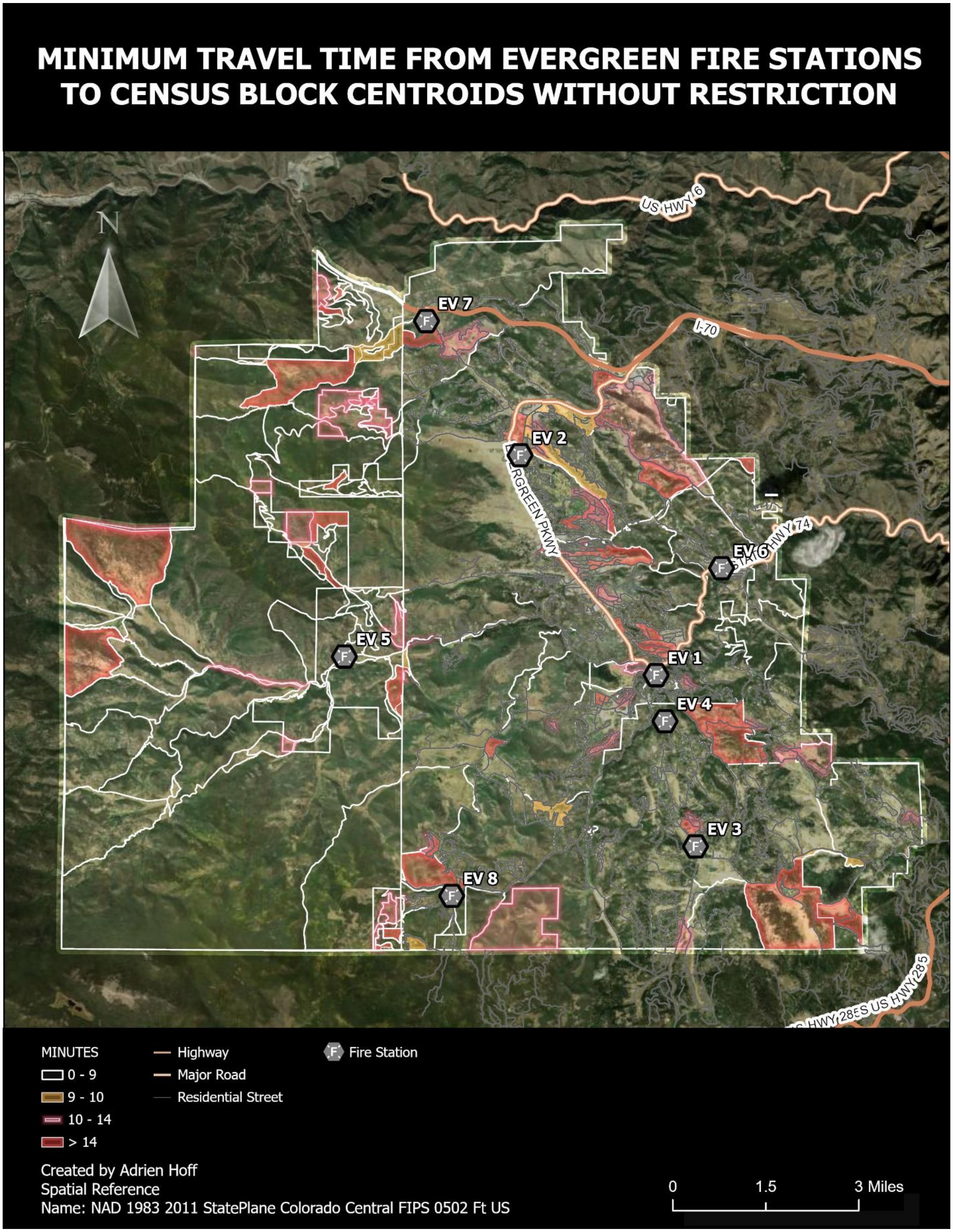


Figure 72: Minimum Travel Time using original CAD network

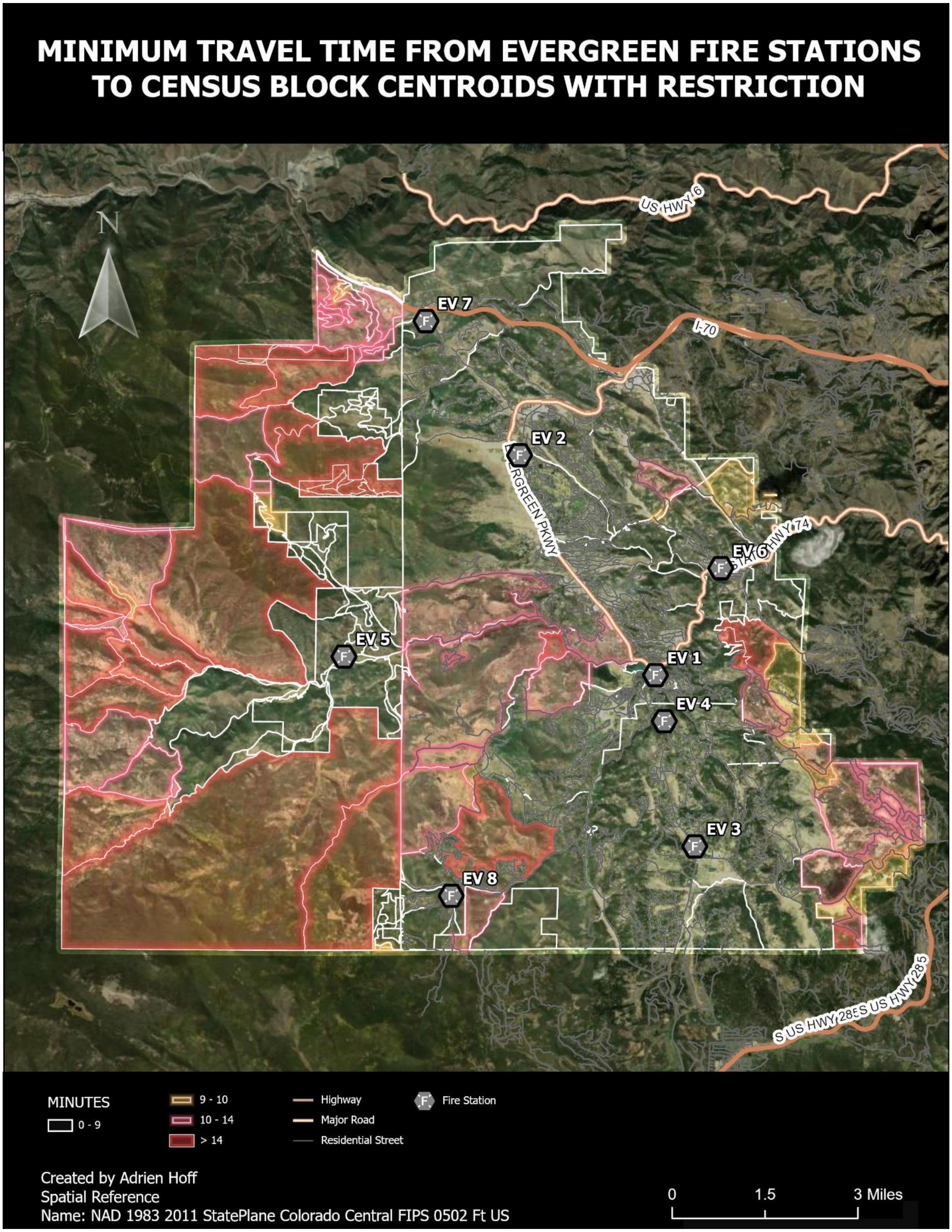


Figure 83: Minimum Travel Time using weight restricted network.

Discussion

Spatial Autocorrelation results indicate clustering hot spots in this annual review are not considered significant and would not be expected to return hot-spot concentrations in the same areas in the following years. The null hypothesis that assumes delays in response should not be significantly dispersed or clustered cannot be rejected and finds distribution in completely spatially random (CSR) distribution. No significance should not be interpreted as a lack of clustering but that the clustering is not significant and these may not be repeated areas in next year's analysis

The original observation of the correlation table suggested the independent variables exhibited a low and negative correlation to the dependent variable. This data was unsuited for the Factor Analysis. Log transformations derived greater significance than the independent variables in their original state. The negative correlation of width and pavement condition to response delay suggests a relationship of longer delay time to less welcoming roads, however, the Adjusted R-Squared was low enough to assume a lack of explanation from the independent variables on the variance of the dependent variable. This, along with a higher P-value than the confidence level suggests that the null hypothesis is to be accepted and no definitive conclusion can be assumed to a connection of pavement condition, width, or road slope.

The original OD Cost Matrix does not factor in road impedances beyond what is already implemented into the system but highlights areas for consideration that are difficult to access, as well as areas flagged for longer response times that may not be necessary. Results from this analysis would encourage reconsideration of the census-derived population zones to include additional remote areas. Initial OD Cost Matrix results highlight that mountainous areas cannot be held to the eight mile distance consideration for remote areas as determined by the NFPA. It suggests that while destinations may be within a short distance, mountain networks offer greater challenges that result in greater travel times than expected on flat terrain. The second OD Cost Matrix results include additional areas for delayed access based on independent variables. While these variables were not significantly correlated to the greatest density areas for delay, it would be beneficial to compare these elements of the network to delayed responses in the areas determined for the greatest delay. This would include a need to reconsider the spatial autocorrelation and regression analysis performed based on a new set of determined delays in census blocks with the greatest minimum expected travel time. Results of both OD Cost Matrices challenge NFPA standards for mountainous areas and suggest further examination for determining population zones. Further examination to find a significant correlation to elements of the road network to response delays may assist in suggested standards for mountain-based fire departments.

Areas for Further research

Following this research, it is recommended that population zones for Evergreen Fire Protection District be recreated to include additional remote areas based on results from the OD Cost Matrices. Results of the OD Cost Matrix would also indicate a need for reassessing the urban and suburban areas with included travel time estimates and consideration for additional station resources near inaccessible areas. It challenges the NFPA suggestions for determining population zones. Based on the need for population zone reconsideration; the response delay records, clustering analysis, and regression analysis should be performed again to account for new response delay numbers and stronger correlation to the independent variables. It is also suggested that the regression analysis be expanded to include additional response delays than those found in the clustering to allow for more observations, with consideration of available AVL data. It is recommended that Jeffcom911 evaluate the lack of available AVL data recorded within the CAD database.

A new regression analysis would benefit from additional considerations for closest vehicle availability and other possible road impedances. Additional road impedances for consideration include traction and speed factors on roads in correlation to weather conditions on sloping roads, as well as the impact of snowbanks on roads. It may also be beneficial to determine the impact on the cause for delay by each call for service, specifically examining medical, wildland, rescue, etc. independently.

Future analysis may also benefit the fire district in their 2023-2024 Master Plan which seeks to recommend appropriate departmental staffing, structure, guidelines, and infrastructure changes. This research may be applied to the creation of the Master Plan and expanded upon with consideration to risk assessment, strategic plans, and response time analyses. Future applications of this research which may benefit the strategic planning portion include the provision of tabular data detailing impedances for each road segment and a thematic road map showcasing problematic areas.

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Appendix

Descriptive Statistics for Multivariate Regression with Log Transformation on independent Variables:

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
LG10OCI	37	1.62	1.93	1.7782	.06149	-.571	.388	1.797	.759
LG10Width	37	1.28	1.65	1.4022	.07859	1.207	.388	3.889	.759
LG10Slope	37	.55	.80	.6627	.06663	.626	.388	.333	.759
Valid N (listwise)	37								

Correlation Statistics for Multivariate Regression with Log Transformation on independent Variables:

Correlations

		TimeDistance	LG10OCI	LG10Width	LG10Slope
TimeDistance	Pearson Correlation	1	-.251	-.035	-.115
	Sig. (2-tailed)		.134	.837	.499
	N	37	37	37	37
LG10OCI	Pearson Correlation	-.251	1	-.277	.481**
	Sig. (2-tailed)	.134		.097	.003
	N	37	37	37	37
LG10Width	Pearson Correlation	-.035	-.277	1	-.584**
	Sig. (2-tailed)	.837	.097		<.001
	N	37	37	37	37
LG10Slope	Pearson Correlation	-.115	.481**	-.584**	1
	Sig. (2-tailed)	.499	.003	<.001	
	N	37	37	37	37

**. Correlation is significant at the 0.01 level (2-tailed).

KMO and Bartlett's Test results:

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.588
Bartlett's Test of Sphericity	Approx. Chi-Square	25.793
	df	6
	Sig.	<.001

Coefficients for log transformed variables:

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Correlations			Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	490.430	289.495		1.694	.100	-98.552	1079.412					
	LG10OCI	-173.391	130.312	-.254	-1.331	.192	-438.513	91.731	-.251	-.226	-.222	.769	1.301
	LG10Width	-82.034	110.147	-.153	-.745	.462	-306.130	142.063	-.035	-.129	-.124	.659	1.518
	LG10Slope	-51.958	142.386	-.082	-.365	.718	-341.645	237.729	-.115	-.063	-.061	.548	1.824

a. Dependent Variable: TimeDistance

Model Summary of log transformed variables with regional dummy:

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.280[a]	.078	-.005	00:42.15	.078	.936	3	33	.434

a. Predictors: (Constant), LG10Slope, LG10OCI, LG10Width

b. Dependent Variable: TimeDistance

Regression Stats for Log Transformed Variables:

Residuals Statistics[a]

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	00:12.10	01:05.27	00:32.66	00:11.77	37
Residual	-01:01.1	02:45.63	00:00.00	00:40.36	37
Std. Predicted Value	-1.746	2.770	.000	1.000	37
Std. Residual	-1.449	3.929	.000	.957	37

a. Dependent Variable: TimeDistance

Table 1: Data for road attribute multiple regression (Created by Adrien Hoff)

MASTER INCIDENT NUMBER	TIME/DISTANCE	MEAN_ESTIMATED_PCI	MEAN_WIDTH	SLOPE

2022EV-0004717	00:45.1	63.44333333	23.10344828	4.911793085
2022EV-0005250	00:04.2	85.12111111	19.55555556	5.32805979
2022EV-0005313	00:18.1	60.33076923	26.28	4.299674412
2022EV-0007584	00:18.3	67.34473684	21.78947368	4.583306383
2022EV-0016613	00:13.1	63.88387097	25.96666667	4.394880953
2022EV-0031536	00:01.0	69.35	21.25	5.051019367
2022EV-0032632	00:09.0	59.97323529	26.27272727	4.32867505
2022EV-0050040	01:24.6	59.601	19	6.327734846
2022EV-0052851	00:39.1	63.4075	26.5483871	4.276614661
2022EV-0054601	00:35.2	61.41193548	24.83333333	4.461676232
2022EV-0059343	00:22.7	58.68884615	26.6	4.258387104
2022EV-0080642	00:29.9	69.916875	24.06666667	5.505944704
2022EV-0081773	00:13.2	65.8969697	24.53125	4.581638569
2022EV-0073262	01:07.9	59.601	19	6.327734846
2022EV-0073157	00:35.4	59.601	19	6.327734846
2022EV-0044147	00:11.8	59.601	19	6.327734846
2022EV-0002922	00:22.8	59.29166667	44.66666667	4.316891977
2022EV-0003487	02:07.2	70.30045455	27.14285714	4.044232895
2022EV-0033906	00:20.8	57.01785714	26	4.501726013

2022EV-0048356	00:35.0	55.51	44	4.379143785
2022EV-0054185	00:35.0	61.27928571	28.16666667	4.393901774
2022EV-0061340	00:13.3	65.72157895	23.27777778	4.944117811
2022EV-0006677	00:44.2	75.48782609	22.43478261	4.514152053
2022EV-0007917	00:04.0	57.01785714	26	4.501726013
2022EV-0014288	00:03.6	42.51166667	25.16666667	3.533235772
2022EV-0021805	00:21.6	56.23916667	25.18181818	5.55624884
2022EV-0026016	00:05.4	44.17111111	28.33333333	3.569944408
2022EV-0026589	00:07.0	57.73777778	24.25	4.35082812
2022EV-0027780	00:02.2	56.64785714	28.33333333	4.45994885
2022EV-0031661	03:50.9	41.59857143	25.78571429	3.559242999
2022EV-0038397	00:49.6	51.61230769	26.38461538	3.796207005
2022EV-0038415	00:15.4	51.61230769	26.38461538	3.796207005
2022EV-0047155	00:45.1	58.67066667	25.69230769	4.676152772
2022EV-0051253	00:31.6	58.67066667	25.69230769	4.676152772
2022EV-0060302	00:04.1	60.33392857	26.48148148	4.286902832
2022EV-0067646	00:06.0	64.44517241	26.75	4.472784328
2022EV-0081716	00:34.9	68.22853659	27.325	4.5658313

Python script used for grabbing counts of delayed calls per census block:

```
#get count of calls per census tract for Moran's I
with arcpy.da.SearchCursor ("Block_Data_Cli_ExportFeature", ["GEOTXT"])
as cursor:
    for row in cursor:
        Block = row[0]
        where_Clause = "GEOTXT= '"+Block+"'"

arcpy.SelectLayerByAttribute_management("Block_Data_Cli_ExportFeature",
"NEW_SELECTION", where_Clause)
        arcpy.SelectLayerByLocation_management('Annual_Delay',
'INTERSECT', 'Block_Data_Cli_ExportFeature', "", "NEW_SELECTION")
        Count =
int(arcpy.GetCount_management('Annual_Delay').getOutput(0))
        with arcpy.da.UpdateCursor('Block_Data_Cli_ExportFeature',
"Call_delay") as cursor:
            for row in cursor:
                row[0] = Count
                cursor.updateRow(row)
                arcpy.SelectLayerByAttribute_management('Annual_Delay',
"CLEAR_SELECTION")

arcpy.SelectLayerByAttribute_management('Block_Data_Cli_ExportFeature',
'CLEAR_SELECTION')
```

Python script used to extract Master Incident Numbers from Moran's I cluster results to extract AVL Data from SQL:

```
import arcpy

fc ="Annual_Delay_Statistics"
column_name = "Master_Incident_Number"

# Use a set to store unique values
unique_values = set()

# Loop through rows and add unique values to set
with arcpy.da.SearchCursor(fc, [column_name]) as cursor:
    for row in cursor:
        value = row[0]
        unique_values.add(value)

# Convert set to list and sort alphabetically
```

```
unique_values = sorted(list(unique_values))

# Print list of unique values
for value in unique_values:
    print(value)
```

Python script for extracting intersecting roads within a 5 meter radius of AVL data to individual tables based on Master Incident Number:

```
import os

# Set the name of the table
unique_values_table = "AVL_EV_WGS_Statistics1"

# Set the name of the field to iterate through
unique_values_field = "Master_Incident_Number"

# Set the name of the table with the data you want to select
target_table = "AVL_EV_WGS_PointsToLine"

# Set the name of the field in the target table that contains the unique
values
target_field = "Master_Incident_Number"

# Set the name of the first road feature class
road_lines1 = "ROAD_Merge1"

# Get a list of unique values from the unique values table
unique_values = []
with arcpy.da.SearchCursor(unique_values_table, [unique_values_field]) as
cursor:
    for row in cursor:
        if row[0] not in unique_values:
            unique_values.append(row[0])

# Loop through the unique values and select the corresponding rows in the
target table
for value in unique_values:
    where_clause = "{} = '{}'".format(arcpy.AddFieldDelimiters(target_table,
target_field), value)
    arcpy.SelectLayerByAttribute_management(target_table,
"NEW_SELECTION", where_clause)
```

```
    # Select the road feature classes that intersect the selected points within
a 10-meter radius
    roadselection = arcpy.SelectLayerByLocation_management(road_lines1,
"INTERSECT", target_table, "5 Meters")

# Create a new output feature class with all fields from the road layer plus a
field for the unique value
    output_name = "{}.shp".format(value.replace("-", " "))
    output_path = os.path.join(r"G:\GIS ORG\GIS
Local\PROJECTS\EVERGREEN POP ZONES\Multicollinearity", output_name)
    arcpy.management.CopyFeatures(road_lines1, output_path)
    #arcpy.AddField_management(output_path, "Unique_Value", "TEXT",'','',
field_length=8)
    #arcpy.CalculateField_management(output_path, "Unique_Value",
"'{}'".format(value), "PYTHON")

    # Clear the selection on the target table and the road feature classes
    arcpy.SelectLayerByAttribute_management(target_table,
"CLEAR_SELECTION")
    arcpy.SelectLayerByAttribute_management(road_lines1,
"CLEAR_SELECTION")
    arcpy.SelectLayerByAttribute_management(target_table,
'CLEAR_SELECTION')
```

SQL script for retrieving AVL data:

```
SELECT Master_Incident_Number, Response_Date, Problem, (convert(float, A.[Longitude]) /
1000000) * -1 as Longitude

    , convert(float, A.[Latitude]) / 1000000 as Latitude

  FROM [Reporting_System].[dbo].[Response_Master_Incident] RMI

  Left join AVL A

  On A.Master_Incident_ID = RMI.ID

  where Master_Incident_Number IN ('2022EV-0000468',

'2022EV-0001288',

…

'2022EV-0082583',
```

```
'2022EV-0082849',
'2022EV-0082875')
Order by Master_Incident_Number, Response_Date
```

Metadata

Metadata for Evergreen Fire Protection District Population Zones:

PopZones_Evergreen

Type File Geodatabase Feature Class

Tags Population Zones, NFPA, Response, Evergreen Fire Protection District

Summary

Population zones for Evergreen Fire Protection District as determined by NFPA population zone standards.

Description

Population zones for Evergreen Fire Protection District as determined by NFPA population zone standards. NFPA determines Urban, Suburban, Rural, and Remote areas as:

Urban Zones with >1000 people/sq. miles.

Suburban Zones with 500-1000 people/sq. miles.

Rural Zones with <500 people/sq. miles.

Remote Zones with a travel distance of 8 miles or over.

Remote Zones for this feature retain and honor remote zones previously found in prior analysis conducted for Evergreen Fire Protection District, as requested by the agency.

This data can be spatially joined to CAD response.dbo tables from Microsoft Excel for response time analysis.

Credits

Created by Adrien Hoff, Senior GIS Specialist - Jeffcom911.

Metadata for Morans I Spatial Autocorrelation Hot-Spot Results:

Call_HotSpots

Type File Geodatabase Feature Class

Tags Spatial Autocorrelation, Delayed Response, NFPA, Evergreen Fire Protection District, Hot Spot

Summary

Delayed Response Hot Spots for Evergreen Fire Protection District.

Description

Delayed Response Hot Spots for Evergreen Fire Protection District as determined by Moran's I Spatial Correlation Analysis of 2022 response delays. Response data was derived from the Jeffcom911 CAD SQL database and joined to Evergreen Population Zones to determine records with delays. Annual delays in response were then analyzed for spatial autocorrelation using Moran's I and nearest neighbor methods. No significant correlation was found for this data. Results of the Moran's I for response delay activity returned a greatest Z-score of 0.811 and a P-value of 0.417. A Z-score of 0.811 falls between -1.65 and 1.65 indicating random patterning of clustering results. Similarity, the p-value also indicates lack of significance in clustering.

Credits

Created by Adrien Hoff, Senior GIS Specialist - Jeffcom911.

Metadata for Expected Minumum Travel Time - Census Blocks derived from OD Cost Matrix of Original CAD Network Dataset:

CENSUS_BLK_ORG_OD

Type Shapefile

Tags Census, Evergreen Fire Protection District, OD Cost Matrix, Minimum Travel Time

Summary

Displays minimum travel time per census block from each Evergreen Fire Protection District Station.

Description

Displays minimum travel time per census block from each Evergreen Fire Protection District Station as found utilizing OD Cost Matrix. The OD Cost Matrix predicted travel times in minutes from each originating station in Evergreen Fire Protection District and the centers of each census block using the original CAD network. Results of the cost matrix were summarized to find minimum travel minutes to each destination and joined to the census layer for display.

Credits

Created by Adrien Hoff, Senior GIS Specialist - Jeffcom911.

Metadata for Expected Minumum Travel Time - Census Blocks derived from OD Cost Matrix of Restricted Network Dataset:

Metadata Geography Table

OD Cost Matrix Results - Restrictions Applied

Type File Geodatabase Feature Class

Tags Evergreen Fire Protection District, Census, OD Cost Matrix, Minimum Travel Time.

Summary

Displays minimum travel time per census block from each Evergreen Fire Protection District Station with Network Restrictions.

Description

Displays minimum travel time per census block from each Evergreen Fire Protection District Station as found utilizing OD Cost Matrix. The OD Cost Matrix predicted travel times in minutes from each originating station in Evergreen Fire Protection District and the centers of each census block using restrictions of slope, width, and pavement condition added to the original CAD network dataset. Results of the cost matrix were summarized to find minimum travel minutes to each destination and joined to the census layer for graduated symbology display.

Metadata for Evergreen Network Dataset

Metadata Geography Table

Evergreen Network Dataset

Tags Evergreen, Network, Road, Impedance

Summary

Evergreen Road Network with width, slope, and Pavement Condition Indexes.

Description

Evergreen Road Network with width, slope, and Pavement Condition Indexes. Designed for use in OD Cost Matrix Analysis. CDOT defines PCIs with a rating under 20 as failed to poor conditions and was set as a restriction within the dataset. A width of <= 20ft and a slope of >= 16% grade was also applied as a restriction for this analysis.

Metadata for OD Cost Matrix layer

OD-Cost Matrix with Network Restrictions

Type File Geodatabase Feature Class

Tags OD Cost Matrix, Evergreen Fire Protection District, Road Centerline, Network Analysis

Summary

Origin-Destination Cost Matrix for Evergreen, Colorado designed with Network Dataset restrictions including width, slope, and Pavement Condition Indexes (PCI).

Description

Origin-Destination Cost Matrix for Evergreen, Colorado designed with Network Dataset restrictions including width, slope, and Pavement Condition Indexes (PCI). CDOT defines PCIs with a rating under 20 as failed to poor conditions and was used as a restriction within the dataset. Per CDOT's Maximum Grade for Design Speed, the maximum grade for mountainous rural areas is suggested to be no greater than 16% for local rural roads (Colorado Department of Transportation, 2018). This percentage was factored in for the slope restriction. Using NFPA standards for fire apparatus access road specifications, a minimum restriction of 20ft in width was applied as a second restriction (NFPA, 2021).